Effect of LiDAR derived DEM resolution on terrain attributes, stream characterization and watershed delineation

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ABSTRACT: A raster grid with 1m spacing was created using simple kriging from LiDAR point clouds. The 2, 3, 4, 5, 8, and 10 m resolution were created from the original 1 m DEM using nearest neighbor resampling method. The derived DEM were used to study the sensitivity of terrain attributes while changing DEM resolution and possibly introduce a minimum required resolution for the study area. A variety of terrain attributes were calculated to analyze their rate of changes in different resolutions. Using a coarser DEM resolution (8 and 10 m) instead of a finer one (1, 2 and 3 m), tends to ignore a variety of valuable features, and changes spatial distribution of terrain attributes. It also changes minimum, maximum and standard deviation of elevation within each unit leading to smoother output images. Large differences were observed between 1 and 10 m on all topographical and hydrological attributes, implying that the 10 m DEM is too coarse for this landscape to extract streamlines, and landform attributes. Landform elements were the most sensitive among other tested attributes. The plan curvature trends indicated that a 4 m DEM is capable to capture the grain and the longest significant relief wavelength across slopes, at least in this landscape; this implies that 4 m grid size can be the minimum DEM resolution to study the relief changes accurately, in this particular landscape.

Keywords: LiDAR; DEM Resolution; Terrain Analysis; Landform Attribute, Watershed Deliniat

INTRODUCTION

Numerous studies have examined the sensitivity of computed topographic and drainage networks to the source and resolution of the DEM, and several researchers specifically explored the resolution required to accurately represent the key hydrologic and geomorphic process operating in selected landscapes (Quinn et al., 1991, 1995, Wolock and Price, 1994, Moore, 1996).

The role of scale of observation of a raster DEM on terrain analysis has also been examined; Zhang and Montgomery (1994) used an algorithm, called D8 to determine flow across the landscape, and generated a series of simulated landscapes for resolutions of 2, 4, 10, and 90 m. Based on calculated frequency distribution of slope and drainage area they concluded that DEM grid size significantly affects computed topographic parameters and hydrographs; a 10-m grid size provided substantial improvement over sizes of 30 and 90 m. It was further suggested that, for many landscapes, a 10-m grid size presents a rational compromise between increasing resolution and data volume for simulating geomorphic and hydrologic processes.

Wang and Yin (1998) compared drainage network extraction at two scales, 1:250000 (250K) and 1:24000 (24K), using various drainage parameters common in hydrology and geomorphology. They compared parameters derived from DEM in 20 watersheds (ranging from 150 to 1000 km²) and concluded that the goodness-of-fit between parameter estimates based on DEM varies, and superior estimates were produced from the 24K DEM.

Thompson et al., (2001) compared terrain attributes and quantitative soil-landscape models derived from grid-based DEM, represented at horizontal resolutions of 10 and 30 m and acquired from different sources. He concluded that decreasing the horizontal resolution of the field survey DEM produced lower slope gradients on steeper slopes, steeper slope gradients on flatter slopes, and narrower ranges in curvatures, larger specific...
catchment areas in upper landscape positions and lower specific catchment area values in lower landscape positions. Overall, certain landscape features were less discernible on the 30-m DEM than on 10-m DEM.

MacMillan et al. (2003) studied the application and issues of DEM on landform quantification, with 3-m LiDAR DEM and 5-m conventional DEM concluding that fine spatial resolution DEM presented problems in extraction of surface water flow. He recommended a filtering method be used to improve spatial resolution and reduce localized errors. Cochrane and Flanagan (2005) studied the effect of DEM resolution on the hill-slope and stream channel length for application in WEPP model. They found that hill-slope methods were not significantly influenced by DEM resolution and there is observable interaction between resolutions and flow-path model. Using coarser DEM resolutions for the topographic input would not decrease the accuracy of erosion prediction using the WEPP model.

Huaxing et al. (2006) used 10, 20, 30, 40 and 50 m raster DEM for computing slope, aspect, watershed boundary and flow path. They only gave a general description of these attributes rather than explaining details of the classes containing landform attributes. Sorensen and Seibert (2007) studied the effect of 5, 10, 25, 50 m DEM resolution on topographic index concluding higher resolution provides more detail than coarser resolution. DEM resolution dependencies of terrain attributes across a landscape using a wide range of DEM resolution (5 to 480 m) was studied by Deng et al. (2007). They calculated only a few attributes (slope, wetness index, plan and profile curvature) and compared the effect of spatial resolution based on Pearson correlation coefficient and concluded that each landscape has different reflection on changing DEM resolution and recommended further testing on different landscapes.

Yang et al., (2010) studied the effect of 1 to 60 m LiDAR DEMs on stream characterization. They found that the DEM based hydrographic extraction process provides more detailed hydrographic features at a finer resolution. RMSE between the known channel location and modeled locations generally increased with larger cell size DEM. Sensitivity analyses on sinuosity demonstrated that the resulting shape of streams obtained from LiDAR data matched best with the reference data at an intermediate cell size instead of highest resolution, which is at a range of cell size from 5 to 10 m likely due to original point spacing. Finally, they suggested that optimal cell size for LiDAR-derived DEMs used for hydrographic feature extraction is 10 m.

Liu et al., (2011) used 5, 10, 25, 50 and 100 m DEM resolution to evaluate the effects of DEM horizontal resolution and processing algorithm on the accuracy of the USLE slope length factor (L) in gently sloped landscapes. The results indicated that L factor calculated with any of the methods is sensitive to horizontal resolution, which strongly affects the accuracy.

Kim and Zheng (2011) investigated scale-dependent predictability of DEM-based landform attributes for soil spatial variability in a coastal dune system and found that fine-scale topographic information would not always be optimal for understanding soil spatial variability. They applied 5, 10, 20, 30 and 40 m DEM resolution for this study.

Based on these works it is evident that, DEM resolution significantly influences the frequency distribution for the slope, aspect, plan curvature, profile curvature, specific catchment's area, topographic wetness index attributes, drainage network and hydrographic and hydrologic response. Most studies have used coarse DEM data sources (large grid cell size, such as 5 to 480 m) to characterize runoff and extract primary and secondary landform attributes. Moreover most authors recommended further testing on different landscapes such as Deng et al. (2007).

There is also little evidence on the application of different scales of high-resolution DEM (fine grid size, such as 1 and 2 m), which is accessible through a LiDAR system. This is because the LiDAR data has been very expensive and moreover needs complicated pre-processing steps to be prepared for such applications. As already shown in several studies, the potential of LiDAR to provide data for hydrological models and terrain analysis applications is high in small study areas. Hollaus et al., (2005) summarized the usefulness of LiDAR data for hydrological models in large mountainous regions. Although past studies have found that the higher the resolution of DEM more detail of terrain attributes is attainable, their results explicitly do not supply sufficient information in terms of applicable studies such as watershed modeling. Lack of calculating a variety of landform parameters using high-resolution digital elevation models is another reason to study the effect of DEM resolution on terrain attributes. Most previous studies have been implemented in different landscapes, and evaluated different terrain attributes with coarser grid size than in this study. It is also evident that these findings may not be generalized for any landscape or geographical locations. The rate of change of class attributes composing each specific terrain attribute (such as slope class in slope gradient) has not been documented well. Moreover, the highest resolution DEM that was readily available for the study area was the 10 m provincial DEM. This is a raster data set covering the entire province of Ontario, Canada. However, these elevation data has been created mostly for the purpose of mapping hydrologic features. Garbrecht and Martz (2001) noted that comparison of DEM-derived networks with maps or aerial photographs often showed discrepancies; this is particularly so in flat areas, where the subtle
differences in elevation that define channels may be below the resolution of the DEM. MacMillan et al. (2003) even have also shown that there are discrepancies between stream channels simulated from the 5 m DEM (re-sampled using 10 m provincial DEM) and the mapped blue-line network. Murphy et al. (2008), in a study in Alberta, Canada, found same discrepancies even with corrected provincial 10 m DEM. Clearly, this will continue to be a significant issue impeding the effective use of fine spatial resolution DEM data that will need to be resolved.

Building on the literature cited above, the goal of this research work was to evaluate the influence of DEM resolution on the quantitative analysis of rolling glacial till landscapes, encountered in many regions of southern Ontario, Canada. Of specific interest were the general classifications of landforms according to simple landscape attributes, on the calculation of compound attributes relevant to overland flow models, as well as to the delineation of watersheds. Such understanding is fundamental to evaluating the minimal data set required to accurately characterize surface runoff potential. The sensitivity of a terrain attribute in different DEM resolutions is evaluated and the response of this landscape for computed terrain attributes as influenced by DEM resolution are also studied. Therefore, a multi-resolution landform characterization in the Huron Slope physiographic region\(^1\) is conducted using LiDAR DEM with 1, 2, 3, 4, 5, 8 and 10 resolution. It is intuitive, and has been demonstrated in many circumstances, that the morphometric characterization of landscapes is dependent on the resolution of DEM used. In Ontario, a province-wide DEM has been available for several years; however, considering the errors arising from its interpolation from existing contour maps (in case of provincial 10 m resolution), this study is based on LiDAR DEM. The use of 10 m DEM, to quantify landforms in the Huron Slope physiographic region, obscures information relevant to understanding processes at the relief and pedon scale. Considering topographic pattern and relief scale (local relief ≥ 1 m) in the study area a 10 m DEM is not adequate to accurately quantify the landform and characterize surface runoff in the study area.

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\(^1\) The Huron Slopes physiographic region is characterized by rolling, slightly hilly to undulating terrain; in such landscapes, soils vary at a magnitude of one to several metres. Rolling topography includes elongated hillslopes that are dominantly between 5 to 26% gradients with local relief greater than 1 meter. Undulating topography are gently sloping hill(s) and hollow(s) with multidirectional slopes generally up 26%; local relief is also greater than 1 meter. In plan, an assemblage of non-linear, generally chaotic forms that are rounded or irregular in cross-profile. This topography made up of unconsolidated materials (glacial tills) sufficiently thick to mask the surface irregularities of the underlying material.
LiDAR data in point cloud format was obtained for the study area by LASERMAP IMAGE PLUS Company (Boisbriand, Quebec, Canada). The LiDAR elevation points were taken in summer (leaf on condition) at 750 m above sea level, with the beam angle of ±15º. These data contain both bare ground and non-ground elevation points. In both cases, the data were provided in text file format. Data file cover an area of 100 ha with 1,000,000 elevation points and their coordinates. The Data was projected in UTM (Universal Transverse Mercator) system located in Zone 17T, with NAD27 datum. The average point cloud density was estimated 1 m prior to delivery; the data was processed to remove vegetation and buildings, yielding a digital elevation model. The study area located between UTM coordinates 451300 and 452300 m Easting, 4867201 and 4868201 m Northing. Elevation measured in this region varies from 257.2 to 279.6 m above sea level.

DATASETS AND METHODS

Study area

This study was conducted within a watershed, drained by Kerry Creek, which is located on the eastern shore of Lake Huron (43° 57´ 23´´N 81º 36´ 22´´W), in the southern portion of the Canadian province of Ontario (Figure 1.1). The area is characterized by glacial till sediments, with dominant landform being a lake plain with gentle slopes to rolling topography. Prior to clearing for extensive agriculture, the vegetation was characterized by oak and sugar maple.

Gridding of LiDAR data

Regular raster elevation grids with 1m spacing were generated from the LiDAR point cloud data using the kriging algorithm contained in the software VESPER (Minasny et al., 2005). Local kriging was applied by fitting the suitable variogram model. The variogram is a plot of the average variance between all points that are separated by certain distances. In this situation the variance is generally called the semi-variance. The distance between points is termed the ‘lag’. The variogram illustrates how variance changes over lag distance. However to use this information in the interpolation process a model was fitted to data, among all the models available in VESPER the chosen model (stable) had the best fit with data. The variogram model window in VESPER allows automatically calculating variogram clouds, automatically fit models to the variogram cloud, manually adjust the variogram models and easily visualizing the results.

The semi-variance formula in VESPER software to create a variogram cloud is calculated by Equation 1.1. The formula which was used for the variogram model is based on Equation 1.2, the stable variogram model;

\[ \gamma(h) = 1/N(h) \sum_{i=1}^{N(h)} [Z(X_i) - Z(X_i + h)]^2 \]  

(1.1)

\[ \gamma_0 = \exp [-2(h/A1)^{\alpha}] \]  

(1.2)

\[ \gamma(h) = C_0 + C_1 * (1 - \gamma_0) \]  

(1.3)

(0<α <2)

Where, C0 is the nugget effect, C1 = Sill - nugget effect, h is lag distance, A1 is optimum lag distance, α is range, Z(\(\text{i}\)) is elevation points, \(\gamma(h)\) is variance between elevation pairs, and N is number of data points. For the variogram calculation, number of lags (number of points on the variogram), lag tolerance (% of lags) and the maximum search distance are defined as below:

No. of lag = 30, Lag tolerance = 50 and Maximum search distance = 40 m.

The variogram model is fitted to the data by using a weighted nonlinear least-squares method (Jian et al., 1996) using Equation 1.4:

\[ R = \sum_{i=1}^{n} W_i [\gamma(h_i) - \gamma^*(h_i)]^2 \]  

(1.4)

The weighting parameters, W_i, were determined based on a combination of the number of data pairs and the standard deviation of the semi-variance estimates at a 40-m lag. The goodness of fit of the variogram model was assessed using the RMSE^2 and Akaike Information Criteria (AIC), which are internally calculated by the VESPER program. The AIC is calculated using the following formulas:

\[ \text{AIC} = -2 \ln (\text{maximum likelihood}) + 2 \times (\text{number of parameters}), \text{and is estimated by: } \text{AIC} = n \ln (R) + 2 \times p \]

\(^{2}\text{ Root Mean Square Error}\)
Positional accuracy of LiDAR derived DEM

Given the role of DEM in terrain analysis and watershed modeling it is important to consider the accuracy of DEM which is controlled by DEM data source, vertical precision, and horizontal resolution. The horizontal and vertical qualities of a DEM are directly linked to the source of data used for its production. The primary stage of processing LiDAR data (strip adjustment, algorithm for separating ground from non-ground points) may produce some error. The company provider (LASER MAP IMAGE PLUS) delivered data without mentioning the inherent error from early-stage processing. Some studies (Flood, 2001) explain that for typical commercial LiDAR systems, the vertical accuracy is 15 cm or higher, the planimetric accuracy is 10 to 100 cm, and the post spacing is 0.5 – 2 m.

Pfeifer and Böhm (2008) concluded that strip adjustment is the task of reducing discrepancies in overlapping strips acquired by airborne laser scanning and discrepancies at control surfaces. These discrepancies originate from poor calibration or deficiencies in the flight path computation. Habib (2008) explained that unlike photogrammetric techniques, LiDAR calibration is not a transparent process, and remains restricted to the system’s manufacturer. Consequently, the total error of derived DEM in this study can be a combination of early-stage processing error by the company provider (not clear here) and the interpolation error.

To analyze the accuracy of derived DEM the positional accuracy was evaluated based on Congalton and Green (2009) method. Number of sample size was determined based on the statistical information of the DEM standard deviation map. When kriging most packages (including VESPER) give a prior estimate of the mean and standard deviation of the population of errors as a standard deviation map. The population of survey points can be determined based on the information from such error maps. With this information it is possible to calculate how many samples should be taken to provide a specified confidence interval around the estimate of the mean error. For this analysis, OrthoEngine module of PCI Geomatica was utilized. This program locates the GCPs inside raster DEM according to their planimetric coordinates and matches them with each DEM value. It is well known that the accuracy of DEM impact the derived terrain attributes that are computed by the DEM. Since the designated objective of this study is the effect of DEM resolution on the computed terrain attributes, only horizontal and vertical accuracy of the derived DEM are calculated and compared together.

When considering the combination of multiple terrain attributes, it is important to simultaneously consider the errors that may be related to the Z value (elevation). General errors affect every terrain model because of the inexact value of elevation in DEM. Calculating the mean, standard deviation, maximum and minimum and analyzing the distribution of the differences gives an indication of possible error between the DEM that may come from early-stage processing and post processing (interpolation).

To compare whether there are significant differences between DEM resolutions, an initial comparison of the Z values was conducted among different resolutions. A 200 m × 200 m subsection of the whole DEM located on the north-west corner of the study area was selected. This sub-section comprises an area with more diverse relief compared to other sections and is hence the best area to examine the accuracy of Z. The number of Z values and their statistics for each resolution are calculated and shown in Table 1.3.

To evaluate whether mean Z values are significantly different between DEM, the one way ANOVA test with univariate statistics was conducted in a statistical program (SPSS). The ANOVA in which there is only one independent variable (here DEM mean value is dependent on resolution) can be used to compare mean differences in two or more groups. This model allows including an enormous amount of information within groups (resolution). A 0.05 % significance level was used in this test. Before conducting ANOVA the Kolmogorov-Smirnov goodness-of-fit test was used to determine whether Z value distribution is not significantly different from one hypothesized on the basis of the assumption of a normal distribution.
Calculation of terrain attributes

The TAS software (Lindsay, 2005a) was used to calculate slope, aspect, profile and plan curvatures for each node in the DEM, using its immediately surrounding 8 neighbors by Wilson and Gallant (2000) method. These attributes were subsequently used to classify each landform unit into one of seven major classes (Table 1.1), using threshold values proposed by Pennock et al. (1987).

<table>
<thead>
<tr>
<th>j</th>
<th>CFO</th>
<th>Concave, &lt; -0.10</th>
<th>Concave, &gt;0.0</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DFO</td>
<td>Convex, &gt;0.10</td>
<td></td>
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<tr>
<td></td>
<td>CSH</td>
<td>Convex, &gt; 0.10</td>
<td>Concave, &lt;0.0</td>
</tr>
<tr>
<td></td>
<td>DSH</td>
<td>Convex, &gt;0.0</td>
<td></td>
</tr>
<tr>
<td></td>
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<td>High &gt;3.0</td>
</tr>
<tr>
<td></td>
<td>DBS</td>
<td>High &gt;3.0</td>
<td>Concave, &lt;0.0</td>
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<tr>
<td></td>
<td>LEV</td>
<td>Low &lt;3.0</td>
<td></td>
</tr>
</tbody>
</table>

Source: Pennock et al. (1987)

C=Convergent, D=Divergent, FO=Footslope, SH=Shoulder, BS=Backslope, LEV=Level

Three compound attributes including Wetness Index (WI), Relative Stream Power (RSP) and Sediment Transport Capacity Index (equivalent to the RUSLE LS factor) were also calculated, as per equations 1.5, 1.6 and 1.7:

\[
WI = \ln\left(\frac{A_s}{\tan S}\right) \quad (1.5)
\]

\[
RSP = \left(\frac{A_s}{22.13}\right)^{0.6} \times \sin S / (0.0896)^{1.3} \quad (1.6)
\]

\[
LS = \left(\frac{A_s}{22.13}\right)^{0.6} \times \sin S / (0.0896)^{1.3} \quad (1.7)
\]

Where \(A_s\) is specific catchment area and \(S\) is local slope.

The computed terrain attributes, stream and watershed characteristics were used to calculate length, area and their statistics. The output results were reclassified to get uniform and suitable units for terrain attributes for this particular landscape. For example, for the aspect there were about 360 initial direction classes; by implementing reclassifying approach, the number of classes was reduced to 8 reflecting main cardinal directions. Reclassification of images may be regarded as class aggregation to amalgamate two or more classes, which represent very similar characteristics, using pre-defined thresholds. This approach conserves the image information, especially elevation and relief properties, of each terrain unit.

Watershed delineation and stream characterization

After creating depression-less DEM, D8 flow algorithms (O’Callaghan and Mark, 1984) were used to extract drainage networks for watershed areas. The deterministic eight-node (D8) single-flow-direction algorithm directs flow from each grid cell to one of eight nearest neighbors based on slope gradient (O’Callaghan and Mark, 1984). The aspect (measured in degrees clockwise from north) marks the direction of steepest descent for each grid cell or point in a catchment and is the direction in which water would flow from that grid cell or point (Moore, 1996).

After extracting the stream network (using the D8 algorithm) an index watershed was delineated for all breached and filled DEM. Within this stage a vector file for raster stream images was created and overlaid with contour vector for better understanding of watershed delineation. The Strahler approach (Strahler, 1952) was used for stream order calculation. Drainage density (total drainage network length divided by catchments area), and watershed shape factors (form factor and circularity ratio) also were calculated. Shape factors have a great impact on a flood’s hydrograph. The form factor, which was represented by Horton (1932) is equal to watershed area divided by the square of the watershed length. Circularity Ratio (CR) was calculated using equation 1.8:

\[
CR = \frac{4\pi A_s}{P^2} \quad (1.8)
\]

Where \(A_s\) is specific catchment area and \(P\) is catchment perimeter.

Circularity ratios are typically less than 1, but approach this value in more circular watersheds.

RESULTS AND DISCUSSION

DEM accuracy assessment
To evaluate the accuracy of DEM produced from the bare ground point cloud with different resolutions the RMSE were used.

<table>
<thead>
<tr>
<th>Accuracy statistics</th>
<th>1 m</th>
<th>2 m</th>
<th>3 m</th>
<th>4 m</th>
<th>5 m</th>
<th>8 m</th>
<th>10 m</th>
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<td>0.08</td>
<td>0.08</td>
<td>0.08</td>
<td>0.08</td>
<td>0.11</td>
<td>0.17</td>
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<td>0.01</td>
<td>0.09</td>
<td>0.17</td>
<td>0.17</td>
<td>0.07</td>
<td>0.08</td>
</tr>
<tr>
<td>RMSE&lt;sub&gt;v&lt;/sub&gt;+1.96×S&lt;sub&gt;RMSEv&lt;/sub&gt;</td>
<td>0.25</td>
<td>0.10</td>
<td>0.26</td>
<td>0.42</td>
<td>0.45</td>
<td>0.31</td>
<td>0.38</td>
</tr>
<tr>
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<td>0.09</td>
<td>0.07</td>
<td>0.10</td>
<td>0.26</td>
<td>0.23</td>
<td>0.03</td>
<td>0.06</td>
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<tr>
<td>Absolute vertical error</td>
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<td>0.07</td>
<td>0.07</td>
<td>0.07</td>
<td>0.08</td>
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<td>0.15</td>
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<tr>
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<td>0.15</td>
<td>0.18</td>
<td>0.20</td>
<td>0.23</td>
<td>0.28</td>
<td>0.29</td>
</tr>
<tr>
<td>RMSE&lt;sub&gt;y&lt;/sub&gt;</td>
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<td>0.12</td>
<td>0.12</td>
<td>0.23</td>
<td>0.21</td>
<td>0.16</td>
<td>0.22</td>
</tr>
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<td>RMSE&lt;sub&gt;h&lt;/sub&gt;</td>
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<td>0.20</td>
<td>0.22</td>
<td>0.30</td>
<td>0.31</td>
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<tr>
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<td>0.16</td>
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<td>0.28</td>
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<td>0.08</td>
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<td>0.15</td>
<td>0.14</td>
<td>0.08</td>
<td>0.14</td>
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<tr>
<td>Absolute Horizontal error (X direction)</td>
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<td>0.09</td>
<td>0.10</td>
<td>0.09</td>
<td>0.15</td>
<td>0.20</td>
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<tr>
<td>Absolute Horizontal error (Y direction)</td>
<td>0.05</td>
<td>0.05</td>
<td>0.04</td>
<td>0.11</td>
<td>0.11</td>
<td>0.06</td>
<td>0.15</td>
</tr>
</tbody>
</table>

*The accuracy statistics have been explained by Congalton and Green (2009).*

- RMSE<sub>v</sub> = Vertical Root Mean Square Error
- S<sub>v</sub> = Estimated standard deviation of vertical error
- S<sub>RMSEv</sub> = Estimated standard error of RMSE

Based on Table 1.2 differences between competing DEM indicate that the vertical RMSE of DEM is less than 10 cm except for 8 and 10 m resolutions. However, the range of vertical accuracy between most accurate DEM (1 m) and least accurate DEM (10 m) is only about 14 cm. Also as DEM becomes coarser the accuracy decreases as well. The differences between RMSE for each resolution are not very large. The largest vertical and horizontal shifting in coarser DEM can be explained by the impact of resampling method on changing elevation value while scaling them at coarser size. Except for 1 m DEM extracted from the original LiDAR point cloud, the other DEM were created using nearest-neighbor resampling method from 1 m DEM. In principle, the resampling operations tend to produce fewer pixels as the DEM scale becomes higher. With respect to the nearest neighbor the new generated pixels in coarser DEM become smoother as a result of the resampling technique. This is shown in the next section by degrading DEM statistics (mean, maximum and minimum value of elevation) as resolution increases.

The range of error both in vertical and horizontal dimensions is shown by the 95 % confidence interval as described by Congalton and Green (2009). This information shows that the error dispersal around the mean RMSE of the DEM is not large enough to induce critical changes while using them for terrain analysis. However the highest error limit (0.38 m in horizontal resolution of 10 m DEM) still is less than the cell size of finest DEM resolution (1 m DEM). This implies that any terrain feature (such as a stream) that is computed using 10 m DEM has a potential of 0.38 m shifting compared to 0.16 m in 1 m DEM. The largest shifting in 10 DEM can be detectable in 1 DEM because the feature displacement is not larger than the 1 m DEM grid size. Consequently the computed terrain attributes using such data sets may not have problematic impact while comparing these attributes together.

An alternative statistic to RMSE is the arithmetic mean of the absolute error values. Since the mean of residuals in this study is not equal to zero, the error distribution is not normal and multiple comparison of residuals between DEM is not possible using ANOVA. The analysis of residuals usually show the DEM precision based on the increment (decimal numbers) that will be included after DEM (LiDAR) point processing. According to the residuals obtained based on the GCP, the LiDAR-derived DEM in this research shows better precision in
planimetric position compared to vertical position. This is different than the accuracy of DEM and does not show that DEM are more accurate in planimetric position. The criterion for accuracy of DEM is the RMSE, the less the RMSE the more accurate the DEM. As indicated in Table 2.2 RMSE in vertical position is less than the RMSE in horizontal position showing derived LiDAR represent better accuracy vertically compared to planimetric position.

Table 3. Z univariate statistics of sub-section DEM and testing data distribution

<table>
<thead>
<tr>
<th>Resolution (m)</th>
<th>N</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>Standard deviation</th>
<th>Kolmogorov-Smirnov statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>40000</td>
<td>260.39</td>
<td>270.14</td>
<td>265.73</td>
<td>2.36</td>
<td>0.01</td>
</tr>
<tr>
<td>2</td>
<td>9900</td>
<td>260.42</td>
<td>270.08</td>
<td>265.73</td>
<td>2.35</td>
<td>0.01</td>
</tr>
<tr>
<td>3</td>
<td>4489</td>
<td>260.45</td>
<td>270.07</td>
<td>265.75</td>
<td>2.36</td>
<td>0.02</td>
</tr>
<tr>
<td>4</td>
<td>2500</td>
<td>260.46</td>
<td>269.87</td>
<td>265.79</td>
<td>2.33</td>
<td>0.03</td>
</tr>
<tr>
<td>5</td>
<td>1600</td>
<td>260.55</td>
<td>269.93</td>
<td>265.79</td>
<td>2.34</td>
<td>0.03</td>
</tr>
<tr>
<td>8</td>
<td>625</td>
<td>260.60</td>
<td>269.52</td>
<td>265.86</td>
<td>2.29</td>
<td>0.04</td>
</tr>
<tr>
<td>10</td>
<td>400</td>
<td>260.63</td>
<td>269.32</td>
<td>265.91</td>
<td>2.28</td>
<td>0.05</td>
</tr>
</tbody>
</table>

*Data distributed normally if Kolmogorov-Smirnov statistics is less than 0.05.

The mean elevation value of sub-section DEM that was used for the ANOVA test showed normal distribution. As indicated in Table 1.3 all mean values extracted from the sub-region of DEM were distributed normally except 10 m DEM. As shown in Table 3.3 as DEM become coarser, the minimum and mean values of elevation increase while maximum and standard deviation decrease. This decreases the range between minimum and maximum values of coarser DEM and leads to smoothing DEM values that can also be explained by the smaller standard deviation in coarser resolution. However, since the Kolmogorov-Smirnov statistic of 10 m DEM is close to p-value (0.05), the elevation values of 10 m DEM were not ignored in the ANOVA test including other mean values of DEM.

Table 4. ANOVA test results between mean elevation values of the chosen DEM sub-region

<table>
<thead>
<tr>
<th>Source</th>
<th>Sum of Squares</th>
<th>df</th>
<th>Mean Square</th>
<th>F</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Between DEM</td>
<td>31.69</td>
<td>6</td>
<td>5.29</td>
<td>0.95</td>
<td>0.46</td>
</tr>
<tr>
<td>Within DEM</td>
<td>331163.98</td>
<td>59507</td>
<td>5.57</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>331195.67</td>
<td>59513</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

For this ANOVA, the null hypothesis is that there may be significant differences between mean elevation values of DEM for different resolutions. Based on Table 1.4 since the p-value is more than 0.05, the null hypothesis is not rejected. This indicates that the limitation of improving the quality of a data set by simply combining the initial pixels into a new set as larger size using nearest-neighbor resampling method significantly does not change DEM mean elevation value in this series of DEM with the resolution of 1, 2, 3, 4, 5, 8 and 10 m, in a slightly undulated till topography of Ontario, Canada.

Primary terrain attributes

MacMillan et al. (2003) used a filtering method prior to landform classification using a 3 m LiDAR-based DEM with 3 m grid size and 5 m conventional field survey DEM (the original point spacing of raw datasets in this study are 1 m, while they were 3 m in spacing in that study). It is generally believed that filtering would improve DEM by filling sinks and removing localized errors. Nowadays, several DEM pre-processing algorithms are available to avoid filtering such as Impact Reduction Approaches. Rather than filtering a simple GIS reclassifying approach was applied to improve differentiation of area based units (landforms, slope etc.) This approach creates very smooth and uniform units and discrete landform classes, yet conserving DEM properties.
In order to understand the rate of changes of each terrain attribute (such as slope) at different grid resolution the number of terrain classes were decreased by reclassifying those classes, which represent similar characteristics. For example, the 360 slope classes decreased to 6 slope categories (class) including 0-2°, 2-5°, 5-10°, 10-20°, 20-40°, and >40°. The selection of slope classes depends on the landscape and the type and the aim of study; for example, a soil scientist may choose different slope classes, which differ from those selected by a geomorphologist or a hydrologist. In order to have well distributed slope classes, they were chosen according to their frequencies in this special landscape. These entire slope classes tend to appear in calculated slope attributes, although their frequencies change. In Figure 1.2 (a) distributions of slope classes with their corresponding DEM illustrate that at any range of slope classes there is a regular changing. The most apparent result is that, as DEM resolution become coarser, the percentage of low slope classes rises. This led to declining steepest area percentage and even eliminates them over coarser resolution. The only DEM, which contained very steep slopes (>40°) was 1 m resolution; the 8 m and 10 m DEM resolution also missed 20-40° slopes class. The slope classes that was least affected was 5-10°; this is because frequency of this category is highest among others in the study area. In Figure 1.2 (b) as DEM resolution becomes coarser (from 1 m to 10 m), average slope decreases from 4° to 2.6°. The rate of decrease in average slope from 1 m to 2 m is about 6 %, while there is a large decline (35 % decrease from 4° to 2.6°) in slope gradient as DEM resolution increase from 1 m to 10 m. The large difference in average slope between 1 and 10 m DEM is important due to its dependency on calculation of other landform attributes such as slope curvature, and its effect on surface water distribution in the landscape.
As shown in Figure 1.3, the area percentage of south (S), northeast (NE) and to some extent east (E) facing slopes remains constant while changing DEM resolution, but others changed considerably. The area of southeast (SE) and southwest (SW) directions declines smoothly, while area percentage of north (N), west (W) and northwest facing slope increased as resolution changes from 1 m to 10 m in this particular landscape. Different aspect trends may be expected in other landscapes. It was found that the rate of change of aspects depends on the frequency of area percentage of slope direction. The most frequent aspect classes tend to reflect the least changes when DEM resolution becomes coarser. The rate of change in slope direction is not as large as slope gradient. In other words, aspect is less affected compared to slope gradient. For example as DEM resolution changes from 1 m to 2 m the average area change of aspect for all directions is about 2%, and the rate of change from 1 m to 10 m is about 7%. However, the 7% change may be important due to the impact of aspect on solar isolation, evapotranspiration, flora and fauna distribution and abundance.

Slope curvature is a very important factor from standpoint of moisture (surface water) distribution over landscape. This is why the effect of DEM resolution on slope curvature was evaluated. As DEM grid sizes changes from 1 m to 10 m, (Figure 1.4), the percentage area of convex slope increases smoothly; while in the concave element it decreases as DEM resolution becomes coarser. However, the rate of increase in convex elements from 1 m DEM to 2 m is about 2%, but there is about an 8% increase from 1 m to 10 m. In other words a larger grid size computes higher convex elements and lower concave elements along a slope profile. Such differences affect flow acceleration and erosion/deposition rate, along hillslopes.

It may seem that using a coarser grid DEM, instead of fine resolution, will lead to more divergence of runoff (because of an increase in convexity), but decreasing of concavity compensates that, which leads to runoff convergence. But the main issue regarding runoff acceleration as a result of slope curvature is that the direction of flowing water over slope differs spatially, because of the impact of plan curvature on both. If the plan curvature trend was the same as profile curvature the assumptions about the degree of runoff acceleration will be the same as mentioned earlier. But there are two different patterns over plan curvature; first, from 1 m to 4 m resolution the degree of concavity across slope increases smoothly, while rising DEM resolution afterward, (i.e. beyond 4) the inverse occurs.

The percentage of convex area also affected across slope. In other words, using DEM resolution also affects convexity of plan curvature in different ways, so that from 1 m up to 4 m the percentage of convex area decreases, while from 4 m up to 10 m it increases. It is supposed that changing the cell frequencies, (because of changing grid size) which contribute in computing slope convexity and concavity is one of the reasons why this happen. Different trend may be expected in other landscapes and topographic regions.
According to data tables (not shown) of plan curvature it was observed that the rate of area change of convex and concave elements with changing DEM resolution from 1 m to 10 m is about 1%, less than what observed with profile curvature (8%). These changes imply that profile and plan curvature substantially may explain how landscape relief dimension changes as DEM resolution increases from 1 to 10 m. Figure 1.4 (a) shows that relief dimension resulted by profile curvature is larger compared to the relief dimension computed by plan curvature (Figure 1.4, b). In other words, the grain (longest relief wave length) in this particular landscape along plan curvature is estimated as 4 m, because different pattern of changes are observed from 1 to 4 m DEM and 4 to 10 m both for convex and concave elements. This may imply that a 4 m DEM can be the smallest or the critical grid size for this particular landscape, at least to capture the grain (large scale relief undulation across slope).

**Compound terrain attributes**

**Landform analysis**

The effect of DEM grid size on distribution of landform units is illustrated in Figure 1.5. The most explicit impact throughout changing DEM resolution is a dramatic increase of LEV (level) area from 6 to 30 percent when increasing DEM grid size from 1 m to 10 m. Such changes considerably affect soil landscape modeling (assigning soil taxa within landform units), and miss-calculation of soil erosion and surface water estimation. The frequency distribution of other landform units also changed considerably. Divergent footslope (DFO) and convergent shoulder (CSH) decline smoothly, (from approximately 12 % to 7%); this pattern also can be seen both for divergent shoulder (DSH) and convergent footslope (CFO) from 30% to 20%. In contrast, divergent back slope (DBS) and convergent backslope (CBS) increase slowly from 1 to 5%.

Figure 1.5 and the corresponding data tables (not shown, but from which Figure 1.5 was drawn) showed that the rate of change of landform elements with changing DEM resolution from 1 to 10 m differ for each element. The rates of change are sorted in ascending order as follows: (- and + show decrease and increase respectively).

CFO (-34 %) < DSH (-40 %) < DFO (-46 %) < CSH (-66 %) < CBS (548 %) < DBS (+556 %) < LEV (+712 %)
The role of Pennock et al. (1987) landform elements is very important in soil moisture and particle distribution. The study of changing area size of these elements with different DEM resolution shows that the elements that contribute to acceleration of sediment detachment (such as shoulder slope position) decreases and those which contribute in sediment deposition (such as level position) increases. This trend possibly will decrease the sediment yield calculated using 10 m DEM compared to 1 m.

Landform relief properties such as minimum, maximum, average and standard deviation of elevation values for each landform class were also calculated. These series of data were obtained using an overlay technique (landform units over DEM). In this way it is possible to compute DEM statistics within each polygon of landform units. It is also applicable while assigning any ecological (e.g. land use) and pedological unit (e.g. soil class) within landform classes. This yields relief and coordinate information for each location of each assigned unit. There are not considerable differences between minimum, maximum and mean elevation of landform units, because the relief range is too small, (250 to 280 m) in DEM. The existence of noticeable differences among standard deviation values confirms that landform classification using different DEM resolution affects relief properties of landforms attributes.
According to Figure 1.6 elevation statistics in back slope units (especially DBS) are less affected in comparison to other positions. This means that elevation characteristics of landform attributes (Mean, Max, Min and Standard deviation) will be more affected in foot slope followed by shoulder and level areas. As DEM resolutions become coarser minimum elevation of landform units increases, while maximum value of elevation decreases. The mean value of CFO, DFO, CBS and DBS units decline smoothly, but it increases for CSH and DSH attributes. Elevation values of (minimum, maximum and standard deviation) LEV area do not change as much as other terrain landforms. This is because the elevation range in levelement is smaller compared to others.

Comparing the rate of change of primary and compound attributes with changing DEM resolution shows that each terrain attribute responds in a different way. It was observed that this landscape is more sensitive to landform attributes of Pennock et al. (1987) followed by slope, profile curvature, aspect and plan curvature. This finding is important for those using Ontario 10 m DEM for a long time. Regardless of errors inherent from provincial DEM (Murphy et al., 2008), still there are large differences between terrain attributes computed using 1 and 10 m LiDAR. The importance of rating change of terrain attributes depends on how the user is taking care of these changes and how large these changes affect their studies.

**Other compound terrain attributes**

The logarithmic nature of the RUSLE’s LS factor against DEM resolution is illustrated in Figure 1.7, to describe how much it will be affected.

Figure 1.7 shows that finer DEM resolutions calculate a variety of LS classes. With coarser DEM, low value of LS categories tends to decrease and they will be substituted by high value classes. This trend depends on slope changes, which was discussed earlier, because based on equation (1.6) it is a function of slope gradient. As a result any changes of slope length and gradients (because of changing DEM resolution) will effectively lead to differences in soil erosion estimation using the USLE model, because soil erosion (A) is a function of soil erodibility
(K), rainfall (R), slope length(L), slope gradient(S), cover and management(C) and supporting practice(P). The weighted average of LS factors shows an increase as DEM resolution increases. For example the average LS in 1 and 10 m DEM are about 34.73 and 43.04 respectively with an increase of 23%.

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**Figure 7.** Relative Stream Power Index distribution computed using different DEM grid sizes, for a glaciated till landscape, southern Ontario, Canada. (Data in legend represent relative stream power index calculated using $\text{RSP} = \text{As}^1 \times \tan S$, where $\text{As}$=specific catchment area and $S$=local slope).

**Figure 8.** Wetness Index distribution computed using different DEM grid sizes, for a glaciated till landscape, southern Ontario, Canada. (Data in legend represent wetness index calculated using $\text{WI} = \ln (\text{As}/\tan S)$, where $\text{As}$= specific catchment area and $S$=local slope).
Figure 9. Discrepancies between drainage network among 1m 2m, 4m and 10m LiDAR DEM over undulating glacial till topography. Black polygons represent watershed area over DEMs, a, b, c, and d represent 1m, 2m, 4m and 10m DEM respectively.

Figure 10. Effect of DEM resolutions on watershed morphometric characteristics
Relative Stream Power Index (Figure 1.8) and Wetness Index (Figure 1.9) follow the same pattern as LS Factor. In other words, the frequencies of low class values tend to decrease by choosing a coarser DEM resolution with high value classes increasing. This is because these parameters are a function of slope (especially channel slope) and stream order numbers. As long as DEM resolution increases, stream frequencies (number of streams per unit area) decrease, as its slope distribution changes. Decreasing the stream’s number also leads to declining number of sub-basins, because the number of sub-basins is a function of number of streams. Consequently, Wetness Index and Relative Stream Power change because of changing specific catchment area and slope gradient.

**Watershed and stream analysis**

The effect of DEM resolution, on watershed delineation and the influence of grid size on watershed shape and area are illustrated in Figure 1.10. This specific watershed was delineated on the same geographical location (451477m easting 4867921m northing, zone 17) over different DEM (1, 2, 4 and 10 m grid sizes). There were noticeable differences among DEM, regarding watershed and drainage network statistics such as their length and frequencies. As DEM resolution changes from 1 m to higher resolution (such as 4 m, 10 m) watershed boarder lines were affected leading to noticeable changes in watershed area, watershed length and watershed shape parameters. Details for the watershed characteristics are illustrated in Figure 1.11.

As DEM becomes coarser from full resolution LiDAR (1 m) to coarser ones, watershed length, perimeter and size (area) decrease smoothly. The rate of decline depends on the landscape topography and especially number of stream order and drainage densities, which have been calculated, based on cell size of DEM (Figure 1.11). This will also affect the degree of catchment’s boarder smoothness and the watershed boundaries become blocky. It is evident that a 10 m DEM cannot capture streams less than 10 m length. To extract a stream with less than 10 m length using a 10 m grid it is compulsory that at least two cells contribute to connect flow accumulation along two consequent cells, which is impossible in 10 m DEM resolution. Therefore, cell-size directly affects stream length. Also a 10 m DEM whether from provincial DEM or LiDAR sources are not able to extract sufficient drainage network compared to finer resolution as it is shown by drainage density. Based on Figure 1.10 (a) and 1.11 (b) a 1 m DEM computes more streamlines compared to 10 m DEM. With 1 and 10-m DEM 548 and 40 streams were extracted respectively. A 1 m DEM computes 430 streams of first order compared to 199 and 30 streams in 2 and 10 m respectively. The rate of change in stream frequency decreases to 54% and 93% when using 2 and 10 m instead of 1 m resolution.
Watershed size and density also change as DEM resolution become coarser. Referring to Figure 1.11 (b), a dramatic decline of the number of streams and network drainage density will directly affect stream length, and numbers of sub-catchments within a specific watershed. In 1 and 2 m DEM, the main stream order rank is fifth, while in 3, 4, 5, 8, and 10 m DEM it is the fourth. Lack of fifth order streams in coarser resolution lead to a dramatic decline in sub-catchments numbers and increases channel lengths (Figure 1.12).

This analysis indicates that the drainage network discrepancies between 1 and 10 m DEM are large and show that a 10 m DEM is not as adequate as 1 m DEM for surface runoff characterization; it is evident that the stream network frequency affects the transmission of water and sediment through the basin. It was also indicated that the frequency of sub-catchment decreases due to the decrease of stream frequency as DEM becomes coarser. This leads to decreasing the frequency of sub-catchment in DEM. Decreasing sub-catchment frequency and the size of a drainage area influences the amount of water discharged from the basin and the total yield of sediment; the length and character of the stream channels affect the availability of sediment for stream transport and the rate at which water and sediment is discharged.

Channel slope and length are very important factors for estimation of surface runoff and erosion modeling. If channel slope changes (declines) because of using coarser DEM it will affect (decrease) the amount of soil erosion. These changes will be more dramatic when trying to estimate sediment budget using soil and water erosion models (such as RUSLE and WEPP).

It was also found that changing DEM resolution not only affected one-dimensional (1D) parameters (stream length) and two-dimensional (2D) parameters (area) of computed attributes, but also shape (watershed form factor) and direction (slope aspect), will be affected. Watershed shape coefficients are defined as a function of watershed area and watershed length. As watershed delineation is based on cell sizes, it was observed that length and area of the watershed changed. Watershed form factor is an index of catchment elongation; the greater the form factor the more elongated the catchment. Long catchments produce a smooth flood hydrograph, which have less peak discharge in comparisons to short catchments. When DEM resolution changes catchment length does not affect considerably; except for 8 and 10 m DEM. In this particular watershed increasing DEM resolution changes watershed shape from long length watershed to a shorter one. Consequently, this lead to changing watershed shape close to a circular shape. Figures 1.10 and 1.11 demonstrate this relationship between DEM grid size and watershed elongation.

CONCLUSIONS

As DEM becomes coarser the accuracy of DEM decreases indicating the limitation of improving the quality of a data set by simply combining the initial pixels into new ones of larger size. The statistical analysis of elevation of the derived DEM showed that increasing DEM grid size from the original 1m grid to coarser resolution (2, 3, 4, 5, 8 and 10 m) significantly did not change DEM value. However, the 1 m point density of the data may not impact the accuracy of the derived DEM with the grid spacing used to sample that source.

Changes in the resolution of the DEM affected length and distribution of area-based parameters such as slope, watershed size, and other landform attributes. The number of streams and their densities decrease as DEM become coarser. The most explicit reason for changing length-and area-based attributes is because of changing pixel size in DEM. The rate of an attribute’s change also depends on the relief. It means that a high relief landscape will be more affected in comparison to low relief topography, because there are more variations and fluctuations in terms of height in high-relief landscapes. For example, it was found that a level landform unit (LEV) showed least changes comparing to dramatic changes of DSH and CSH attributes. Therefore, it is recommended that any environmental studies (landform quantification, erosion modeling, and so on) should be done using high-resolution DEM (less than 4 m grid size) in hilly and mountainous areas. At the 4 m grid size, curvature-based attribute (plan curvature) had fewer changes in comparison to higher grid size.

A consistent trend was observed across all classes composing unique terrain attributes. In other words, within each topographical attribute the classes with lower frequency and higher relief were more affected by changing DEM. In finer DEM (1, 2, 3 and 4 m) a wider range of attribute class values are preserved (unchanged) while in coarser DEM resolution (5, 8 and 10 m) the range decreases. Assume that a hydrologist is interested to estimate soil erosion along a hillslope with a slope of 10-20°. At 8 or 10 m DEM, 10-20° slope class is lost, while the frequency distribution of that slope category is 3% in 1m grid size, and its percentage decreases as long as DEM resolution increases. The frequency of low class values (non-steep class) is less than their frequency in coarser DEM and vice-versa. For instance, the frequency of 0-5° slope class in 1m DEM is 31% while it changes to 37% in 10 m DEM. Stream power index follows the same pattern as slope does. For the wetness index and LS factor finer DEM (1, 2, 3 and 4 m) contain varieties of classes, while in coarser DEM (5, 8 and 10 m) very low and very high...
value classes are lost and substitute by medium value classes. It is recommended that sensitivity studies have to be carried out for the hydrological models on the individual slope and slope lengths parameters. With these assumptions complex interactions will be observed between the changes in DEM slopes, flow paths lengths, and changes in hillslope shapes. This can only be quantified by experimentation using actual watersheds and DEMs. With comparisons between measured data and simulation results, thus it can be determined if changes in resolution affected the overall results and at what level, and whether changes in resolution affected the watershed outlet results, or not.

Standard deviation of elevation changes within landform attributes and its trend depends on the location of landforms over slope. The average, and maximum landform values decrease while the minimum of area-based parameters value increases as the DEM resolution becomes coarser. This simply reinforces the observation that a smoothing of elevations occurs as resolution is degraded, although the overall spatial distribution remains inconstant. In other words, a smoothing of the topographic features of the landform units occurs when DEM resolution is coarser. For coarser DEM (5, 8 and 10 m), slope, aspect, compound landform attributes of Pennock et al. (1987) methods become smoother, which is the result of removing detail and very small components of each attributes.

It was also determined that a simple reclassifying approach improved differentiation of area based units (landforms, slope etc.) for better visualization of output images and more realistic manner without destroying DEM properties, instead of applying filtering. In order to remove a very small proportion of an unwanted attribute classes within a major attribute, it is recommended that the user reclassify those details with a higher attribute class rather than filtering and removing DEM details.

In the study of effect of DEM resolution on terrain analysis in this landscape, hydrological and topographical attributes responded to changing resolution in different ways. Pennock et al. (1987) landform elements are the most sensitive among other tested attributes, whereas plan curvature is the least sensitive; this implied that the longest significant wavelength along plan curvature in this landscape is about 4 m and showed the 4-m DEM may be the smallest grid size that can be used effectively for the study area.

Large differences were observed between 1 and 10 m resolutions on all topographical and hydrological attributes, showing that 10 m DEM may be too coarse for this landscape, as it was indicated by plan curvature that 4 m DEM at least can capture the grain (longest significant relief wavelength) in this landscape.

Application of a wide range of DEM resolutions (1 to 10 m) indicated that the more sensitive attributes with changing DEM resolution are landform attributes computed using Pennock et al. (1987) threshold values. This finding is important because these landform elements are deterministic in distribution of moisture and sediments along hillslopes. It is expected that decreasing shoulder element (erosion area) and increasing level element (deposition area) play a critical role in interpreting effect of DEM resolution on watershed modeling.

Finally, it is believed that using these series of DEM (1 to 10 m grid size) may create different results in another landscape. Therefore, it is recommended that other topographic landscapes need to be tested using a wider range of DEM data. Intuitively and empirically is shown that resolution of DEM will influence interpretation of landscape. This research has shown that for a typical rolling glaciated till topography in southern Ontario, several types of interpretation/use of DEM resolution (1, 2, 3, 4, 5, 8, 10 m) is influenced.

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