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Semantic Calibration of Digital Terrain Analysis Scale

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Abstract

Digital terrain analysis (DTA) provides efficient, repeatable, and quantified metrics of landscape characteristics that are important to the Earth sciences, particularly for detailed soil mapping applications. However, DTA has not been field tested to the extent that traditional field metrics of topography have been. Human assessment of topography synthesizes multiple parameters at multiple scales to characterize a landscape, based on field experience. In order to capture the analysis scale used by field scientists, this study introduces a method for calibrating the analysis scale of DTA to field assessments. This method is used to calibrate land-surface derivatives of relative elevation, profile curvature, and slope gradient in the context of the commonly used field description of hillslope position. For a topographically diverse landscape in Michigan, USA, a peak in agreement between field assessment and digital terrain analysis was found at field equivalent distances of 135 m for relative elevation, 63 m for profile curvature, and 9 m for slope gradient. Given the field experience of soil scientists, these calibrations of DTA metrics are likely to have stronger correlations with hillslope properties and could be used together to classify hillslope position consistently across large extents.

Keywords: digital terrain analysis, analysis scale, semantic calibration, land-surface derivatives

Introduction

Digital terrain analysis (DTA) metrics are typically scale dependent (Wood 1996a; Albani et al. 2004; Hupy et al. 2004; Roecker and Thompson 2010). Therefore, when used as parameters in models, attention needs to be given to using the optimal analysis scale for the process being represented. Otherwise, the use of the incorrect analysis scale could result in erroneous model outcomes or mistakenly disregarding important parameters (Claessens et al. 2005). Prior to digital techniques, cartographers utilized tacit knowledge to identify the optimal analysis scale for the parameters in their mental model for creating a spatially predictive map. This study calibrates the analysis scale of three land-surface derivatives to the expert knowledge of hillslope position classification.

Processes occur at certain phenomenon scales. Analysis scale, on the other hand, is the generalization that is best able to detect that phenomenon (Montello 2001). In DTA terms, analysis scale is the combination of cell resolution and the number of cells incorporated in an analysis neighborhood (Thompson et al. 2001; Albani et al. 2004). Experience has calibrated scientists' sense of analysis scale for measuring landscape characteristics. Similar calibration of analysis scale needs to be derived for digital terrain metrics. This is especially true for expert knowledge-based models and models that seek to predict or be validated by human-made classifications in the field (e.g. digital soil mapping). Until more field studies are conducted to quantitatively determine the scale at which the processes influencing the variation of landscape properties operate, utilizing the scale learned by field scientists provides the best supported method for predicting metric-process relationships. Through semantic calibration, DTA can be parameterized to the tacit knowledge of scientists (Dehn et al. 2001).

Despite the importance of analysis scale, analysis neighborhoods are often set to a 3 by 3 cell area for all land-surface derivatives, leaving the analysis scale dependent on cell resolution (e.g. Zevenbergen and Thorne 1987; Gallant and Wilson 1996; Lapen and Martz 1996; MacMillan et al. 2000; Shi et al. 2009). In some cases, neighborhood size is considered to be such a fundamental assumption that it is not specified in research methods (e.g. Mitášova and Hofierka 1993; Joel et al. 1994; Florinsky et al. 2002). By focusing on cell resolution alone, the analysis scale can be inadvertently determined by the best available resolution and computational efficiency (Moore et al. 1993; Sharma et al. 2011).

Many studies have identified the impact of analysis scale via the effect of DEM resolution on geomorphic models (e.g. Chang and Tsai 1991; Chaplot et al. 2000; Schoorl et al. 2000; Florinsky and Kuryakova 2000; Thompson et al. 2001; Kienzle 2004; Wu et al. 2008). However, a distinction should be made between varying cell resolution and analysis neighborhood size, because they are different methods of generalization. Also, cell resolution can be associated with elevation accuracy (Gao 1997), especially if the DEMs are generated by different methods. By using algorithms that can calculate land-surface derivatives from neighborhoods larger than 3 by 3 cells, analysis scale can be tested independently of grid resolution (Wood 1996b).

In the context of digital soil mapping, several studies have determined that analysis scale affects results. However, the complex interactions between different land-surface derivatives, combinations of soil properties, and value systems inherent within soil classification systems, have clouded interpretation of those results. Smith et al. (2006) varied the analysis scale of slope gradient, plan curvature, and profile curvature as inputs to the SoLIM soil mapping model. Because analysis scale for the different parameters was not allowed to vary independently, it is unclear if the determination of different optimal analysis scales for different terrain types (i.e. 24-36 m for high relief, 33-48 m for gently rolling) reflects different phenomenon scales for different landscapes, or a shift in the dominant parameter. In other words, model performance could have been improved not by the optimal analysis scale of the respective parameters changing between landscapes, but rather by the optimal parameter for prediction changing between soil classes used in different landscapes. Behrens et al. (2010) tested analysis scale for land-surface derivatives independently and found that the optimal analysis scale varied by soil class. The variability of optimal analysis scale between soil classes may be produced by the complexity and values built into the classification system, rather than processes acting at different scales. Therefore, point observations for single attributes need to be examined for determining optimal analysis scale. Roecker and Thompson (2010) did this and concluded analysis scales between 117-189 m to be optimal for correlating point observations of soil carbon, rock fragment content, and clay content at different depths with profile curvature.

Recognizing the value of accumulated field experience, expert knowledge models seek to capture tacit knowledge to improve model performance. Hillslope position is a useful, tacit knowledge based, metric for many geomorphic studies; soil scientists have long used this field metric extensively across the United States in their efforts to inventory soil resources. For this reason, I argue that data collected by the U.S. Soil Survey has the large quantity of observation points needed to calibrate DTA with field terrain analysis and to reduce the noise that is inherent in human observations of continuous variables. Therefore, the purpose of this study is to semantically calibrate the land-surface derivatives of slope gradient, profile curvature, and relative elevation to the analysis scale used by soil scientists in determining hillslope position. Because of the categorical nature of hillslope position and high variability of human interpretation, a method of percent agreement is introduced for identifying the analysis scale with the strongest signal. The resulting calibrated metrics can be used as parameters to a variety of models, including fuzzy and discrete classifications.

Methods

Relating Field Assessment of Hillslope Position to Digital Terrain Analysis

Terrain characteristics for describing hillslope process zones and predicting soil properties has been an important area of study in soil geography (e.g. Milne 1935; Ruhe 1960; Burras and Scholtes 1987; Carter and Ciolkosz 1991; Donald et al. 1993; Stolt et al. 1993; Cerdá 1998; Yoo et al. 2005). Although largely qualitative, the use of hillslope position has been tuned through decades of scientific study and field experience. Hillslope position is a contextual metric that divides a landscape into areas where the interaction between hydrology and relief affect the properties of the soil in different ways (Wysocki et al. 2000). Summit positions are often flat and higher in elevation than their surrounding areas, which tends to result in more infiltration than runoff, and less influence from the water table. Shoulder positions are also relatively high in elevation, but their convex shape and steep slope shifts the balance to a greater likelihood of runoff over infiltration. Backslopes are generally considered to be transition zones, and although the slope shape is generally linear, the slope gradient is generally the highest of the hillslope positions, and steeper slope gradients promote runoff. Footslope positions are concave in profile curvature and lower on the slope, causing these sites to be wetter and sediment accumulating positions. The toeslope is flatter and lies at the lowest relative elevation along the slope. Its juxtaposition makes it the zone with the most accumulation of materials transported from upslope and the most affected by the water table.

In the field, soil scientists synthesize the terrain characteristics of slope gradient, profile curvature, and relative elevation to identify the functional zones as defined by hillslope position (Figure 1). Although hillslope position is one of the most basic and widely used terrain descriptions for soil geomorphology, it is primarily based on tacit knowledge without quantitative definitions. Soil scientists have calibrated a mental model for identifying soil-landscape patterns. This study focuses on identifying the analysis scales of land-surface derivatives equivalent to the analysis scales used in the soil scientists' mental model.

Semantic Calibration of Analysis Scale

DTA was performed at multiple analysis scales for comparison with soil scientists' field assessments. Slope gradient and profile curvature were calculated with varying neighborhood sizes using the r.param.scale function in GRASS 6.4.2 (GRASS Development Team 2012). The r.param.scale function calculates both slope and profile curvature by fitting a quadratic trend surface using least squares (Evans 1979). The analysis scale can be expanded by including more grid cells in the parameters for the polynomial and solving the least squares via a matrix (Wood 1996b).

In order to have a user controlled analysis scale for relative elevation, I developed a procedure in ArcGIS 10.1 (ESRI 2012). This method for calculating relative elevation subtracted the inverse elevation from the original elevation by analysis neighborhoods. The inverse elevation was the elevation subtracted from the sum of the minimum and maximum elevation values in the analysis neighborhood. The neighborhood size was controlled via the focal statistics used to determine the minimum and maximum elevation. The resulting relative elevation grid had increasing positive values above and decreasing negative values below the analysis neighborhood's middle elevation (Figure 2).

A LiDAR-derived, 3 m resolution, elevation grid was aggregated to resolutions of 9 m and 27 m to reflect the resolutions of 1/3 arc second and 1 arc second that other elevation grid products are commonly available in, while still preserving cell alignment. Then, all three grids were processed for the three land-surface derivatives using varied neighborhood sizes by the experimental matrix in Table 1. The experimental matrix was designed to cover the full range of reasonable analysis scales and to use combinations of cell resolution and neighborhood size where analysis scale would align across cell resolutions.

Table 1. Experimental matrix for varying combinations of DEM cell size and neighborhood size for varying analysis scale.

	Neighborhood Size							
Distance	**9 m**	**15 m**	**27 m**	**45 m**	**63 m**	**81 m**	**135 m**	**189 m**
LiDAR (3 m)	3x3	5x5	9x9	15x15	21x21	27x27	45x45†	63x63†
(9 m resample)			3x3	5x5	7x7	9x9	15x15	21x21
(27 m resample)						3x3	5x5	7x7

†only used for relative elevation

Field observation points of hillslope position and slope gradient, collected by U.S. Natural Resource Conservation Service (NRCS) soil scientists, were then intersected with each of the DTA grids. The resulting match-up allowed for the comparison of DTA calculations with soil scientists' assessment in the field by location. The soil scientists recorded slope gradient as an integer, allowing for a quantitative comparison. Agreement for slope gradient was evaluated by the mean absolute difference between the field observed and the DTA calculated slope gradient in degrees. Because profile curvature and relative elevation are included in hillslope position as categorical attributes, not quantitative measures, comparison between field observation and DTA were compared on a basis of percent agreement by categorical definition (Table 2).

Table 2. Definition table for relating qualitative hillslope position descriptions to the DTA of profile curvature and relative elevation. Attributes highlighted in gray were used for the semantic calibration.

Hillslope Position	**Profile Curvature**	**Relative Elevation**
Summit	Linear	High
Shoulder	Convex	High
Backslope	Linear	Middle
Footslope	Concave	Low
Toeslope	Linear	Low

Due to the fuzzy nature of landscape elements and the subjectivity of human assessment, agreement was only tested for the definitional extremes. For profile curvature, agreement was evaluated for negative values corresponding to concave slope shape and positive values corresponding to convex slope shapes. Relative elevation was quantified as distance above (positive) or below (negative) the mid-elevation of the analysis neighborhood. Agreement was evaluated as negative values corresponding with low hillslope positions and positive values corresponding with high hillslope positions.

The level of agreement between digital and field assessment should increase as the digital analysis scale is more closely aligned with the analysis scale used by the soil scientists in the field. Therefore, the optimal semantic calibration was determined to be the analysis scale with the highest percent agreement for the qualitative metrics. Specifically, for profile curvature and relative elevation, percent agreement was calculated for each definitional category separately and then summarized with the mean of those results. Using the mean of the categorical results avoided over emphasizing a category that may have more observations than the other. In other words, the mean percent agreement for a particular analysis scale equally weights the two categories used for evaluation. For slope gradient, agreement could be measured on a continuous scale. Therefore, the optimal semantic calibration for slope gradient was determined by the lowest mean absolute difference between the DTA calculation and the field estimate.

Consistent analysis scale calibration between grid resolutions provided support for the determination that calibration was due to the matching of analysis scales and not to matching an artifact pattern in the source DEM. Therefore, a consistent peak in percent agreement at the same analysis scales was considered to be a strong signal for identifying the analysis scale used by the soil scientists and that analysis scale being used consistently.

Study Area

This study analyzed data for Ottawa County, Michigan, on the eastern shore of Lake Michigan (Figure 3). Large dunes have formed on the western edge of Ottawa County (Figure 4a). The central part of the county is lake plain formed beneath Glacial Lake Chicago (Figure 4b). This glacial lake plain is flat with interspersed dunes of decreasing size (from west to east) that have encroached from the west. The northeast and southeast portions of the area grade into a hummocky terrain, more characteristic of till plains (Figure 4c). Across the entire 1,488 km^2 study area the elevation ranges from 173 to 292 meters above sea level.

Ottawa County was chosen because of the availability of a LiDAR-based elevation grid (2004) and a number of georeferenced observations of hillslope position, by NRCS soil scientists, taken in the field. The LiDAR-based elevation grid has a 3 m resolution and was provided by the Ottawa County government. Georeferenced field observations of hillslope position were provided by the Grand Rapids, Michigan Soil Survey Office.

Recorded GPS points at observation sites were joined with a database created from the paper records of field observations. Observations were made by the Grand Rapids Soil Survey Office staff between 2007 and 2009. The GPS recorded observations used in this study were all 8-10 point transects, of typically 40-80 m point spacing, for a total of 1,068 points (Figure 3).

The hillslope position assessment of the soil scientists was converted into categorical attributes in terms of profile curvature and relative elevation (Table 2), as interpreted from the hillslope position diagram presented in Schoeneberger et al. (2012). Not all recorded observations were interpretable for these two land-surface derivatives. For example, observation points that were recorded simply as “flat,” could not have a relative elevation interpreted from it. From the transect observation points, 966 were interpretable for profile curvature and 572 were interpretable for relative elevation. Field observed values of slope gradient were available for all 1,068 points. Using only points in the categories that were least likely to overlap reduced the number of field observations that could be used in the calibration. Therefore, 216 points were used for the evaluation of profile curvature and 406 points were used for the evaluation of relative elevation.

Results

Analysis Scale Calibration

The calibration of all three land-surface derivatives showed a pattern of increasing agreement up to a certain analysis scale and then decreasing agreement with scales coarser than the optimal matching analysis scale. In describing the result details, the different combinations of grid resolution and neighborhood size will be referred to by the field distance equivalent for the particular analysis scale. Because all analysis scales are based on square neighborhoods of square cells, it is simpler and more relatable to the field environment to use the field equivalent distance for the linear dimension of the analysis scale. However, it should be noted that field observations of hillslope position are likely more linear (aligned with the profile of the hillslope) than the square area used by DTA.

Profile curvature had the highest agreement between digital calculations and field observations at a field equivalent distance of 63 m (Table 3). Because the minimum possible analysis scale for a grid resolution of 27 m is 81 m (3 cells * 27 m = 81 m), the same signal could not be observed with the 27 m grid. Instead, the highest percent agreement was at the smallest analysis scale, which is closest to the scale signal observed in the other two resolutions. An exception to this signal was the concave profile curvature agreement for the 9 and 27 m resolution grids, where the highest percent agreement was at a scale of 135 m. However, for the 9 m resolution grid, the percent agreement at 81 m and 63 m was only 3% less than at 135 m. These increases in analysis scale for the highest percent agreement could be caused by the scale effect of the modifiable area unit problem (MAUP), which increases the probability of categorical agreement by decreasing the variability at larger analysis scales. The percent agreement peak for the combined concave and convex categories still showed a strong signal at 63 m, or the closest possible analysis scale.

Table 3. Percent agreement results for profile curvature. Concave and convex 'agree' are the count of points where the digital and field assessments of slope profile shape were in agreement. Percent is the proportion of agreement out of the total number of points identified by the soil scientists to be in the respective category (105 concave and 111 convex points).†

Profile Curvature	3 m Grid					
Distance	**9 m**	**15 m**	**27 m**	**45 m**	**63 m**	**81 m**
Concave agree	60	59	72	72	73	70
Convex agree	67	72	75	77	77	76
% concave agree	57.1%	56.2%	68.6%	68.6%	69.5%	66.7%
% convex agree	60.4%	64.9%	67.6%	69.4%	69.4%	68.5%
Mean % agreement	58.8%	60.5%	68.1%	69.0%	69.4%	67.6%

	9 m Grid					
Distance	**27 m**	**45 m**	**63 m**	**81 m**	**135 m**	**189 m**
Concave agree	64	65	71	71	74	65
Convex agree	72	75	76	73	68	74
% concave agree	61.0%	61.9%	67.6%	67.6%	70.5%	61.9%
% convex agree	64.9%	67.6%	68.5%	65.8%	61.3%	66.7%
Mean % agreement	62.9%	64.7%	68.0%	66.7%	65.9%	64.3%

	27 m Grid		
Distance	**81 m**	**135 m**	**189 m**
Concave agree	68	75	68
Convex agree	77	69	75
% concave agree	64.8%	71.4%	64.8%
% convex agree	69.4%	62.2%	67.6%
Mean % agreement	67.1%	66.8%	66.2%

†Analysis scale with strongest signal highlighted in dark gray; other strong agreements shown in lighter gray.

The signal for relative elevation was at 135 m (Table 4). To confirm this for the 3 m resolution grid, the experimental matrix needed to be extended beyond a field equivalent distance of 81 m. The signal for an optimal analysis scale at 135 m was consistent for nearly all measures. The only exception was the percent agreement for relatively high elevation using the 27 m resolution grid. In that case, one more point was in agreement for the 81 m over the 135 m scale, increasing the amount of agreement by 0.5%. The analysis scale for the relative elevation signal indicates relative elevation is considered contextually over a larger area in the field, by mappers, as compared to the other terrain metrics.

The numeric field observations of slope gradient provided a quantitative determination of matching analysis scales. Although it is unrealistic to expect integers recorded by human observation to exactly match the rational numbers calculated by DTA, a minimal difference provides a calibration of the digital method to the analysis scale used in the field. For each grid resolution, the mean difference was lowest at the finest analysis scale possible (Table 5). The trend of decreasing mean differences with decreasing neighborhood size suggests the optimal analysis scale for digitally determining slope gradient similar to a soil scientist’s characterization in the field is relatively small.

Table 4. Percent agreement results for relative elevation. Low and high 'agree' are the count of points where the digital and field assessments of relative elevation were in agreement. Percent is the proportion of agreement out of the total number of points identified by the soil scientists to be in the respective category (206 low and 200 high points).†

Relative Elevation	3 m Grid							
Distance	**9 m**	**15 m**	**27 m**	**45 m**	**63 m**	**81 m**	**135 m**	**189 m**
Low agree	101	115	135	148	158	163	176	173
High agree	109	117	123	136	137	140	144	140
% low agree	49.0%	55.8%	65.5%	71.8%	76.7%	79.1%	85.4%	84.0%
% high agree	54.5%	58.5%	61.5%	68.0%	68.5%	70.0%	72.0%	70.0%
Mean % agreement	51.8%	57.2%	63.5%	69.9%	72.6%	74.6%	78.7%	77.0%

	9 m Grid					
Distance	**27 m**	**45 m**	**63 m**	**81 m**	**135 m**	**189 m**
Low agree	125	152	159	164	177	172
High agree	129	133	139	139	148	132
% low agree	60.7%	73.8%	77.2%	79.6%	85.9%	83.5%
% high agree	64.5%	66.5%	69.5%	69.5%	74.0%	66.0%
Mean % agreement	62.6%	70.1%	73.3%	74.6%	80.0%	74.7%

	27 m Grid		
Distance	**81 m**	**135 m**	**189 m**
Low agree	153	167	166
High agree	145	144	138
% low agree	74.3%	81.1%	80.6%
% high agree	72.5%	72.0%	69.0%
Mean % agreement	73.4%	76.5%	74.8%

†Analysis scale with strongest signal highlighted in dark gray; other strong agreements shown in lighter gray.

Table 5. Mean absolute difference results for slope gradient.

Slope (degrees)	3 m Grid					
Distance	**9 m**	**15 m**	**27 m**	**45 m**	**63 m**	**81 m**
Mean difference	3.1°	3.2°	3.4°	3.8°	4.0°	4.1°

	9 m Grid					
Distance	**27 m**	**45 m**	**63 m**	**81 m**	**135 m**	**189 m**
Mean difference	3.4°	3.8°	4.0°	4.1°	4.4°	4.5°

	27 m Grid		
Distance	**81 m**	**135 m**	**189 m**
Mean difference	4.1°	4.4°	4.5°

Discussion

The observed convergence in agreement as neighborhood size approaches an optimal analysis scale suggests 1) soil surveyors are relatively consistent in their use of analysis scale and 2) the calibration methodology was able to capture the analysis scales used by the soil scientists. By comparing a series of analysis scales for land-surface derivatives with the soil scientists' mental model assessments, the analysis scales of land-surface derivatives that best correspond to the soil scientists' field experience were identified. In the context of soil scientists describing hillslopes, the analysis scale used decreases from relative elevation to profile curvature to slope gradient. To many field scientists, this hierarchy of analysis scale for these components may sound intuitive, but DTA parameters are often calculated at identical analysis scales for use in environmental models. The field scientists' use of different analysis scales for these parameters should inform quantitative modelling and thereby improve geomorphic and soil predictions.

Comparisons of DTA scales demonstrated the impact of analysis scale choice for each land-surface derivative, particularly for capturing expert knowledge. For example, when characterizing relative elevation with a 3 m resolution grid, choosing between a field equivalent distance of 9 m versus 135 m had the impact of agreeing with the field scientists 52% of the time or 79% of the time, respectively. Similarly, when simply characterizing profile curvature as concave or convex, choosing an analysis scale of 63 m over 9 m improved agreement with scientists in the field by 10%.

Although the method introduced would need to be applied in additional study areas to determine transferability, the results of this study are supported by the observations of other researchers investigating the optimal analysis scale for these land-surface derivatives in other soil related contexts. The semantic calibration of profile curvature scale in this study corresponds to the optimal scale Drăgut et al. (2009) determined for predicting crop yield from profile curvature on an alluvial plain of the Danube River. The increasing agreement between digital and field measurements of slope gradient with decreasing neighborhood size to at least 9 m is also consistent with the results of Shi et al. (2007). The results of Roecker and Thompson (2010) indicated a coarser analysis scale for profile curvature, but the smaller quantity of samples in their study may have been susceptible to issues of sampling and the scale effect of MAUP.

The use of only categories that are better separated definitionally was successful in reducing the noise in the soil scientists' mental model outcomes. The high variability of human assessment greatly reduces the predictability of qualitative field metrics such as hillslope position, but does not negate the ability to capture the logic in the experts' knowledge. At a minimum, the DTA should be expected to produce values definitionally compatible with the field observations. That is, profile curvature should be positive for convex slope shapes and negative for concave slope shapes (note, some profile curvature algorithms may have those definitions switched). Similarly, it would be expected that summits and shoulders would have positive relative elevations with footslopes and toeslopes expected to have negative relative elevations. The calibrated analysis scale at which the DTA has the highest agreement with these definitional relationships provides insight to how the soil scientists conceptualized the landscape in the field.

The similar rates in calibration agreement for matching analysis scales across grid resolutions indicate that resampling to larger cell sizes did not have a major impact on the analysis. Using more cells in the analysis neighborhood or aggregating to larger cell sizes and then using fewer cells in the analysis neighborhood are two different routes for generalization, with the potential for different outcomes. However, the effect of using one or the other method of generalization did not affect the results as much as changing the realized analysis scale.

As high resolution, digital elevation products from technologies such as LiDAR become more available, smaller objects on the ground have the potential to affect DTA results. Although the elevation grid used in this study was processed from the LiDAR point cloud to be bare earth, the influence of either non-soil or at least man-made features are present in the elevation data. This noise in the DEM could affect land-surface derivatives. Therefore, the semantic calibration in this study may be influenced by not only the scale used by soil scientists, but also the DTA scale that sufficiently smoothes the digital representation of terrain to minimize the influence of features that would naturally be ignored by scientists in the field.

Conclusions

Based on data from the soil scientists in this study, this research suggests that there are optimal analysis scales for relating DTA to observations made in the field. However, the optimal analysis scale is likely to be different for each land-surface derivative. The method of semantic calibration presented was able to identify analysis scales that optimized the agreement between DTA and field observations.

Results from this study suggest that the optimal analysis scales for slope gradient, profile curvature, and relative elevation are the field equivalent distances of 9 m, 63 m, and 135 m, respectively. As analysis scales tested were limited to multiples of the grid cell size, these calibrated analysis scales are approximate. Application of the method introduced in this study in additional areas is needed to determine the transferability of these calibrated analysis scales, but similarity of these results with other studies suggests the possibility that they are not unique to this study area.

This method of semantically calibrating analysis scales for DTA provides documentation of the soil scientists' field perspective and experience in the assessment of hillslope processes. Models attempting to predict landscape features traditionally identified by field scientists will likely benefit from using the same analysis scales utilized by those scientists. Similarly, other models using DTA as parameters will likely benefit from the lessons of analysis scale accumulated by scientists in the field over centuries.

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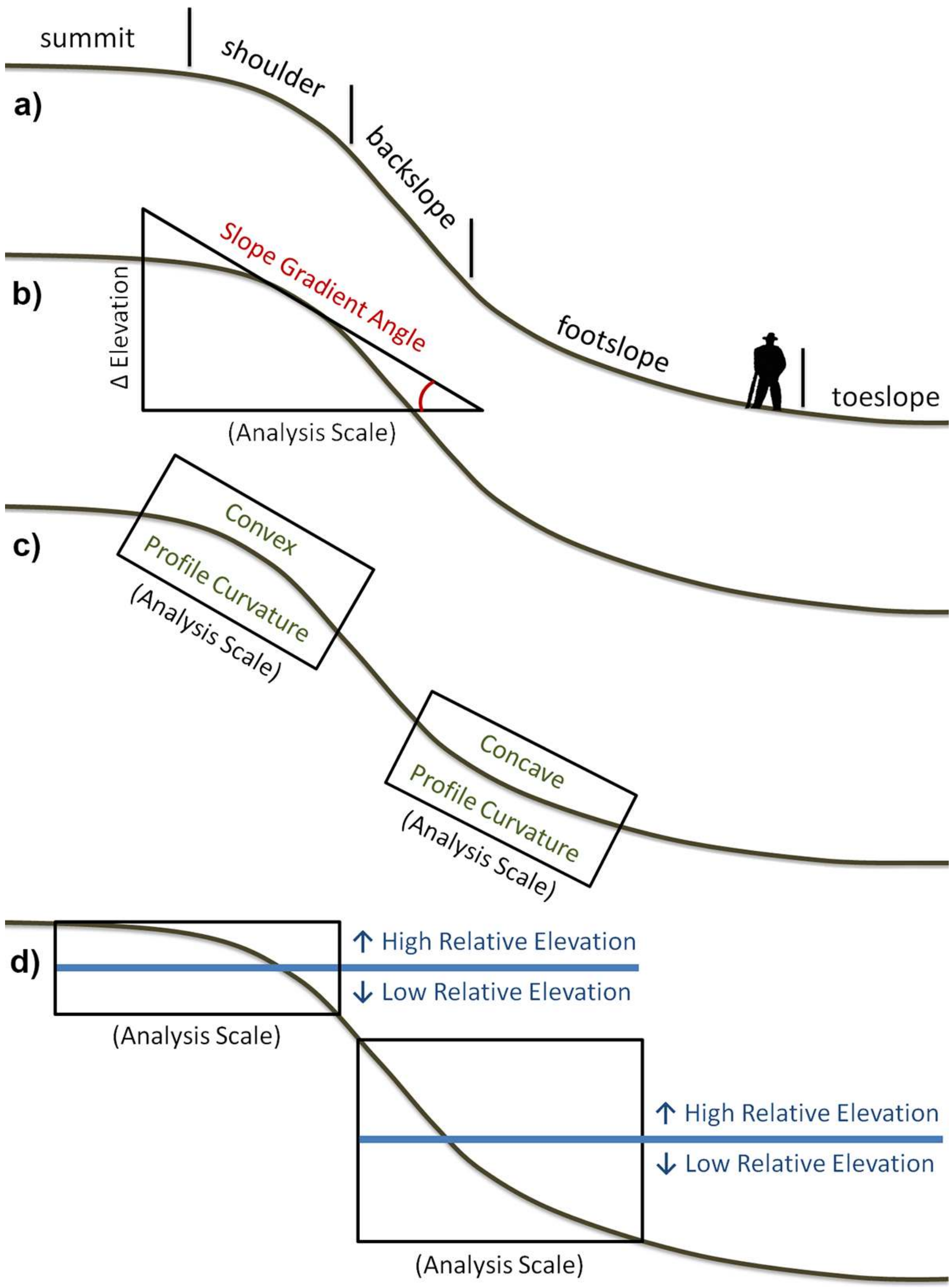
482 Figures



483

484 Figure 1. In order to classify the functional zones of hillslope position, a) soil scientists in the
485 field synthesize their assessment of b) slope gradient, c) profile curvature, and d) relative
486 elevation to determine the hillslope position of a location.

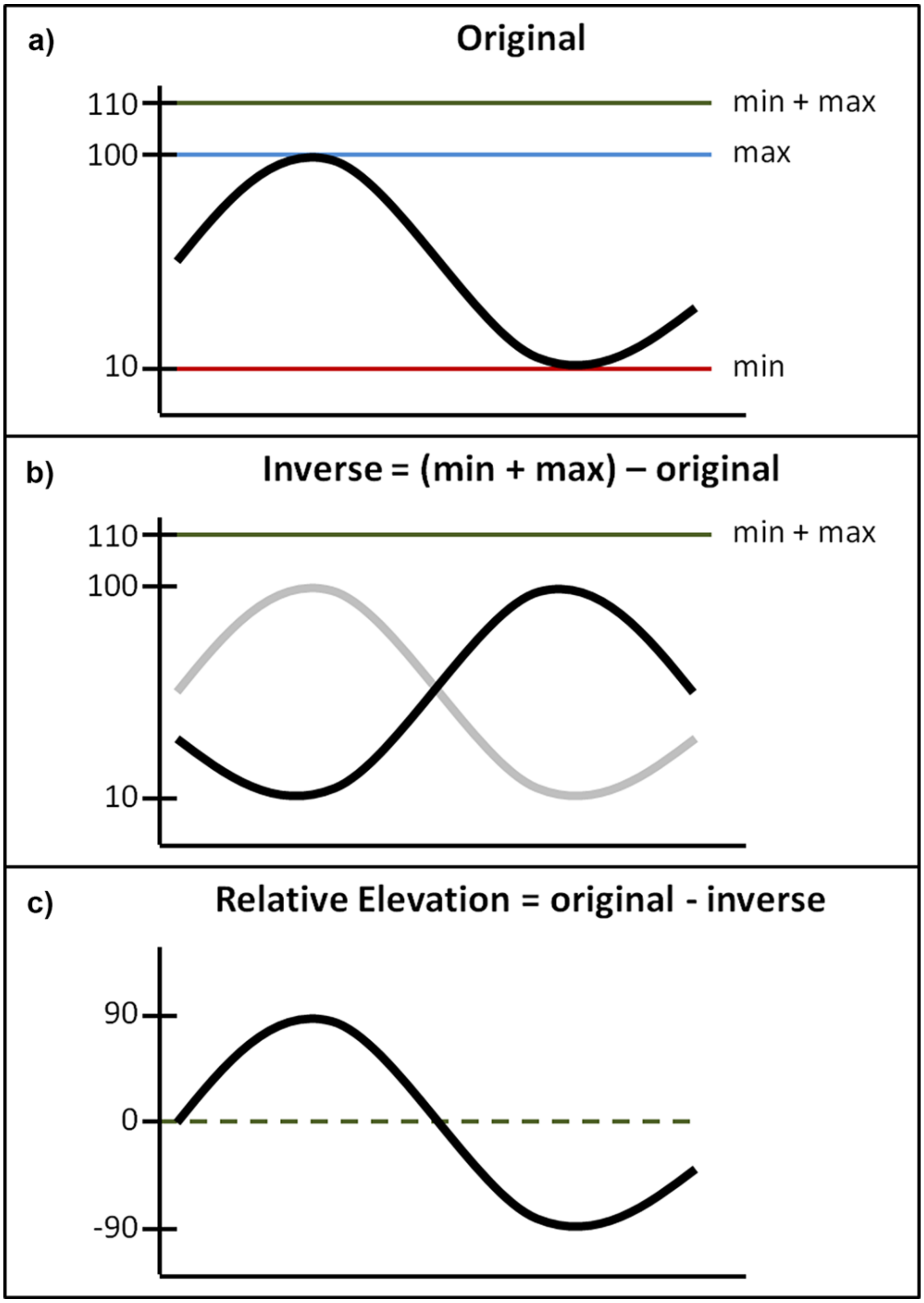


Figure 2. In this research, relative elevation is calculated on a neighborhood by neighborhood basis for each cell. a) First, a reference elevation ceiling is calculated by summing the neighborhood minimum and maximum elevations. b) Then, the central cell elevation is subtracted from the elevation ceiling to calculate an inverse elevation. c) By subtracting the inverse from the original elevation, a relative elevation grid is created with the mid-point between the neighborhood minimum and maximum having a value of zero. Elevation values above the mid-point are increasingly positive. Below the elevation mid-point, values are negative and decrease with vertical distance.

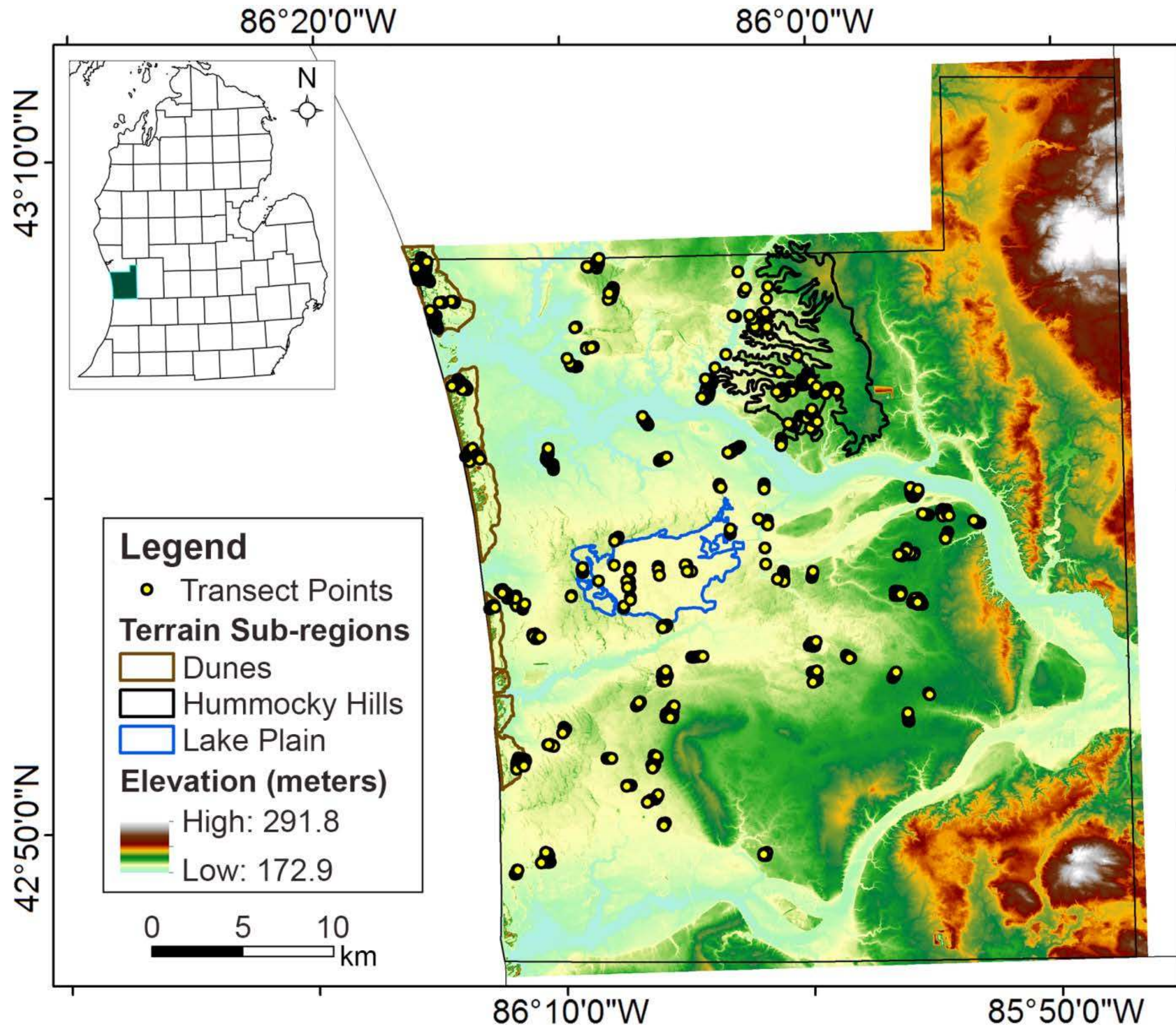


Figure 3. Relief and location of study area, Ottawa County, in the lower peninsula of Michigan, U.S. The map also includes locations of field observation transect points.

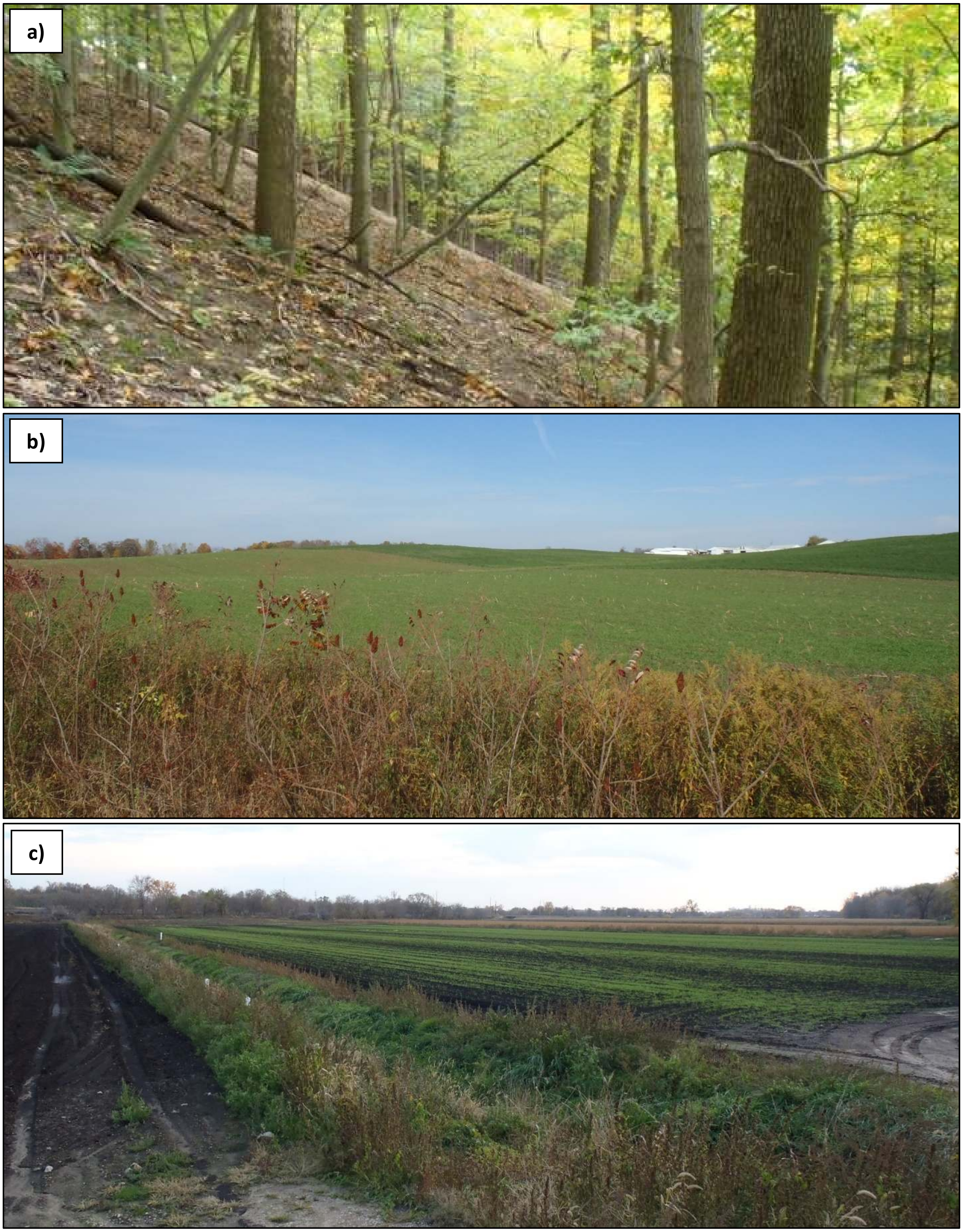


Figure 4. Examples of terrains within study area: a) dune landscape, b) glacial lake plain landscape, and c) hummocky landscape. Photos by the author.