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Effects of DEM resolution on the calculation of topographical indices: TWI and its components

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Summary A variety of landscape properties have been modelled successfully using topographic indices such as the topographic wetness index (TWI), defined as $\ln(a/\tan\beta)$, where a is the specific upslope area and β is the surface slope. Previous studies have shown the influence of scale on TWI values when converting standard-resolution DEMs to coarser resolutions. In this study a high-resolution digital elevation model (DEM) with a 5 m grid size derived from LIDAR (light detection and ranging) data was used to investigate the scale-dependency of TWI values when converting from high-resolution elevation data to standard-resolution DEMs. First, a set of DEMs was generated from an initial DEM by thinning to resolutions of 10, 25, and 50 m grid sizes to study the effects of lower grid size and decreased information content. Next, to investigate the impact of different information content on DEMs with the same grid size, the three lower resolution DEMs were all interpolated to the original 5 m grid size. In addition to comparing index distribution functions, a second objective was to evaluate differences in spatial patterns. Thus the values of TWI and its components as computed for the seven different DEMs were compared in three different ways: (1) distribution functions and their statistics; (2) cell by cell comparison of four DEMs with the same resolution but different information content; and (3) comparison of blocks of cells within different resolution DEMs with different information content. Like previous TWI studies, the computed specific upstream area decreased on average for higher resolution DEMs while computed slope values followed a narrower distribution. TWI variation between neighbouring cells in 50×50 m areas decreased largely with increasing grid size. A cell by cell comparison of the TWI values of the four 5 m DEMs with different information content showed a clear decrease in correlation with the TWI based on the original DEM with decreasing information content. The results showed considerable differences between topographic indices computed for DEMs of different grid resolution. Interpolating the DEMs to a higher resolution (i.e. a smaller grid size) provided more

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similar TWI distributions, but the pixel by pixel comparison showed that different information contents caused clearly different TWI maps.

Introduction

Topography is a significant control on the spatial distribution of several environmental variables. Rodhe and Seibert (1999), for instance, tested the value of topography to predict the location of wetlands. Western et al. (1999) used topography to predict soil moisture patterns. Topography has also been used to predict soil chemistry (Chen et al., 1997; Johnson et al., 2000; McKenzie and Ryan, 1999; Welsch et al., 2001). Zinko et al. (2005) estimated spatial variations in biodiversity based on topography. Flow of water, which at the landscape scale generally follows topography, is often the most important single factor for many of these variables. Therefore it is possible to estimate spatial variations of hydrological, pedological, and biological properties in a landscape from the information contained in topographic maps. The general approach is to use topographic indices calculated from digital elevation models (DEMs) as a measure of the topographic control on the flow of water.

Different topographic indices allow the quantification of topographic features. These indices are widely used, especially as digital elevation models (DEMs) have become readily available. The topographic wetness index (TWI) was first introduced by Beven and Kirkby (1979) as part of the runoff model TOPMODEL and is probably the most commonly applied topographic index. The TWI is defined as $\ln(a/\tan\beta)$, where $\tan\beta$ is the local slope of the ground surface and a [m] is the upslope area per unit contour length; a is also called specific upslope area and computed as $a = A/L$, where A [m^2] is the upslope area and L [m] is the contour length. This means that locations with a large upslope area receive a high index value and are expected to have relatively higher water availability than locations with a small upslope area that are assumed to have relatively lower water availability and therefore receive a small index value. Steep locations receive a small index value and are expected to be better drained than gently sloped locations, which receive a high index value. Consequently, TWI is a relative measure of the hydrological conditions of a given site in the landscape. The TWI is based on several assumptions. The slope of the ground surface is assumed to represent the slope of the groundwater table while soil hydraulic conductivity and precipitation are both expected to be uniform over the studied landscape. These assumptions can be relaxed, but this requires additional information such as the spatial variation of hydraulic conductivities, which usually is not available. Within boreal forested landscapes, however, the assumptions are generally assumed to be fulfilled (Rodhe and Seibert, 1999). This does not mean that the applicability of this study is limited to boreal landscapes, results of this study can in principle be applied to all areas with a similar topography.

Several studies validate the usefulness of the index, which is increasingly used to estimate landscape features such as hydrological variables (e.g. Band et al., 1993; Rodhe and Seibert, 1999; Western et al., 1999; Whelan and Gandolfi, 2002), variables indirectly influenced by hydrology, such as soil chemistry (Band et al., 1993; Johnson et al., 2000; Welsch et al., 2001; Whelan and Gandolfi, 2002), and plant species richness (Holmgren, 1994; Moore et al., 1993; White and Running, 1994; Zinko et al., 2005). The effect of different methods of calculating the index values is the subject of several studies. These studies mainly focus on computed TWI patterns (Quinn et al., 1991; Tarboton, 1997; Wolock and McCabe, 1995), and only a few compare different methods based on the correlation between TWI computed in different ways and different environmental variables (Sørensen et al., 2006).

Topographic indices are usually computed from gridded elevation data with the resolution of the elevation data influencing the computed index values. Therefore, an important question is how index values are affected by resolution and how index values from DEMs of different resolution can be compared. Previous studies that investigated TWI and its components found that different grid resolutions result in different values of TWI (Wolock and McCabe, 2000). When comparing 30 and 90 m resolutions, the mean of the upslope area is affected. This effect is caused partly by the difference in grid size and partly by the difference in DEM information content (Wolock and Price, 1994). Zhang and Montgomery (1994) determined that for many landscapes a 10 m grid size is sufficient for hydrologic modelling, and that increasing the resolution to 2 or 4 m would provide no important additional information. Lassueur et al. (2006) found that a resolution of 1 m is too fine for predicting plant species richness. Saulnier et al. (1997) observed an increased mean of the TWI with increasing DEM grid size. Similar results were obtained by Wolock and McCabe (2000) who found that the differences in the average values of the topographic characteristics computed from 100 and 1000 m resolutions can be corrected with simple linear equations. Usery et al. (2004) found a gradual decrease in correlation between the original 30 m resolution and the resampled DEMs of 60–1920 m resolution as resolution decreased. Hancock (2005) also found the TWI to be sensitive to changes in grid size even below 10 m grid sizes.

Except for Zhang and Montgomery (1994) and Lassueur et al. (2006), who both used high-resolution data, these previous studies mainly look at grid resolutions in the range of 20–1000 m. In recent years high-resolution data has become more available, and in this study we focus on smaller grid sizes; the finest resolution we used was a 5×5 m DEM derived from LIDAR data (light detection and ranging). From this DEM we generated further six DEMs of different resolution and information content and subsequently analysed the effect on the computed values for TWI and its components (i.e. slope and upslope area). This analysis was based on (1) distribution functions and statistics, (2) cell by cell comparison among four DEMs of same resolution but different information content, and (3) comparison of blocks of cells among DEMs of different resolution and information content. This study thereby focused on effects of using high-resolution DEMs on the computed TWI values.

Materials and methods

Elevation data

LIDAR-measured elevation data was available for a boreal forest area in central Sweden (E 15°10′ N 61°00′). LIDAR is an active remote sensing technique, analogous to radar, but using laser light. LIDAR instruments measure the distance between the instrument itself and a target using laser pulses. The term ''laser altimetry'' is synonymous with LIDAR (Dubayah and Drake, 2000; Hodgson et al., 2003).

The study area is forested (predominantly coniferous) and the soils are mainly glacial till soils. Elevation range from 225 to 350 m with slopes ($\tan\beta$) up to 0.33 averaging at 0.05 (based on the DEM with a 5 m grid-cell resolution). The mean annual precipitation in the study area is about 600 mm of which about 50% become runoff and 50% evapotranspirates.

The raw LIDAR data was filtered to remove points where the vegetation had been measured but not the ground surface elevation (Axelsson, 1999) using the software TerraScan from Terrasolids (Finland). Using the median of all ground surface data points within 5 m × 5 m grid cells (on average 5), a DEM with a grid resolution of 5 m was generated. DEMs of 10, 25, and 50 m grid resolutions were generated using pixel thinning (Software tool: IDRISI 32 software, version I32.21, The Clark labs®, Clark University, MA, USA) of the 5 m DEM. With this pixel thinning algorithm the values of every 2nd, 5th or 10th cell were selected and used for the three new DEMs with coarser resolution. In the following text these three thinned DEMs are called T_{10}, T_{25}, and T_{50}. The thinned DEMs were then transformed back to a grid resolution of 5 m using bilinear interpolation to give three resampled DEMs termed R_{10}, R_{25}, and R_{50} (Fig. 1). While the resampled DEMs had the same grid resolution as the original DEM, they contained less information and were characterized by smooth planes the size of the grid resolution that had been generated by the thinning in the first step; in the following we call these planes 'squares' (Fig. 2). The purpose of the resampled DEMs was to address the question of how much of the differences between values of the TWI and its components for different grid resolutions can be attributed to the resolution solely and how much can be attributed to the varying information content in the DEMs. This also addressed the general suitability of resampling a DEM to a finer resolution to obtain a more detailed basis for topographic index calculations.

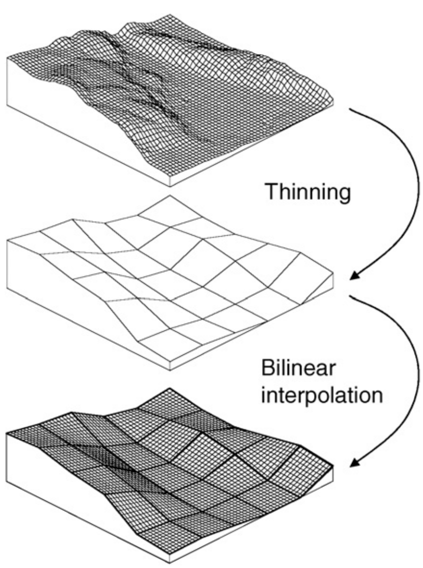

Figure 1 Extraction of lower resolution DEM from the original 5 m DEM by thinning, and the bilinear interpolation back to 5 m. Note the lower information content in the interpolated DEM.

Index calculation

We routed the area from upstream cells to downstream cells as suggested by Quinn et al. (1995). In this process the accumulated area from a certain cell was allowed to take any of the eight cardinal and diagonal directions to a neighbouring grid cell, if this cell had a lower elevation. The portion of area routed to a certain downslope cell, F_i, was computed using the slope towards this direction, $\tan\beta_i$ and the sum of all $\tan\beta_j$ values of the downslope directions. As suggested by Holmgren (1994) an exponent h was used for this computation (Eq. (1)) and in this study h was set to 2, based on the findings of Sørensen et al. (2006). The accumulated upslope area (A) was then divided by an estimate of the contour length (L) to provide the specific upslope area ($a = A/L$). In the comparison we looked only at specific upslope area. The upslope area without division by contour length is obviously scale dependent because in larger grid cells more upslope area is accumulated:

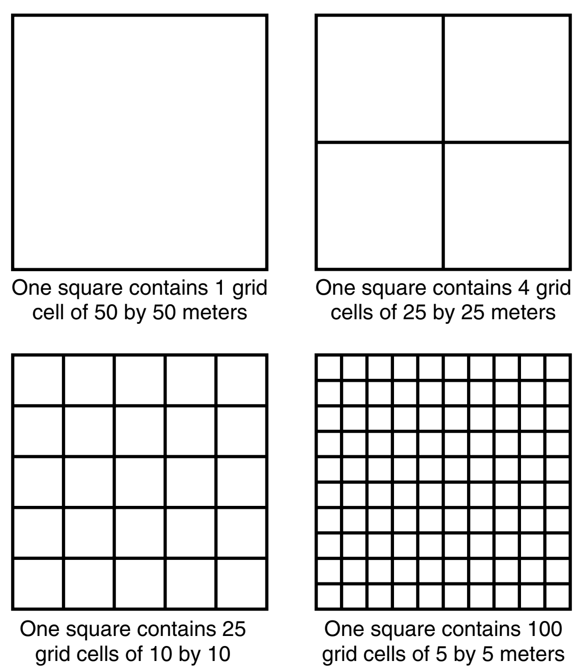

Figure 2 The computed indices based on the DEMs T_{50}, T_{25}, T_{10} and T_5 were compared based on squares of equal size. Each square contained a different number of grid cells in the different DEMs.

$$F_i = \frac{\tan \beta_i^h}{\sum_j \tan \beta_j^h} \quad (1)$$

Traditionally the slope for the TWI is calculated as the steepest local slope from a certain grid cell or as a mean slope of all downslope directions (Quinn et al., 1991); in this study the latter method was used.

Hjerdt et al. (2004) introduced a different slope measure, the downslope index ($\tan \alpha_d$). This index is defined as the angle between the point of interest and a point in the steepest downslope direction that is d meters lower than the point of interest. It is proposed that this slope measure more accurately describes the drainage conditions as it takes downslope topography into account. With small values for d the downslope index equals the usual slope, whereas differences become larger with increasing d. In this study d was set to 5 m, which had previously been used in similar areas (Hjerdt et al., 2004; Sørensen et al., 2006). The average distance to a point located 5 m below a certain point was about 80 m.

In our comparison, the different components of the TWI were considered. For each of the seven DEMs, five topographic features were calculated for each raster cell: specific upslope area (Quinn et al., 1995), $\tan \beta$ (Quinn et al., 1995), $\tan \alpha_5$ (Hjerdt et al., 2004), TWI_β (using the $\tan \beta$ slope), and TWI_α (using the $\tan \alpha_5$ slope).

The downslope index $\tan \alpha_5$ integrates over several cells and, thus, values are generally less extreme than for the local slope between neighbouring cells. However, since $\tan \beta$, as used in this study, is a mean value of the slopes towards all downslope directions, it does not have as high values in steep regions as the $\tan \alpha$ slope, which considers only the steepest slope direction.

All index values from the various DEMs were calculated for an area of 24 km^2 measured by the LIDAR scanner. Within these DEMs we selected a 6.25 km^2 window (2.5×2.5 km^2) for further analysis. This was done to avoid any edge effects of the DEM and to limit the analysis to a comparatively homogenous region. A larger window would have included areas with glaciofluvial deposits and, therefore, different geomorphologic features. In this study no creek initiation was considered, i.e. all accumulated area was routed downwards. This is because the stream initiation threshold area itself is scale dependent. In the area used for this study there were only a few small creeks in the selected window and we argue that this did not influence the results since only a few cells would have been classified as stream cells. Instead of filling up sinks in the DEM, the accumulated area was routed to the closest downslope cell 2, 3, or more cells away from a sink (Rodhe and Seibert, 1999).

Data analysis

We compared the computed maps of TWI and its components based on the seven different DEMs in three different ways. First we compared the distribution functions and different statistical measures such as percentiles, mean, and median for the different maps. This comparison, however, does not take the geographic position or pattern of the different maps into account.

Next, we compared the effects of the different resolutions on a pixel-by-pixel basis for the maps derived from the resampled DEMs. Correlation coefficients (r) and the root mean square differences (RMSD) were calculated as measures of the (dis)agreement between the different maps.

Finally, we investigated the variation of topographic index values based on T_5, T_{10}, and T_{25} within each 50×50 m square of the 50 m grid resolution DEM (T_{50}). The mean, the coefficient of variation, and minimum and maximum were computed for each 50×50 m square, i.e. based on 100, 25, or 4 values for T_5, T_{10}, and T_{25} respectively (Fig. 2). Subsequently, these measures were sorted according to the value for the index in question for T_{50}, and running mean values (window of 200 data points) were computed. This analysis allowed us to address the question of whether sub-grid variability is homogenous, i.e. whether the range of sub-grid values is equally large in the whole spectrum or if either lower or higher values suffer more from the generalisation of a coarser grid size.

Results

Mapping the various topographic indices computed for the different DEMs showed clear variation with resolution. Using DEMs of larger grid size resulted in different patterns on the computed maps in which fine-scale features disappeared. For the $\tan \beta$ slope, for instance, steep slopes along rather flat valley bottoms could not be seen in the 50 m DEM T_{50} but could partly be recognized in T_{25} and showed up clearly in T_{10} and T_5 (Fig. 3). However, comparing the indices based on R_{50} and T_5, i.e. the same grid resolution, showed a substantial influence of the information content on the resulting maps (Fig. 4). The underlying larger squares could be seen in the maps based on T_{50}. The slope was basically constant for each square, whereas the maps of the upslope area indicated some artefacts at the borders between the squares.

The visual impression was confirmed by comparing the distribution functions (Figs. 5–7) and the various statistical measures (Fig. 8). The distribution functions for the specific upslope area (Fig. 5) clearly showed the difference in distribution among the seven DEMs with narrowing and increasingly skewed distribution with decreasing information content and increasing grid size. The statistics summarized in Fig. 8 illustrate that T_{10}, T_{25}, and T_{50} showed gradually lower similarity to T_5. Part of this difference was explained by the grid size, since R_{10}, R_{25}, and R_{50} also gradually decreased in similarity to T_5. The rest of the difference was caused by the lower information content in the DEMs. The values for the specific upslope area were generally higher when the grid resolution increased, especially for the smaller areas, and most clearly for the lower resolution DEMs. This increase was partly reduced when using the resampled DEMs where the minimum area was the same because the grid sizes, and thus smallest possible accumulated areas, were identical. The deviation between the distribution functions was also smaller but still significant. The skew increased with resolution and information content, except for R_{50} for which the skew decreased slightly.

With lower DEM resolution and information content, the distribution of slope was, as expected, more concentrated

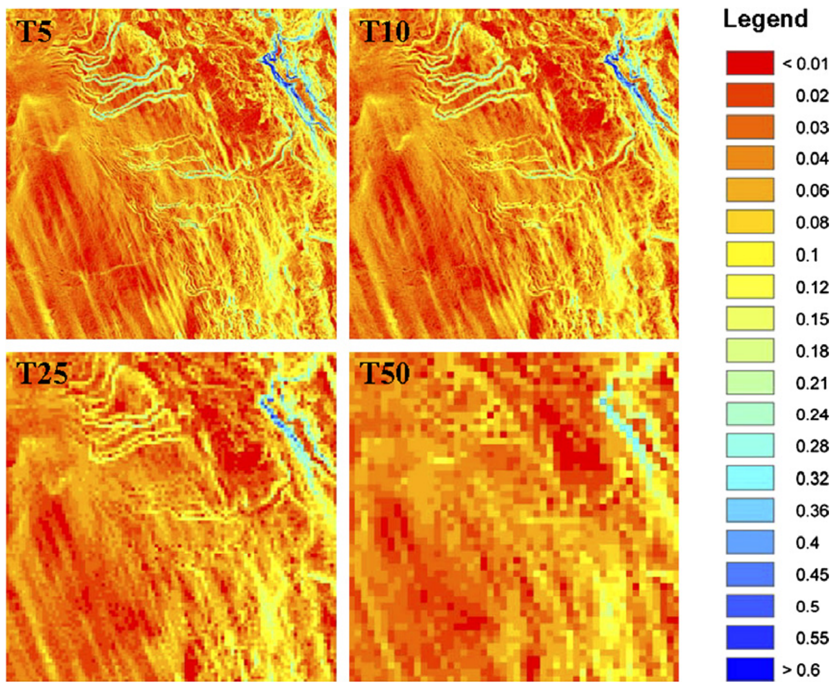

Figure 3 Maps of $\tan\beta$ for T_5, T_{10}, T_{25}, and T_{50}.

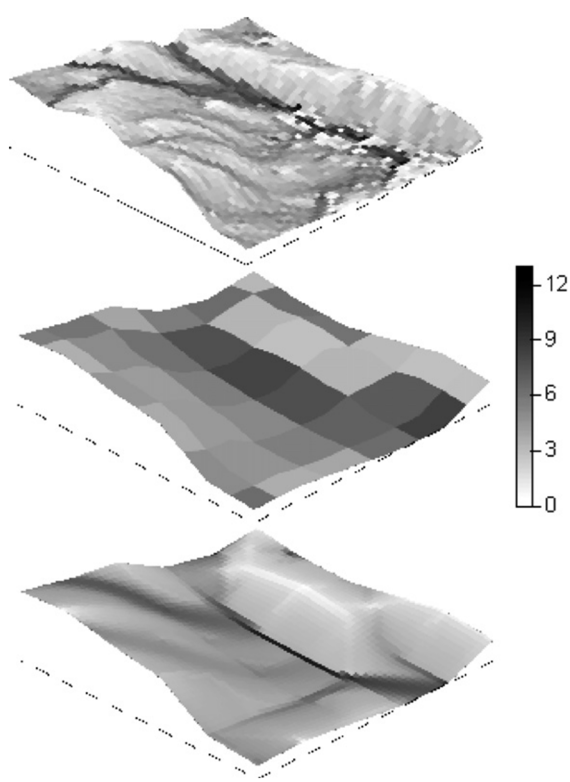

Figure 4 Example from the maps of the specific upslope area, ln(a), for T_5, T_{50} (500×500 m^2 window) and R_5.

to intermediate slope values than to extreme slope values (Figs. 3 and 6). The $\tan\beta$ distributions were almost identical for the resampled and the corresponding lower grid resolution DEMs (e.g., T_{50} and R_{50}, Fig. 6c). For the coarser resolutions $\tan\beta$ was generally more even, i.e. the most gentle slopes were steeper and the steepest slopes less steep. The $\tan\alpha$ deviated from the T_5 less than the $\tan\beta$ (Fig. 6). For the $\tan\alpha$ distribution the resampled DEMs were closer to the T_5 than the lower resolution DEMs. For both slope measures the skewness decreased with resolution (Fig. 8).

Since the TWI_β and the TWI_α are ratios between the specific upslope area and the slope ($\tan\beta$ or $\tan\alpha$), even the TWI_α appeared more robust than the TWI_β in general. But the differences in the specific upslope area were much higher than the differences in slope and therefore had more influence on the resulting TWIs. The distributions of the resampled DEMs differed less from T_5 than the DEMs of different resolution, i.e. T_{10}, T_{25}, and T_{50} (Fig. 7).

Cell by cell comparison of resampled DEMs

The cell by cell correlation among the resampled DEMs decreased with information content (Fig. 9). The specific upslope areas changed largely with information content (see Fig. 3). At the 10 m resolution the cell by cell correlation between the values for upslope area was only $r = 0.70$ and the RMSD was 1.57. At T_{25} the correlation was $r = 0.41$ and the RMSD was 2.16. The slope measures, $\tan\beta$ in particular, also lost correlation strength with decrease in DEM information. Again, this was reflected in the resulting TWI_α and TWI_β measures.

Square by square comparison of lower resolution DEMs

The square by square comparisons showed that the variability of the index values based on the finer resolution DEMs in the 50×50 m was quite substantial. The variability of the specific upstream area, evaluated by the coefficient of

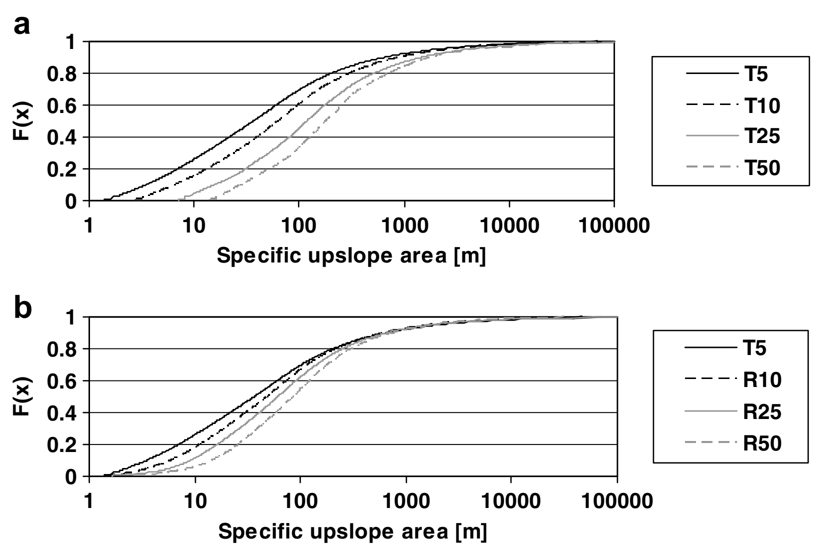

Figure 5 Distribution functions for the specific upslope area: (a) for the lower resolution DEMs and (b) for the resampled DEMs.

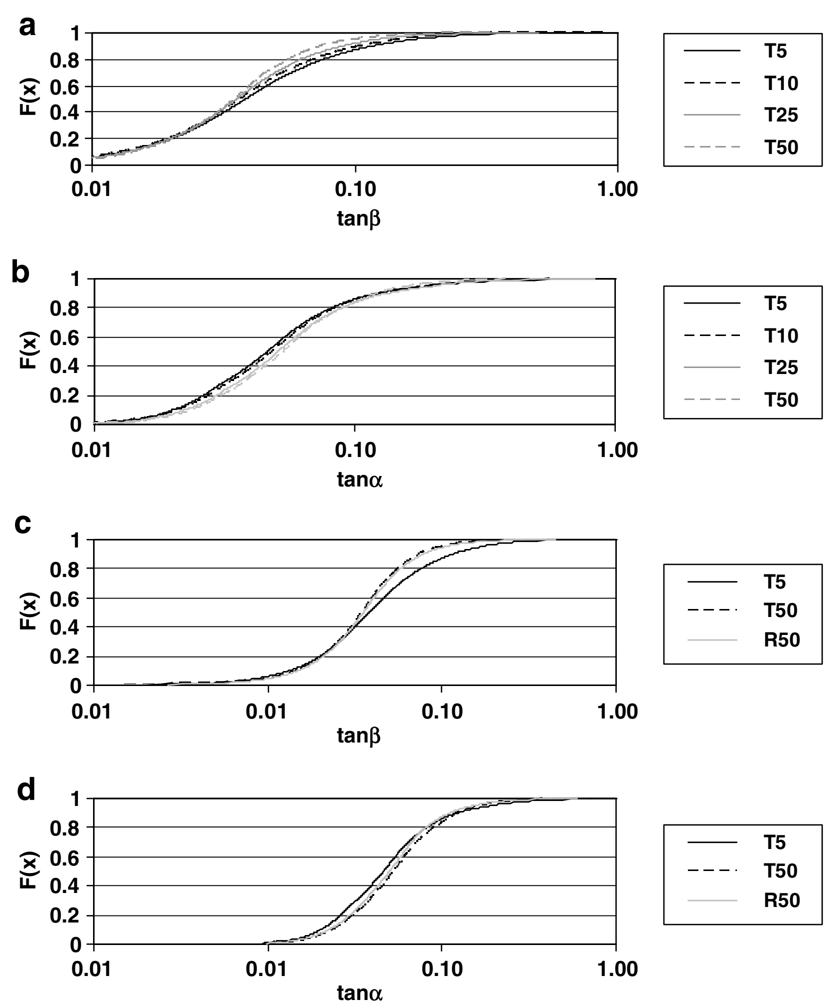

Figure 6 Distribution functions for (a) the $\tan\beta$ slope of the T_5, T_{10}, T_{25}, T_{50}, (b) the $\tan\alpha$ slope of the T_5, T_{10}, T_{25}, T_{50}, (c) the $\tan\beta$ slope of the T_5, T_{50}, R_{50}, and (d) the $\tan\alpha$ slope of the T_5, T_{50}, R_{50}.

variation (C_v), first decreased and then increased with the corresponding values based on T_{50} (Fig. 10a). The high variation in the squares was also shown by the smaller minimum values and higher maximum values of the finer resolution DEMs than those of the T_{50} (Fig. 10b). A similar pattern was observed for the variation of slope. For the

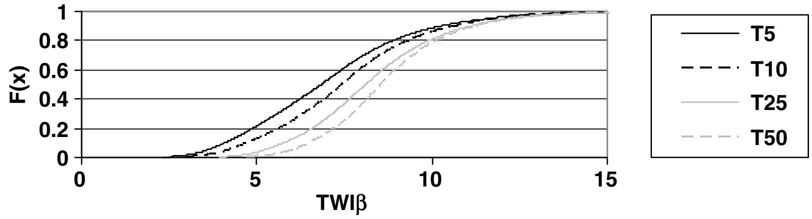

Figure 7 Distribution functions for TWI_β of the T_5, T_{10}, T_{25}, T_{50}.

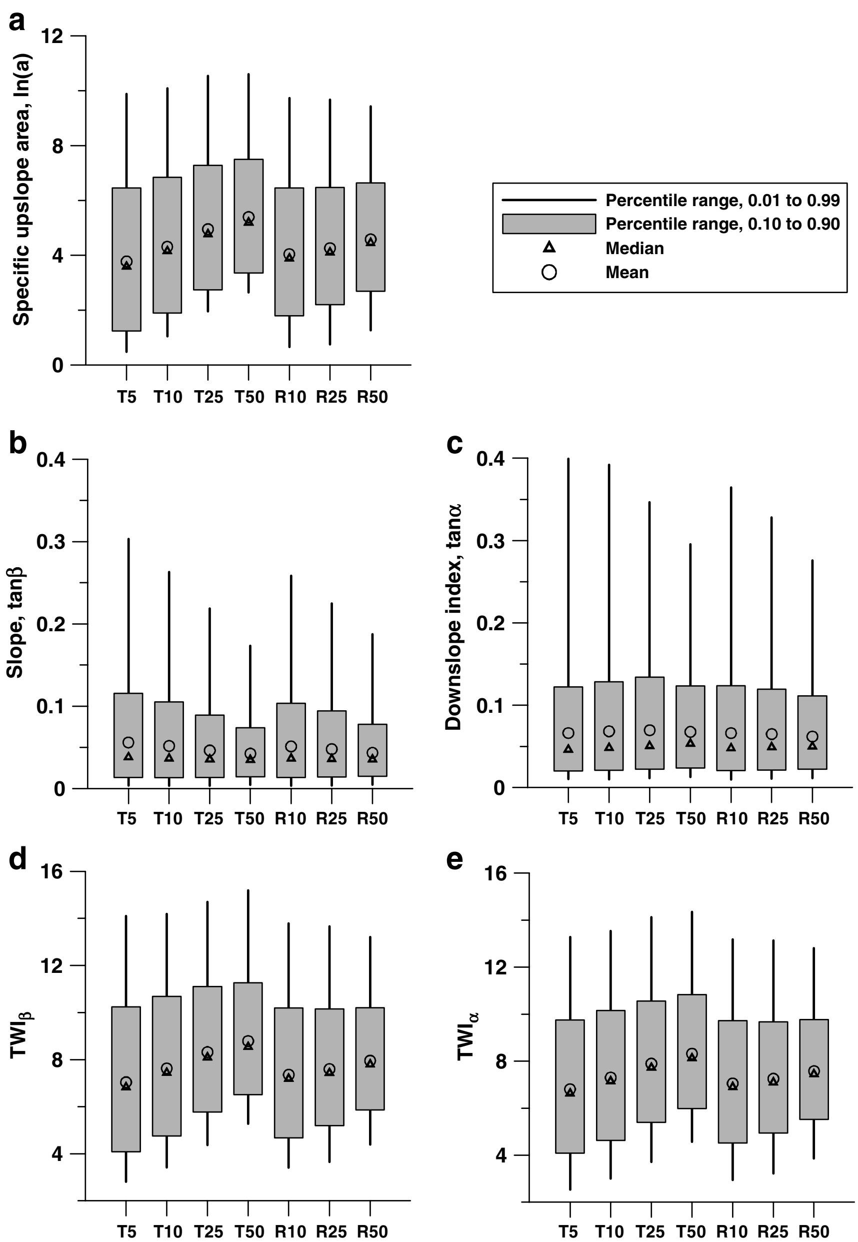

Figure 8 Statistical summary for the seven DEMs: (a) specific upslope area, (b) $\tan\alpha$, (c) $\tan\beta$, (d) TWI_β, (e) TWI_α.

higher resolution DEMs the minimum values increased less and the maximum values increased more than for the T_{50}. This effect was higher for $\tan\beta$ than for $\tan\alpha_5$. Again, the TWI_α and TWI_β reflected the trends of the specific upslope area and the slope measures.

Discussion

The distribution functions of the indices computed for the resampled DEMs (R_{50}, R_{25}, and R_{10}) were more closely correlated to those based on the original T_5 than the distribution

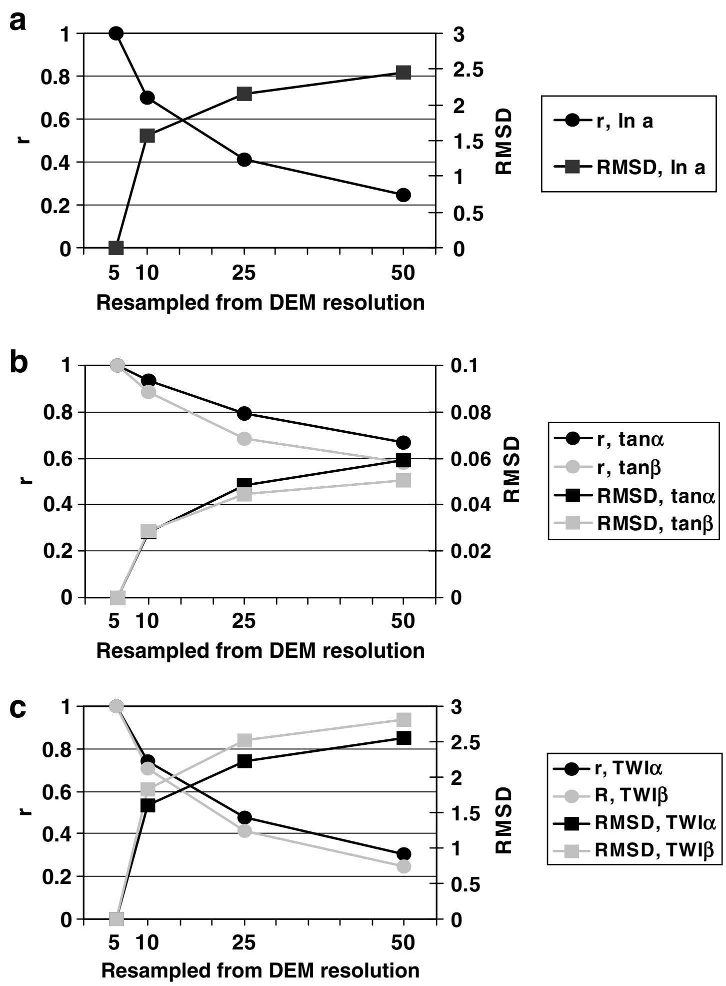

Figure 9 Cell by cell correlation for (a) specific upslope area, (b) $\tan\alpha$ slope and $\tan\beta$ slope, and (c) TWI_{α} and TWI_{β}.

functions of the indices based on the lower grid resolution DEMs (T_{10}, T_{25}, and T_{50}). From this it can be concluded that generating DEMs with a higher grid resolution from DEMs with lower information content is one way to obtain higher resolution topographic index maps. The pixel by pixel comparison, however, indicated that the differences between the original and the resampled DEMs have significant effects on the computed index maps.

The upslope area was largely affected by the resolution and information content of the DEM used. One obvious reason for this is that the smallest accumulated area equals one grid cell. The minimal specific upslope area corresponds, thus, to the grid-cell length. When using a more detailed DEM the flow pathways become more irregular, creating the possibility for some channelling of accumulated area. While for T_{50} a grid cell in a downslope valley position will have a large upslope area, cells in similar positions in a higher resolution DEM might have a large upslope area if they happen to be located along the main flow pathway. However, cells from a higher resolution DEM might also have smaller upslope areas if they have a slightly higher elevation than the surrounding cells and, therefore, are located next to the main flow pathways. This observation agrees with previous studies for coarser resolutions (Band and Moore, 1995; Usery et al., 2004; Wilson et al., 2000; Wolock and Price, 1994; Zhang and Montgomery, 1994).

The difference in slope was generally smaller than the difference in specific upslope area. The slope distribution became narrower for coarser DEMs. This is consistent with the findings of Thompson et al. (2001) who compared DEMs of 10 and 30 m. The $\tan\alpha$ slope was less affected by resolution than the $\tan\beta$ slope. This confirms the findings of Hjerdt et al. (2004). Since there were smaller differences for the slopes compared to the upslope area, the latter dominated the differences in the TWIs. Likewise we observed that with the same amount of information but at different resolution (the T-series) there was a shift in the distribution of the indices and their components, in agreement with the findings of Wolock and Price (1994).

Zhang and Montgomery (1994) argue that a 10 m DEM resolution is sufficient for estimating geomorphic and hydrologic processes. Also, Usery et al. (2004) found that elevation values compare well ($r = 0.9$) for DEM resolutions between 3 and 30 m and that this correlation decreases gradually as resolution becomes coarser. For landscapes with high variation in elevation, Cai and Wang (2006) found that a 90 m DEM might be as good as a 30 m DEM for deriving TWI. In this study we found that simply going from a 5 to 10 m resolution affected the computed topographic indices considerably (Fig. 5).

Topographic features with smaller length scales than the DEM resolution will not be captured in the computed

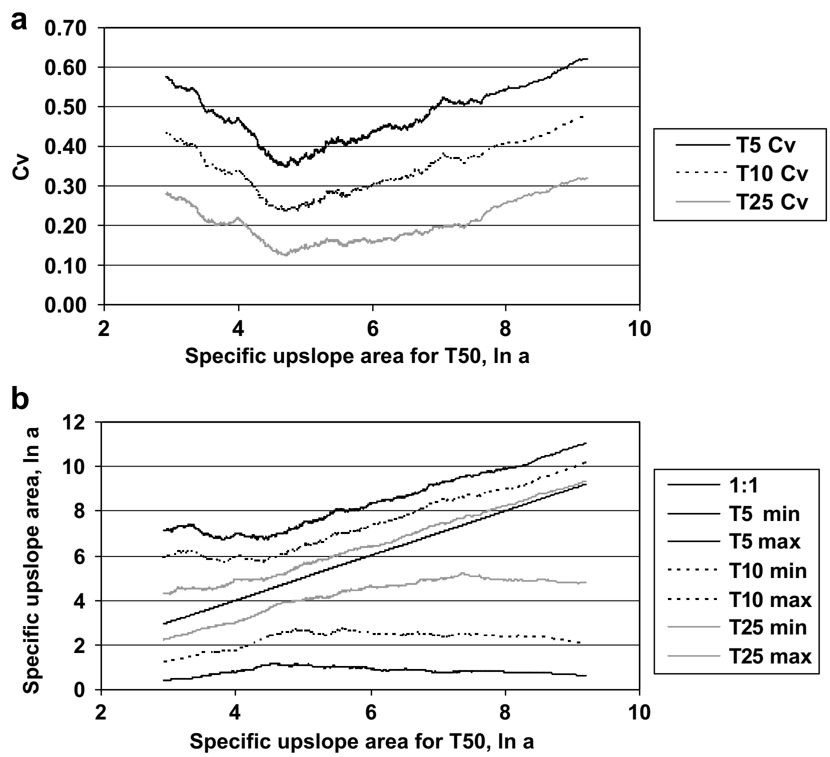

Figure 10 Running mean values (window of 200 values): (a) for the coefficient of variation, (b) minimum and maximum values, for the specific upslope area for T_5, T_{10}, and T_{25}.

topographic indices. Depending on the landscape scale, the loss of information may be of importance to hydrologic prediction based on topographic indices. Kuo et al. (1999) compared hydrographs for different grid sizes and found that increasing grid-cell size misrepresented the curvature of the landscape. On the other hand, it is not necessarily the case that indices computed from high-resolution DEMs are a better representation of the real spatial patterns. Walker and Willgoose (1999) found grid spacing finer than 25 m had no significant effect on the ability to extract the inferred stream network and catchment boundary. Also, while the groundwater flow can be expected to follow the general topography, it cannot be expected to follow all details in the ground surface. Wolock and Price (1994) argue that, for TOPMODEL, coarse resolution DEMs are not necessarily inappropriate because it is assumed that the water table configuration mimics surface topography and may even be smoother and better represented by a coarser resolution DEM.

The question of an optimal resolution remains to be answered and probably depends on the variable as well as the properties of the landscape of interest. Sørensen et al. (2006) found that different computation methods were more suitable for the hydrological properties and the chemical properties of a site. Similarly, different resolutions might be more suitable for different variables. This issue is also discussed by Lassueur et al. (2006) who studied the usefulness of high-resolution DEMs to estimate plant species richness in an alpine landscape.

Within the 50×50 m squares with a higher value of a and TWI we found a larger variability among the respective index values computed from high-resolution DEMs. This supports Zinko et al. (2005), who hypothesize that their observed increase of vascular plant species richness with TWI might be caused by a larger degree of variability of wetness conditions for grid cells with high TWI. A high-resolution DEM could thus be useful for locating areas of high species richness which are also highly correlated with several soil properties such as moisture and pH (Zinko et al., 2005).

In this study we investigated how the DEM resolution influenced the computed topographic index maps. While not explicitly demonstrated here, these results obviously have implication for hydrological predictions using index-based models such as TOPMODEL. In TOPMODEL the local groundwater level or soil moisture deficit is computed based on the difference of local index value and catchment average. This means that spatial predictions of local hydrological state variables are a direct function of the spatial TWI variation. Previous studies have also demonstrated that simulated catchment runoff is affected by the catchmentwide distribution function of TWI values (Wolock and Price, 1994; Franchini et al., 1996; Saulnier et al., 1997; Brasington and Richards, 1998; Thieken et al., 1999; Vivoni et al., 2005), although the differences in simulated runoff sometimes can be compensated for by using different parameter values (Armstrong and Martz, 2003; Saulnier and Datin, 2004).

Concluding remarks

The resolution and information content of a DEM has a great influence on the computed topographic indices. The estimation of upslope area seemed to be more affected than that of slope. Just interpolating the DEMs to a higher resolution (i.e. a smaller grid size) might give a more similar TWI distribution, but quite different patterns can be obtained compared to TWI computed from the original 5 m DEM.

The results obtained in this study indicate that information content can indeed have a large influence on computed maps of topographic indices, even for small changes in information content. However, this does not automatically mean that the highest resolution DEM is always the most useful. Given the length scale of the topographic features controlling certain processes, a lower resolution DEM might in some cases be more useful for landscape analyses and modelling. Groundwater, for instance, can be expected to follow the general topographic pattern and might depend less on small-scale variations.

While it formerly was regarded as a matter of course to use the best available resolution DEM this might not always be the case with extremely high-resolution data becoming more readily available. The optimal resolution should represent the important topographic features for a certain variable of interest; using a finer resolution might actually weaken rather than improve correlations with topographic indices. More research and especially field mapping is needed to address the issue of an optimal resolution. One interesting approach could also be to combine the topographic indices computed for DEMs of different resolutions.

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