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Pedology

Digital Classification of Hillslope Position

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Hillslope position has long been important in soil geomorphology. At the scale of county-level soil maps, more soil boundaries are based on topography than any other soil-forming factor. However, the inability to accurately delineate topographic breaks across hillslopes—either due to lack of sufficient topographic resolution or the proper technology to develop and/or model them—hinders soil mapping efforts. In this research, we developed a decision tree model for classifying hillslope position, which was calibrated and validated using the observations of soil scientists in the field. Different decision tree structures were tested with classification breaks based on calibration groups' mean midpoints, median midpoints, and fuzzy membership. The final model objectively and quantitatively classifies the five major hillslope positions and performs well on different landscapes, making it suitable for efficient application to large areal extents. The resulting maps of hillslope position represent base maps that can be used to (i) improve research on toposequences by providing explicit definitions of each hillslope element's location, (ii) facilitate the disaggregation of soil map unit complexes, and (iii) identify map unit inclusions that occur due to subtle topographic variation. Base maps developed by the model can also help identify areas of possible inaccuracies in soil maps, especially where soil boundaries cross topographic breaks. Predictions from the model enable the mapper to better place soil map unit boundaries at locations where defendable landscape breaks exist.

Abbreviations: CI, confidence index; DEM, digital elevation models; DTA, digital terrain analysis; MLRA, major land resource area; MO, MLRA office; OSD, official soil series description; PDF, probability density function; PrcP, profile curvature priority decision tree; PrcP-ci, PrcP based on confidence index; PrcP-mean, PrcP based on mean midpoints; PrcP-med, PrcP based on median midpoints; ReeP, relative elevation priority decision tree; ReeP-ci, ReeP based on confidence index; ReeP-mean, ReeP based on mean midpoints; ReeP-med, ReeP based on median midpoints; SlgP, slope gradient priority decision tree; SlgP-ci, SlgP based on confidence index; SlgP-mean, SlgP based on mean midpoints; SlgP-med, SlgP based on median midpoints; SSURGO, Soil Survey Geographic dataset.

In 1968, Ruhe and Walker defined the five major hillslope profile positions (Fig. 1). The transferability of this model for fully developed slopes, regardless of climate, landscape age, or parent material, has been clearly demonstrated (Wood, 1942; King, 1957; Frye, 1959; Ruhe, 1975), becoming the standard for guiding myriad soil toposequence studies as well as for landscape description and segmentation in general (Conacher and Dalrymple, 1977; Pennock et al., 1987; Giles, 1998; Park and van de Giesen, 2004). Numerous studies—some of them landmark papers—have leaned on or otherwise built on this framework to examine the variability of soil properties across hillslopes (e.g., Furley, 1971; West et al., 1988; Stolt et al., 1993; Kagabo et al., 2013; Tsatskin et al., 2013). Because of the interrelationships that exist between soil and vegetation, hillslope position has also become a useful framework in ecological studies (Monger and Bestelmeyer, 2006;

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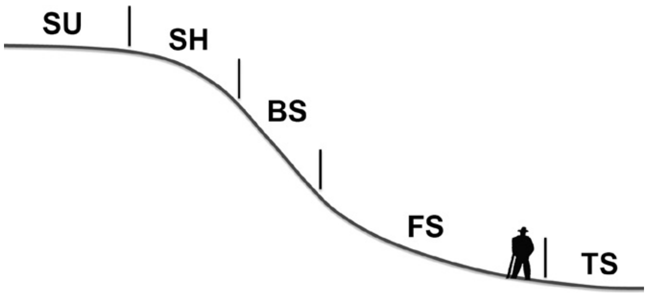

Fig. 1. Schematic of the five hillslope positions: summit (SU), shoulder (SH), backslope (BS), footslope (FS), and toeslope (TS) (after Wysocki et al., 2000 and Schoeneberger et al., 2012).

Arnold et al., 2009; Jien et al., 2010; Khalili-Rad et al., 2011; Koné et al., 2013).

For these reasons, topographic relationships have been used successfully by the USDA-NRCS Soil Survey Division (hereinafter referred to as Soil Survey), especially at scales where hillslope processes are a major factor in explaining the spatial variation of soils (e.g., Pregitzer, 1972; Dermody, 2009; Pulido, 2011). Unfortunately, many county-scale soil maps were compiled using stereophotograph interpretations of terrain, which, although quite useful and predictive, suffer from three main shortcomings: (i) resolution visible in the base map (mainly aerial photographs) prevented the manual delineation of hillslope elements that may have been identifiable in the field, (ii) the minimum delineation size was limited by the cartographic medium of paper maps, and (iii) stereophotograph interpretation was a subjective evaluation of the landscape, and hence, varied from person to person. Therefore, along with others (Hall and Olson, 1991; Smith and Hudson, 2002), we contend that topographic relationships need to be better represented in soil mapping endeavors. One possible way to accomplish this would be the establishment and application of more accurate and more objective definitions of landscape components such as hillslope position, using modern geographic technologies, and incorporating better base maps of topography into the mapping process (Miller and Schaetzl, 2014). Indeed, due to the limited resolution of stereophotographs and the manual interpretation of digital geographic data, current Soil Survey maps only differentiate *some* of the hillslope positions needed to make an accurate soil map (Zhu et al., 2001), often resulting in soil complexes rather than consociations, and many consociations are not as taxonomically pure as they could be.

Recent advances in data and base maps have, however, helped alleviate some of these issues. For example, digital elevation models (DEM), such as those produced by LiDAR, provide the resolution necessary to identify small variations in topography. Nonetheless, these data are often not fully leveraged to improve soil maps. Instead, high-resolution data are commonly used to predict map units that were designed for mapping with stereophotographs (e.g., Qi et al., 2008; Shi et al., 2009; Yang et al., 2011). Calibrating models on existing map unit delineations is problematic because those delineations carry with them the limitations of the base maps on which they were derived as well as the biases of the original mappers. In contrast, redefining map units to correspond with quantitative breaks associated with established process zones would likely produce map units with less internal variability and greater consistency.

Soil Survey maps often contain complexes and consociations with known inclusions, largely because of the manual methods of delineation at the designated cartographic scale. When drawing map unit boundaries on paper maps, minimum map unit size restrictions become an issue (Hupy et al., 2004; Arnold, 2006). In some cases, when the properties of such an inclusion are deemed important, it is indicated as a point or spot symbol (Soil Survey Staff, 1993). However, the symbol provides no information about spatial extent. Even if a higher resolution base map had been available, the time it would have taken to make the additional delineations would not have been practical with the available resources of the USDA-NRCS (Simonson, 1952). With GIS, however, complexity and cartographic scale no longer limit minimum delineations. Classifications can now be automated, greatly reducing time demands. The process of differentiating composite soil map unit delineations into spatially explicit soil components is known as "disaggregation" (Thompson et al., 2010; Odgers et al., 2014). Adding this additional level of detail to soil maps essentially results in the separation of areas that do not fit the taxonomic classification of the map unit, which results in increased map unit purity. Many of the differences for these inclusions are topographic in nature.

Finally, delineations on current Soil Survey maps have at times been relatively subjectively determined. Some criteria were developed by the soil scientists via customized soil series keys for the respective survey areas (Soil Survey Staff, 1993). However, those keys only reduced, but not completely eliminated, the subjective interpretations of the features observable on stereophotographs. When using manual methods, any placement of a boundary line based on topography depends on the mapper's judgment. Further, in that situation, the level of detail actually included in a soil map is also dependent on the mapper's judgment. GIS and, more specifically, digital terrain analysis (DTA) offer quantitative tools for consistently placing delineations using a clearly defined set of rules.

Hillslope position represents a composite of terrain characteristics, that is, profile curvature, slope gradient, and relative elevation, which are mentally synthesized by soil scientists in the field (Ruhe and Walker, 1968; Fig. 1). Previous efforts have attempted to derive digital models for landform elements (MacMillan et al., 2000; Schmidt and Hewitt, 2004; Drăguț and Blaschke, 2006; Qin et al., 2009), but none have sought to directly capture the expert knowledge of soil scientists. Perhaps for this reason, hillslope position has not yet been translated to digital methods. A robust model for hillslope position can bridge the gap between digital technologies and a large body of research that has established the utility of hillslope position to soil geomorphology. Theoretically, soil mapping efforts could take advantage of such a hillslope position base map and combine it with field knowledge to create soil maps using the increased precision and efficiency of DTA. However, to do so, the five hillslope positions need to be defined in a manner that is accurate, repeatable, and transferable across landscapes.

The purpose of this research is, therefore, to develop a digital model that standardizes the definition of hillslope position as identified by field soil scientists. Once developed, hillslope position classifications can be applied consistently and objectively as improved base maps for soil mapping endeavors.

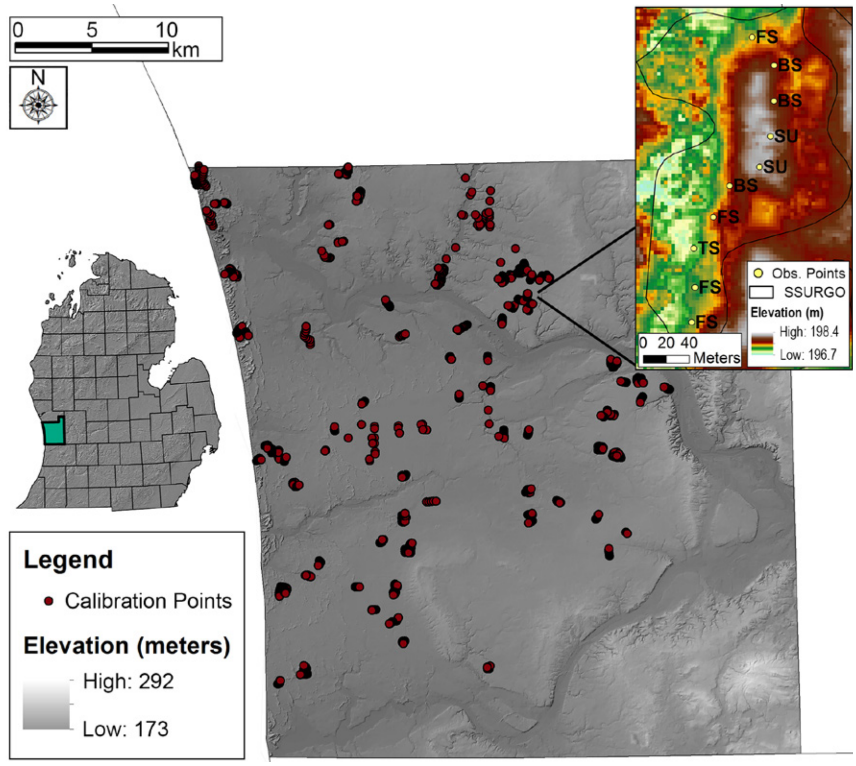

Fig. 2. Distribution of calibration points in Ottawa County, MI. Each set of points represents a transect, walked by NRCS field soil scientists, usually with 8 to 10 field observations.

METHODS

General Setup

We utilized experts' (soil scientists from the Soil Survey) observations of hillslope position in the field to determine the optimal segmentation of hillslopes. We then used land-surface derivatives from a LiDAR-based DEM as parameters for predicting these experts' assessments.

The parameters for determining hillslope position are scale dependent, requiring soil scientists in the field to mentally calibrate their analysis scale for each land-surface derivative. To this end, Miller (2014) calibrated the optimal digital analysis scale for each of these terrain derivatives to the analysis scale used by soil scientists assessing hillslope position (i.e., slope at 9 m, profile curvature at 63 m, and relative elevation at 135 m). The present study builds on that work by using the same parameter analysis scales as inputs to a hillslope classification model. All terrain analyses of slope gradient and profile curvature were conducted on LiDAR-derived, 3-m resolution elevation grids using the r.param.scale function in GRASS 6.4.2 (GRASS Development Team, 2014). Relative elevation was calculated on the LiDAR data using ArcGIS 10.1 (ESRI, 2014) with the analysis scale dependent method presented by Miller (2014).

Calibration of Decision Tree Structure

The hillslope position model was calibrated in Ottawa County, MI. The county includes a wide variety of terrain, mostly derived from Late Wisconsin glaciation (Pregitzer, 1972). Its topography ranges from flat, lake, and outwash plains to hummocky till plains. Areas of high relief sand dunes also occur near the Lake Michigan shore. Slope gradients range from 0 to 80%, with a mean slope gradient of 5% (9-m analysis scale).

Field observations of hillslope position in Ottawa County were collected by NRCS soil scientists working out of the Grand Rapids office (MLRA office [MO] 11-7, major land resource area [MLRA] 97). These observations were commonly collected to better understand boundaries between map units that have proven difficult to delineate. A pool of 1039 GPS-located, field observations recorded by the soil scientists and taken as 8 to 10 point transects with 40- to 80-m spacing were used for calibration in this study (Fig. 2). At each point, the mapper made notes regarding soil properties and their interpretation of hillslope position. These points were intersected with the DTA grids of the model parameters and grouped by the field assessment of hillslope position. Due to limitations in detecting subtle variations for classifying some locations, especially in flat areas, not all observation points included a description applicable to all components of hillslope position determination. For example, 411 points were described as "flat." Although these points could not be used to calibrate breaks for relative elevation, they were, however, used to populate assessment groups for slope gradient and profile curvature.

Next, a decision tree approach was used to model the synthesis and differentiation of the land-surface derivatives for determining hillslope position. In all decision trees, the first level of criteria was calibrated for two classification breaks to create three overall categories. The remaining levels of the decision trees then only required a single break to make two categories within the respective branches of the tree. There were only three possible combinations of the parameters for the decision trees due to the use of three categories at the top tier. This research tested all three decision tree hierarchy structures. The initial decision tree hierarchy differentiated hillslope positions first by profile curvature, then by slope gradient, and finally by relative elevation. Because this hierarchy emphasized profile curvature at the top level, it will be referred to as the profile curvature priority decision tree (PrcP) (Fig. 3a). The second hierarchy differentiated hillslope positions first by slope gradient and then by profile curvature and relative elevation (Fig. 3b) and will be referred to as the slope gradient priority decision tree (SlgP). The third

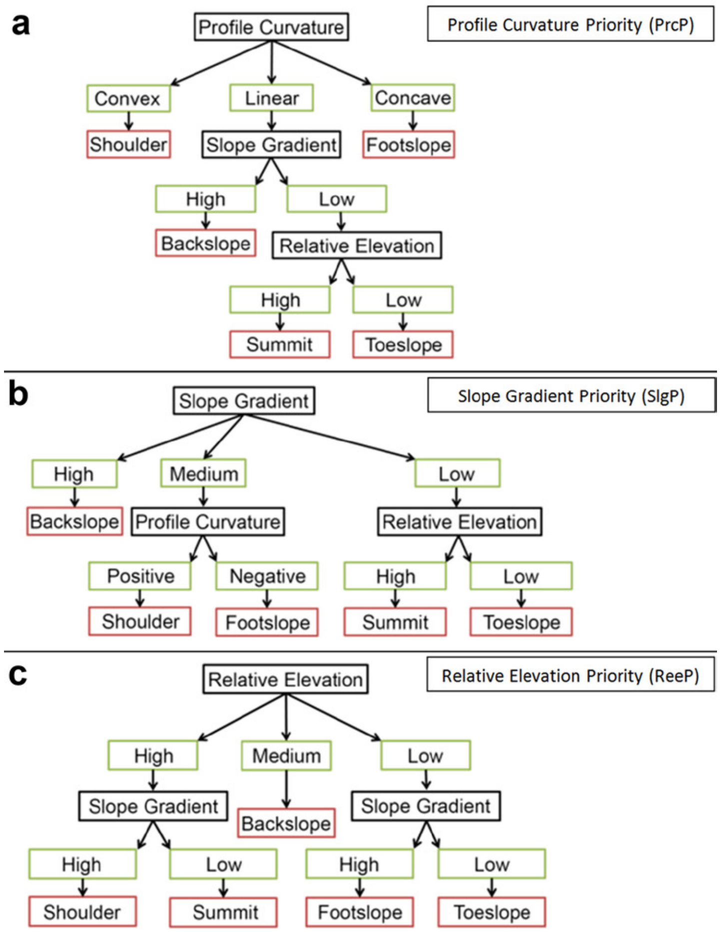

Fig. 3. Flow diagrams for the three classification tree hierarchies that were tested.

hierarchy differentiated hillslope positions first by relative elevation and then slope gradient and will be referred to as the relative elevation priority decision tree (ReeP) (Fig. 3c). In this last hierarchy, the classification did not use profile curvature because the first two tiers fully differentiated all five hillslope positions.

Calibration of Classification Breaks

Three methods for assigning category membership were tested on each of the three decision tree structures, leading to nine experimental iterations. For each model parameter, the calibration points were sorted into assessment groups as per the definitional category of the observed hillslope position (Table 1). The assessment groups were concave, linear, and convex for profile curvature (reduced to concave vs. convex when only two categories were needed). For slope gradient and relative elevation, the assessment groups were low, medium, and high (reduced to low vs. high as needed). Descriptive statistics for the DTA values within the assessment groups were calculated and used as a basis for quantitative calibration of breaks between groups.

The first method for calibrating classification breaks used the assessment group means as the central concept for the respective groups. The mean of two adjacent central concept values (midpoint) was used as the break between the two groups. Because of a few extreme values, particularly with regard to slope gradient, the second calibration method used the assessment group medians, instead of the mean, as the central concept. The third method evaluated for calibrating classification breaks allowed for the possibility that assessment groups had dissimilar variability. A confidence index (CI) of membership was constructed based on a normal probability density function (PDF) generated from the respective group's mean and SD. The resulting values were then scaled to set the group mean with a CI value of one. Parameter values on the opposite side of the mean from all other assessment groups were assigned a CI of one plus the inverse result of the PDF. The resulting theoretical CI distribution is illustrated in Fig. 4. For hillslope classification purposes, locations were categorized into the group for which the location had the highest CI of membership, essentially "hardening" the fuzzy memberships.

Validation and Transferability

To test the validity of the respective models, the maps produced by each of the models for Ottawa County were compared with 262 field observations taken by the same staff that collected the calibration points; these latter points were individual observations not taken as part of the transects used for calibration. Of these latter points, the field observer was able to classify the point to hillslope category in 189 instances. In the 73 cases where the field soil scientist associated a point with two different hillslope positions (e.g., summit–shoulder), a prediction of either position from the model was accepted as valid. Each calibrated model was evaluated by determining the agreement (percent) between soil scientists' field observations and the model prediction, as well as with confusion matrixes (Longley et al., 2011).

The transferability of the model to other terrains was tested by applying the models calibrated in Ottawa County, MI to two counties in Iowa (Dickinson and Cedar) (Fig. 5), using 3-m resolution elevation grids obtained from the Iowa Department of Natural

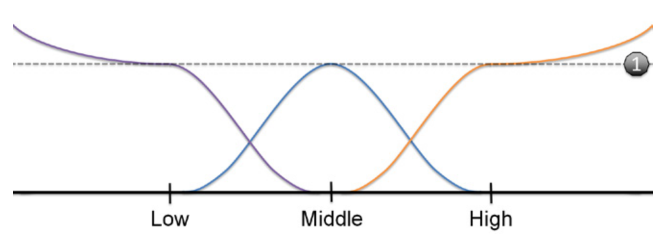

Fig. 4. Conceptual illustration of the confidence index (CI) used for determining fuzzy class membership. The shape of the CI curve for the middle class is calculated by a normal probability density function (PDF) based on the calibration assessment group's mean and SD. Confidence index values for the low and high classes are calculated in the same manner, except that values on the opposite side of the mean from other classes are calculated as one plus the inverse of the PDF result.

Table 1. Categories of terrain parameters employed in this study.

Hillslope position	Slope	Profile curvature	Relative elevation
Summit (SU)	Low	Linear	High
Shoulder (SH)	Medium	Convex	High
Backslope (BS)	High	Linear	Middle
Footslope (FS)	Medium	Concave	Low
Toeslope (TS)	Low	Linear	Low

Resources, which were based on 2007 to 2009 LiDAR data (IDNR, 2009). Hillslope position validation points here were field observations with locations recorded by GPS and obtained from the Soil Survey Office in Waverly, IA (MO 10-11, MLRA 104). Dickinson County had 75 and Cedar County had 35 field observations. The amount of agreement was assessed in the same manner as for Ottawa County.

Like the Michigan study area, Dickinson County, IA is dominated by glacial landforms but with a large proportion of closed basins (Pulido, 2011). The area consists primarily of till, glaciolacustrine, and outwash plains. The mean slope gradient in the area is 3% (9-m analysis scale). Cedar County's physiography has been classified as southern Iowa drift plain except for some Iowan erosion surface in the northern part of the county (Ruhe, 1969; Dermody, 2009). Across the county, pre-Illinoian glacial deposits have been dissected through several episodes of landscape development (Bettis, 1989). Slope gradients in the area have a mean of 5% (9-m analysis scale).

The model determined to have the highest agreement with validation points in all three study areas was subsequently compared with the current Soil Survey map delineations. Zonal statistics of the hillslope position classifications based on map units in the Soil Survey Geographic dataset (SSURGO; Soil Survey Staff, 2013b) were used to compare the two maps. This test identified the percent of existing map unit delineations that were classified into the different hillslope positions by the selected model.

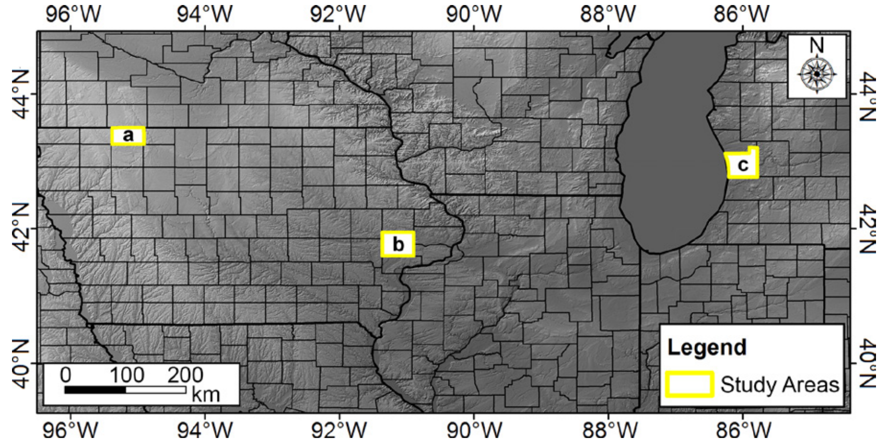

Fig. 5. Map of the counties used for developing the hillslope position classification model. Dickinson County, IA (a) and Cedar County, IA (b) were used to test the transferability of the models that were originally calibrated and validated in Ottawa County, MI (c).

Table 2. Statistics of calibration points categorized into the assessment groups of each model parameter.

Model parameter	Assessment group	Mean	Median	SD	Count
Slope gradient (9-m analysis scale)	Low	2.20%	1.61%	2.60%	577
	Medium	6.41%	3.16%	8.27%	218
	High	14.17%	7.02%	15.78%	171
Profile curvature (63-m analysis scale)	Concave	−0.00538° m^{-1}	−0.00120° m^{-1}	0.02193° m^{-1}	105
	Linear	−0.00021° m^{-1}	−0.00004° m^{-1}	0.01938° m^{-1}	751
	Convex	0.00388° m^{-1}	0.00136° m^{-1}	0.01500° m^{-1}	111
Relative elevation (135-m analysis scale)	Low	−2.16 m	−0.74 m	4.41 m	206
	Middle	−1.18 m	−0.03 m	8.53 m	166
	High	1.35 m	0.55 m	6.33 m	200

RESULTS AND DISCUSSION

Calibration

Using data obtained from the calibration points, we generated descriptive statistics of the assessment groups (Table 2) and used them to calculate classification breaks for the hillslope classes. Each of the assessment groups, two to three per model parameter depending on the decision tree, exhibited non-normal distributions and different amounts of variation. Therefore, the use of assessment groups' mean vs. the median and the consideration of respective assessment groups' SD resulted in unique classification breaks for each calibration method. For comparison, the determined classification breaks for the mean midpoint, median midpoint, and the equivalent break values for the CI (after hardening the fuzzy classification) are presented in Table 3. The calibrated breaks for concave–convex profile curvature and low–high relative elevation should, by definition, be zero. Compared to the other two calibration methods, the median midpoint based breaks are the closest to meeting that definition. The hardened CI breaks are generally similar to the mean midpoint calibration method but are tempered by the larger SDs for steeper slope groups and the middle relative elevation group.

Ottawa County Validation

For Ottawa County, the decision tree models correctly predicted between 36 and 59% of field scientists' assessments of hillslope position (Table 4). Disagreements occurred because of a

Table 3. Classification breaks calibrated from the assessment group statistics of each model parameter.

Model parameter	Breaks	Mean midpoint	Median midpoint	Hardened CI†
Slope (9-m analysis scale)	Low–medium	4.30%	2.37%	3.19%
	Medium–high	10.28%	5.08%	9.08%
	Low–high	8.19%	4.31%	3.89%
Profile curvature (63-m analysis scale)	Concave–linear	−0.00279° m^{-1}	−0.00062° m^{-1}	−0.00263° m^{-1}
	Linear–convex	0.00184° m^{-1}	0.00066° m^{-1}	0.00210° m^{-1}
	Concave–convex	−0.00075° m^{-1}	0.00008° m^{-1}	0.00012° m^{-1}
Relative elevation (135-m analysis scale)	Low–middle	−1.67 m	−0.38 m	−1.83 m
	Middle–high	0.09 m	0.26 m	0.28 m
	Low–high	−0.40 m	−0.10 m	−0.71 m

† CI, confidence index.

Table 4. Percent agreement between soil scientists' field assessments and each hillslope position models' prediction by each classification break calibration method for Ottawa County, MI.

Model†	Mean	Median	Confidence index
PrcP	58%	46%	57%
SlgP	59%	53%	58%
ReeP	38%	42%	36%

† PrcP, profile curvature priority decision tree; ReeP, relative elevation priority decision tree; SlgP, slope gradient priority decision tree.

combination of DEM errors, positional uncertainty, and the subjectivity associated with human judgment of slope position. The SlgP decision tree, using the classification breaks based on mean midpoints, had the highest level of agreement with field assessments; the agreement rates for the CI based SlgP were nearly as high. The agreement rates were also nearly as high for the mean midpoints and CI calibration methods for PrcP. Although the influence of different SDs between assessment groups shifted the CI based breaks, the shift did not have a large impact on general agreement results for any of the decision tree structures. Greater differences in model results were observed in the confusion matrices (Fig. 6–8).

To compare models, the classification break calibration method was abbreviated in conjunction with the decision tree structure abbreviation (e.g., PrcP based on mean midpoints [PrcP-mean], PrcP based on median midpoints [PrcP-med], PrcP based on confidence index [PrcP-ci]). The PrcP-mean and PrcP-ci models tended to over classify points as summits and toeslopes, particularly for those points identified as backslopes by the soil scientists. This issue implied that the break between low and high slope gradient was set too high (mean midpoint = 8.19%, CI = 3.89%) for those models (Fig. 3a). A similar pattern can be seen in the confusion matrixes for the SlgP-mean and SlgP-ci models, but these models had more misclassifications for shoulder and backslope positions. This issue for the SlgP-mean and SlgP-ci models implied a similar problem: the break between low and medium slope gradients (mean midpoint = 4.29%, CI = 3.19%) was set too high (Fig. 3b).

The overall performance levels of the PrcP-med and SlgP-med models were lower than the PrcP-mean, SlgP-mean, PrcP-ci, and SlgP-ci models. However, the PrcP-med and SlgP-med confusion matrices showed closer agreement between field observations and model predictions when they did not agree exactly. For both of these models, the highest number of misclassifications was always in a neighboring category. The SlgP-med performed better than the PrcP-med model; more often it correctly classified backslope positions. The SlgP-med model separated all areas classified as having high slope gradients as backslopes, suggesting

a Field Observation (rows: Model)

PrcP-mean	SU	SH	BS	FS	TS	User*
SU	74	16	20	8	6	59.7
SH	4	4	7	0	0	26.7
BS	1	4	25	1	1	78.1
FS	0	0	4	0	4	0.0%
TS	1	3	11	16	48	60.8
Producer*	92.5	14.8	37.3	0.0%	81.4	

b Field Observation (rows: Model)

SlgP-mean	SU	SH	BS	FS	TS	User*
SU	71	5	1	0	0	92.2%
SH	12	9	3	1	2	33.3%
BS	16	14	28	0	9	41.8%
FS	6	6	0	2	11	8.0%
TS	4	3	1	2	44	81.5%
Producer*	65.1%	24.3%	84.8%	40.0%	66.7%	

c Field Observation (rows: Model)

ReeP-mean	SU	SH	BS	FS	TS	User*
SU	52	14	18	5	1	57.8%
SH	1	4	21	0	1	14.8%
BS	8	7	19	16	15	29.2%
FS	0	0	6	0	1	0.0%
TS	0	1	2	4	24	77.4%
Producer*	85.2%	15.4%	28.8%	0.0%	57.1%	

*User's and Producer's accuracy calculated by correct classification divided by all classifications in category.

Fig. 6. Confusion matrixes for classification breaks based on the midpoint between assessment groups' means for (a) profile curvature priority (PrcP) decision tree (kappa = 0.44), (b) slope gradient priority (SlgP) decision tree (kappa = 0.49), and (c) relative elevation priority (ReeP) decision tree (kappa = 0.27). SU, summit; SH, shoulder; BS, backslope; FS, footslope; TS, toeslope.

a Field Observation (rows: Model)

PrcP-med	SU	SH	BS	FS	TS	User*
SU	49	7	13	4	1	66.2%
SH	10	14	20	1	1	30.4%
BS	3	2	12	4	3	50.0%
FS	0	3	14	7	17	17.1%
TS	4	2	8	9	38	62.3%
Producer*	74.2%	50.0%	17.9%	28.0%	63.3%	

b Field Observation (rows: Model)

SlgP-med	SU	SH	BS	FS	TS	User*
SU	43	7	6	4	0	71.7%
SH	8	8	8	3	1	28.6%
BS	6	8	41	7	4	62.1%
FS	0	1	6	6	12	24.0%
TS	2	3	7	5	40	70.2%
Producer*	72.9%	29.6%	60.3%	24.0%	70.2%	

c Field Observation (rows: Model)

ReeP-med	SU	SH	BS	FS	TS	User*
SU	37	7	10	2	1	64.9%
SH	3	10	26	1	1	24.4%
BS	8	6	11	5	5	31.4%
FS	1	2	10	7	3	30.4%
TS	0	2	9	11	44	66.7%
Producer*	75.5%	37.0%	16.7%	26.9%	81.5%	

*User's and Producer's accuracy calculated by correct classification divided by all classifications in category.

Fig. 7. Confusion matrixes for classification breaks based on the midpoint between assessment groups' medians for (a) profile curvature priority (PrcP) decision tree (kappa = 0.35), (b) slope gradient priority (SlgP) decision tree (kappa = 0.46), and (c) relative elevation priority (ReeP) decision tree (kappa = 0.36). SU, summit; SH, shoulder; BS, backslope; FS, footslope; TS, toeslope.

that slope gradient was the most important parameter for identifying backslopes.

The ReeP models all had difficulty classifying backslope positions. Although using group medians to define central concepts improved model performance, the ReeP-med model still had successful prediction rates substantially lower than the PrcP and SlgP models. The classification errors for the ReeP models suggested that the range for middle relative elevation was too wide and the break between middle and high relative elevations was too low (classification ranges for middle relative elevation: mean midpoint = −1.67–0.09 m, median midpoint = −0.38–0.26 m, and CI = −1.83–0.28 m; Fig. 3c). The ReeP-ci model's performance was slightly improved by a higher middle-high classification break but not enough to improve its correct prediction rate. The ReeP-med model had the highest performance of the ReeP calibration methods because it was unaffected by a few extremely low relative elevation values in the calibration data set.

Validation in Different Landscapes (Transferability)

Using the classification breaks calibrated in Ottawa County, the decision tree models were applied to the two counties in Iowa. The performance of most of the models was reduced when applied outside of the calibration area (Table 5). The models performed better in Cedar County, probably because its relief was more similar to that of Ottawa County. However, unlike the other models, the SlgP-med model performed consistently well in all three landscapes. Despite not being calibrated for the respective counties, the SlgP-med model was still able to predict field assessment of hillslope position at a rate comparable to the best performing models in the calibration area (Fig. 9).

The SlgP-med decision tree consistently had the highest prediction success rates (52–54%), indicating that its logic best matches the mental model used by soil scientists in the field. This model first determined if a location had a low, medium, or high slope gradient. Medium slope gradients were then differentiated by slope shape as either convex (shoulder) or concave (footslope). Finally, any remaining flat areas were examined as to whether they had a high (summit) or low (toeslope) relative elevation. This sequence may not necessarily match every field scientists' thought process; many may determine hillslope position more by intuition than a stepwise decision process. Nonetheless,

Table 5. Percent agreement between soil scientists' field assessments and each hillslope position models' prediction by each classification break calibration method.

Model†	Mean	Median	Confidence index
Dickinson County, IA			
PrcP	19%	21%	25%
SlgP	29%	52%	36%
ReeP	12%	12%	11%
Cedar County, IA			
PrcP	49%	34%	51%
SlgP	46%	54%	49%
ReeP	34%	37%	31%

†PrcP, profile curvature priority decision tree; ReeP, relative elevation priority decision tree; SlgP, slope gradient priority decision tree.

a

Field Observation

Model

PrcP-ci	SU	SH	BS	FS	TS	User*
SU	74	12	13	7	4	67.3%
SH	3	3	6	0	0	25.0%
BS	5	10	40	8	6	58.0%
FS	0	0	4	0	4	0.0%
TS	0	1	7	10	33	64.7%
Producer*	90.2%	11.5%	57.1%	0.0%	70.2%	

b

Field Observation

Model

SlgP-ci	SU	SH	BS	FS	TS	User*
SU	73	13	12	6	4	67.6%
SH	4	9	14	2	1	30.0%
BS	2	4	30	1	2	76.9%
FS	1	1	6	6	7	28.6%
TS	0	1	5	10	33	67.3%
Producer*	91.3%	32.1%	44.8%	24.0%	70.2%	

c

Field Observation

Model

ReeP-ci	SU	SH	BS	FS	TS	User*
SU	37	7	6	2	1	69.8%
SH	3	11	30	1	1	23.9%
BS	9	9	23	18	15	31.1%
FS	0	1	5	3	4	23.1%
TS	0	0	2	2	20	83.3%
Producer*	75.5%	39.3%	34.8%	11.5%	48.8%	

*User's and Producer's accuracy calculated by correct classification divided by all classifications in category.

Fig. 8. Confusion matrixes for classification breaks based on the confidence index (CI) to differentiate parameters for (a) profile curvature priority (PrcP) decision tree (kappa = 0.45), (b) slope gradient priority (SlgP) decision tree (kappa = 0.49), and (c) relative elevation priority (ReeP) decision tree (kappa = 0.28). SU, summit; SH, shoulder; BS, backslope; FS, footslope; TS, toeslope.

Dickinson County

Field Observation

Model

SlgP-med	SU	SH	BS	FS	TS	User*
SU	5	1	1	1	2	50.0%
SH	3	0	1	3	1	0.0%
BS	1	1	23	2	6	69.7%
FS	0	0	1	11	3	73.3%
TS	1	0	0	8	0	0.0%
Producer*	50.0%	0.0%	88.5%	44.0%	0.0%	

Cedar County

Field Observation

Model

SlgP-med	SU	SH	BS	FS	TS	User*
SU	6	1	1	2	1	54.5%
SH	2	2	1	0	1	33.3%
BS	0	1	6	0	0	85.7%
FS	1	0	1	0	0	0.0%
TS	2	0	1	1	4	50.0%
Producer*	54.5%	50.0%	60.0%	0.0%	66.7%	

*User's and Producer's accuracy calculated by correct classification divided by all classifications in category.

Fig. 9. Confusion matrix for slope gradient priority (SlgP)-med model prediction of field assessments of hillslope position in Dickinson (kappa = 0.35) and Cedar Counties (kappa = 0.37). SU, summit; SH, shoulder; BS, backslope; FS, footslope; TS, toeslope.

the SlgP decision tree, using classification breaks determined by the median midpoint method, best predicted the field scientists' classification in the three different landscapes. The 52 to 54% success rate was excellent, given that the three model parameters only agreed with the field scientists' assessment of the landscape 69 to 79% of the time. This suggested that the largest issue in digitally replicating expert knowledge was not in the classification process but rather in the characterization of terrain properties. Methods for measuring landscape morphology in the field are different from digital methods. This leads to many potential discrepancies between expert knowledge and digital models.

A Quantified Definition for Hillslope Position

Based on the consistent performance of the SlgP-med model for predicting field assessment of hillslope position, an expert-based definition for digital classification of hillslopes was established. In this model, which we present and utilize in the rest of this paper, the median midpoint calibrated breaks for profile curvature (convex–concave = 0.00008° m^{-1}) and relative elevation (low–high = 0.1 m) are practically zero. Simply setting these breaks as zero would be consistent with model tests. Therefore, we recommend the classification model shown in Fig. 10 for digitally determining hillslope position. This model is available at www.geographer-miller.com/relief-analysis-toolbox.

Although the calibrated breaks for slope gradient appear low, as compared to slope gradients typically observed in the field, the break at 5% corresponds with a well-established threshold for slope processes (Pennock et al., 1987). For example, Savat and DePloey (1982) and Govers (1985) observed that slope gradients below 2 to 3° (3.5–5.2%) did not produce sufficient erosive energy to form rills.

Map–Model Comparisons

Visual Assessment

Soil Survey Geographic dataset soil map delineations were overlaid onto maps generated by the selected hillslope position model (SlgP-med) to identify differences between the digital hillslope position map and the Soil Survey map. We began with visual assessments. Landscapes often do not match the idealized illustrations of hillslope position presented in textbooks and guidebooks. For this reason, the consistent application of quantitative hillslope classification rules resulted in a map that did not always have sequential patterns of hillslope position in their complete sequence. Nonsequential hillslope positions often do occur, for example, shoulders directly above toeslopes, as can be observed in both the digital hillslope position classification map and the Soil Survey map (Fig. 11). Landscape mapping of hillslope positions focuses on classifying areas that meet functional definitions for processes rather than always dividing hillslopes into the five "classic" components. For example, there may be no true summit positions if the landscape does not have upland areas that are low enough in slope gradient or linear enough in profile curvature to *function* like a summit. Similarly, a slope that does not include an area that is sufficiently steep or linear in curvature to be a backslope will have shoulders directly adjacent to footslopes.

The hillslope position maps created using the model add high-quality topographic detail to current Soil Survey map delineations (Fig. 11b). The Soil Survey maps would not have been expected to agree exactly with the model equivalents because of the poorer quality base maps used to create the 1:15,840 Soil Survey maps. Maps generated by the hillslope position model should be more accurate classifications of the landscape because they apply soil scientists' logic consistently (without the need to generalize inclusions) and because they utilize much better topographic data. Also, LiDAR-based, bare Earth, digital elevation data (used to generate the model maps) include subtleties in the landscape often obscured on aerial photographs by vegetative cover or otherwise undetectable in the field.

Zonal Statistics

Using the SSURGO map units (Soil Survey Staff, 2013b) as zones, zonal statistics were performed on classifications from the hillslope position model for each of the three study areas. The digitally classified hillslope positions were summarized by the percent of the map unit classified in the respective hillslope positions. For simplicity, we focus on the major soil associations within each study area.

For the majority of Soil Survey map units, the model classified the various hillslope units consistently with the official soil series description (OSD; Soil Survey Staff, 2013a). For example, on the loess parent material in Cedar County, the Muscatine soil series (fine-silty, mixed, superactive, mesic Aquic Hapludolls) were predominantly mapped on summits (Fig. 12). The pattern of agreement continued through the summit–shoulder Downs (fine-silty, mixed,

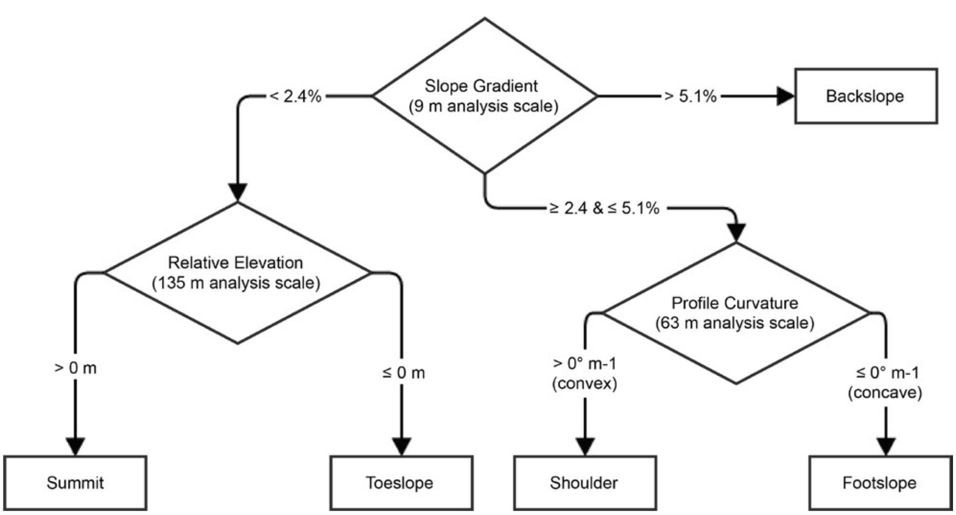

Fig. 10. Flow diagram for the calibrated, digital hillslope position model. Note that profile curvature was calculated as described by Wood (1996) and relative elevation was calculated as described by Miller (2014).

superactive, mesic Mollic Hapludalfs) and Tama (fine-silty, mixed, superactive, mesic Typic Argiudolls) soils. The Soil Survey's block diagrams suggested that both Downs and Tama soils are mapped across summit, shoulder, and backslope positions (Soil Survey Staff, 2009). As the slope class increased, the percentage of the soil series mapped within backslopes increased. The upland depressional, Garwin soil series (fine-silty, mixed, superactive, mesic Typic Endoaquolls) had the majority of its area mapped on toeslopes. The floodplain complex of the Colo and Ely soil series (fine-silty, mixed, superactive, mesic Cumulic Endoaquolls and fine-silty, mixed, superactive, mesic Aquic Cumulic Hapludolls, respectively) was predominantly mapped on footslopes and toeslopes. This example illustrates how the hillslope position model generally matched soil series concepts as mapped in the field. We will argue below that the model also can add important information about the precise locations of the map unit boundaries between many of these soil series. This information can be invaluable in upgrading such maps and in assessing error or uncertainty for them.

On the hummocky till plain of Dickinson County (Fig. 13), where hillslope segments tend to be small, a change in dominant hillslope position could be observed through a sequence of slope classes. The upland convex Clarion soil series (fine-loamy, mixed, superactive, mesic Typic Hapludolls) progressed from being mapped primarily on summits, to more so on shoulders, to predominately on backslopes on the sequence of B, C, and D slope classes. In this landscape of numerous closed basins, the swales between convex hills have been filled in with local alluvium, resulting in only small areas meeting the definition of footslopes. Concave and depressional soil series such as Canisteo (fine-loamy, mixed, superactive, calcareous, mesic Typic Endoaquolls), Harps (fine-loamy, mixed, superactive, mesic Typic Calciaquolls), and Okoboji (fine, smectitic, mesic Cumulic Vertic Endoaquolls) were mapped on footslopes in some areas but were predominantly delineated on toeslopes.

Where the OSD did not specify slope position or shape, such as for many of the soils in Ottawa County (Fig. 14), a correspondence between hillslope position and drainage class (DC) was used to match delineations. For example, the poorly drained Sims soil series (fine, mixed, semiactive, nonacid, frigid Mollic Epiaquepts) was predominantly mapped on toeslopes. However, slope class still distinguished the B slope Kawkawlin soils (fine, mixed, semiactive, frigid Aquic Glossudalfs) that were mapped on footslopes from the Kawkawlin soils on A slopes, which were mostly mapped on toeslopes. In contrast, the Nester soil series (fine, mixed, semiactive, frigid Oxyaquic Glossudalfs) was illustrated in the Soil Survey's block diagram as occurring on various types of upland sites. Nester soils, therefore, represent an example of a consociation that could benefit from disaggregation based on hillslope position. For example, Nester soils on backslope and shoulder slope areas may better match a different series definition, perhaps one that has a thinner solum or has different interpretations as to land use.

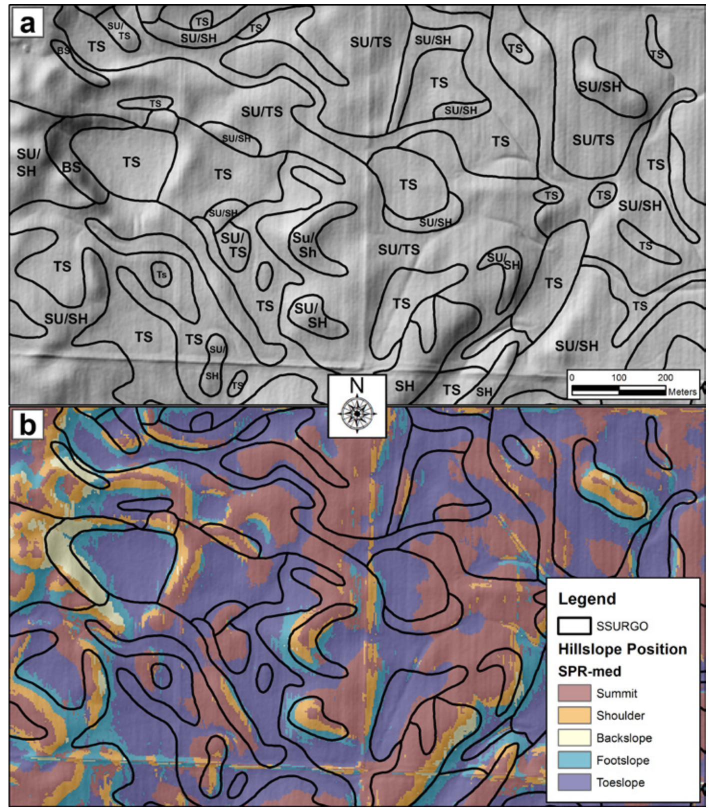

Fig. 11. (a) Soil Survey Geographic dataset (SSURGO) map unit delineations (Pulido, 2011) overlain onto a hillshade of the LiDAR elevation grid in Dickinson County, IA. (b) The same map but also showing hillslope positions as determined by the terrain classification of the selected (slope gradient priority [SlgP]-med) hillslope position model. Note the many areas that transition directly from summit to toeslope or shoulder to footslope. SU, summit; SH, shoulder; BS, backslope; FS, footslope; TS, toeslope.

Use and Applicability Classification of Finer Details

For topography, the problem of coarse resolution base maps has largely been solved by the advent of technologies such as LiDAR. Further, GIS data formats remove the cartographic limitation of a minimum area that can be represented on a soil map. However, neither of these developments addresses the issue of the time required to manually delineate the additional boundary lengths. Fortunately, classification models in a GIS can automate the delineations with quantified definitions. The classification model presented here solves the automation problem with quantified definitions that have been substantiated by field soil scientists working in multiple environments.

An example of where automated classification of hillslope position can delineate small inclusions can be observed in Dickinson County, IA. Here, many obvious map unit inclusions have been identified by the Soil Survey as point locations, probably because of map scale limitations. Most occur as small, isolated depressions of wetter soils, often in close proximity to areas classified as toeslopes. The positional offset between some of the inclusion (spot) points and the areas digitally identified as isolated toeslopes is shown in Fig. 15. This offset is likely due to the resolution limitation of the base map on which the original inclusion points were drawn and the orthorectification process required to digitize the paper soil map. This

SSURGO				Hillslope Position Model					
Name	Parent Material	Geographic Setting	DC*	Max	SU	SH	BS	FS	TS
Colo-Ely	Alluvium	Floodplain	PD-SPD	FS	4%	3%	9%	44%	39%
Colo-Ely {B}	Alluvium	Floodplain	PD	TS	26%	3%	13%	19%	39%
Downs {B}	Loess	Summit-Shoulder	WD	SH	36%	41%	7%	14%	3%
Downs {C}	Loess	Summit-Shoulder	WD	SH	6%	36%	21%	33%	4%
Downs {D}	Loess	Summit-Shoulder	WD	BS	1%	14%	45%	36%	3%
Ely	Loess	Transitional Swale	SPD	FS	6%	4%	4%	53%	33%
Fayette {B}	Loess	Interfluves-Sideslopes	WD	SH	35%	42%	12%	10%	2%
Fayette {C}	Loess	Interfluves-Sideslopes	WD	BS	7%	41%	39%	12%	1%
Fayette {D-G}	Loess	Interfluves-Sideslopes	WD	BS	1%	10%	71%	16%	2%
Garwin	Loess	Summit-Flat	PD	TS	35%	2%	2%	10%	51%
Muscatine	Loess	Summit-Flat	SPD	SU	72%	6%	2%	7%	14%
Muscatine {B}	Loess	Summit-Flat	SPD	SU	37%	10%	2%	30%	21%
Tama	Loess	Summit-Shoulder	WD	SU	67%	13%	1%	10%	10%
Tama {B}	Loess	Summit-Shoulder	WD	SU	42%	30%	3%	20%	5%
Tama {C}	Loess	Summit-Shoulder	WD	FS	5%	30%	10%	48%	6%
Tama {D}	Loess	Summit-Shoulder	WD	FS	1%	15%	34%	46%	4%
Judson {B}	Colluvium	Transitional Swale	WD	FS	6%	5%	9%	57%	23%

*DC = drainage class

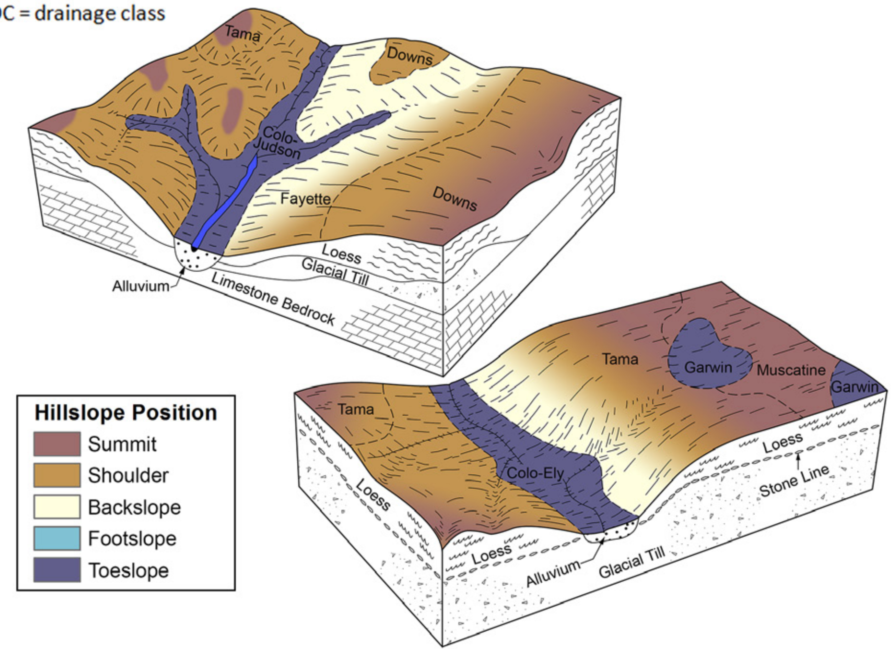

Fig. 12. Zonal statistics for the hillslope position model by the Soil Survey Geographic dataset (SSURGO) map units in Cedar County, IA. For reference, block diagrams of the Tama–Downs–Muscatine soil association are also provided (modified from the NRCS Soil Survey Staff, 2009). SU, summit; SH, shoulder; BS, backslope; FS, footslope; TS, toeslope; PD, poorly drained; SPD, somewhat poorly drained; WD, well drained.

positional difference illustrates the advantage of utilizing the more spatially accurate LiDAR data for the construction of soil maps. Further, the resolution of this digital base map removes the need to separately represent these inclusions as points. The digital hillslope position model delineated these small areas in an accurate, automated, and efficient manner.

Opportunities for Disaggregation of Soil Map Units

Disaggregation is the separation of a map unit into component parts. This effort has become a priority of the NRCS, as the agency strives to produce more homogeneous map units, particularly using remote methods with increased user knowledge-based models (NCSS, 2014). If these types of soil bodies were not mapped separately, it is because the mapper (i) was unable to observe the differences in the field or on the aerial photograph, (ii) was unable to map these areas out because of minimum mapping area issues, and/or (iii) determined that the differences were so small as to not affect classification, use, or management.

Perhaps the best way to conceptualize a homogeneous and taxonomically pure map unit is to consistently define or map it on only one hillslope position. Map units that span several hillslope positions are more likely to contain inclusions of other soil series. The digital model can accurately and objectively identify these topographically different areas and, hence, better assist in the disaggregation effort.

Across our study areas, we have observed that most soil map units that span different hillslope positions occur on flat landscapes such as glaciolacustrine plains and floodplains. As described above, the model recognizes most flat areas as either summits or toeslopes. A slight rise in elevation in an area like a floodplain will force the model to classify the area as a summit. Similarly, the model can easily identify small depressional areas on such surfaces. If the hillslope position classification is being used as a base map, the mapper can decide if the differences in soil properties for these small areas are significant, relative to the soil map's purpose. Areas of slightly higher elevation on a floodplain may have slightly deeper water tables and will be slightly less flood-prone. Depressional areas will be wetter. Use of the hillslope position model to identify such areas has great potential to improve existing soil maps, especially regarding to disaggregation and reducing map unit error. Obviously, land use decisions using maps with this additional amount of detail (and accuracy) would be greatly enhanced. Additional examples and applications of the model for desegregation of soil map units are provided below.

Soil series like Nester, which occurs across a number of landscape positions (Fig. 14), are likely to contain considerable variation in soil properties due to the effect of topography (i.e., hillslope position). Areas like these are often not mapped in great detail

SSURGO				Hillslope Position Model					
Name	Parent Material	Geographic Setting	DC*	Max	SU	SH	BS	FS	TS
Canisteo	Dows Till Alluvium	Upland Concave	PD-VPD	TS	13%	3%	7%	16%	60%
Clarion {B}	Dows Till	Upland Convex	MWD	SU	27%	25%	19%	21%	9%
Clarion {C}	Dows Till	Upland Convex	MWD	BS	8%	19%	55%	15%	3%
Clarion {D}	Dows Till	Upland Convex	MWD	BS	3%	8%	82%	6%	1%
Harps	Dows Till Alluvium	Upland Depression	PD	TS	22%	6%	3%	13%	56%
Nicollet	Dows Till	Upland Flat	SPD	TS	25%	10%	10%	24%	30%
Okoboji	Dows Till Alluvium	Upland Depression	VPD	TS	5%	2%	5%	13%	76%

*DC = drainage class

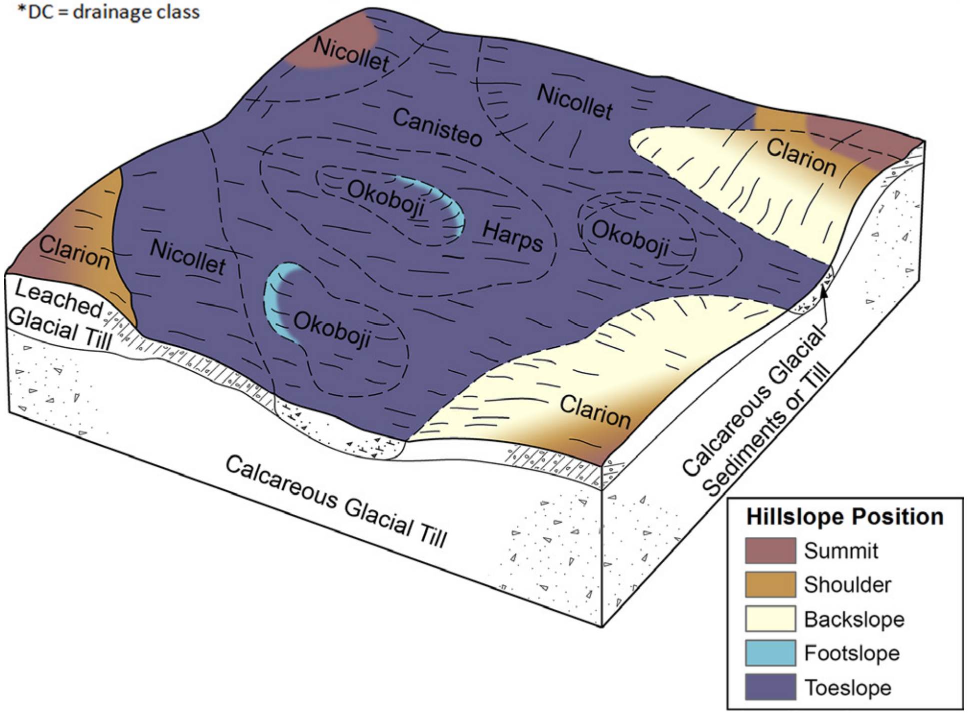

Fig. 13. Zonal statistics for the hillslope position model by Soil Survey Geographic dataset (SSURGO) map units of the Canisteo–Clarion–Nicollet (Nicollett: fine-loamy, mixed, superactive, mesic Aquic Hapludolls) soil association in Dickinson County, IA. For reference, the block diagram of this soil association is also provided (modified from the NRCS Soil Survey Staff, 2000). SU, summit; SH, shoulder; BS, backslope; FS, footslope; TS, toeslope; PD, poorly drained; VPD, very poorly drained; SPD, somewhat poorly drained; MWD, moderately well drained.

SSURGO				Hillslope Position Model					
Name	Parent Material	Geographic Setting	DC*	Max	SU	SH	BS	FS	TS
Iosco {A}	Outwash	Plain	SPD	SU	29%	15%	15%	18%	24%
Kawkawlin {A}	Till	Plain	SPD	TS	24%	12%	13%	20%	30%
Kawkawlin {B}	Till	Plain	SPD	FS	22%	15%	17%	23%	23%
Nester {B}	Till	Plain	WD-MWD	BS	18%	23%	31%	20%	8%
Nester {C}	Till	Plain	WD-MWD	BS	6%	14%	61%	15%	4%
Nester {D-F}	Till	Plain	WD-MWD	BS	3%	7%	81%	6%	3%
Sims	Till	Plain	PD	TS	13%	8%	18%	24%	36%

*DC = drainage class

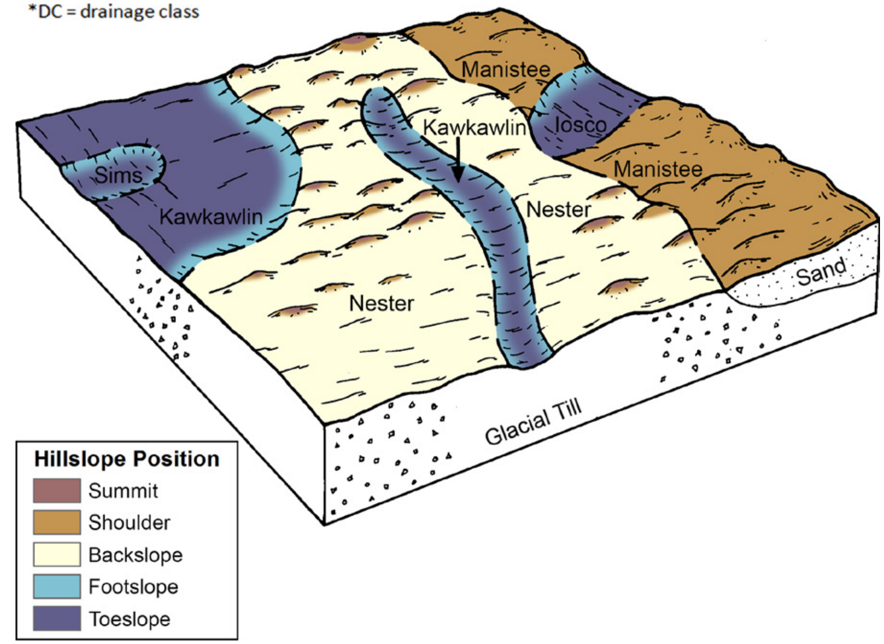

Fig. 14. Zonal statistics for the hillslope position model by Soil Survey Geographic dataset SSURGO map units of the Nester–Kawkawlin–Manistee (Manistee: sandy over clayey, mixed, active, frigid Alfic Haplorthods) soil association in Ottawa County, MI. For reference, the block diagram of this soil association is also provided (modified from the NRCS Soil Survey Staff, 1985). The sandy Manistee soil series is not currently mapped in Ottawa County. SU, summit; SH, shoulder; BS, backslope; FS, footslope; TS, toeslope; PD, poorly drained; SPD, somewhat poorly drained; MWD, moderately well drained; WD, well drained.

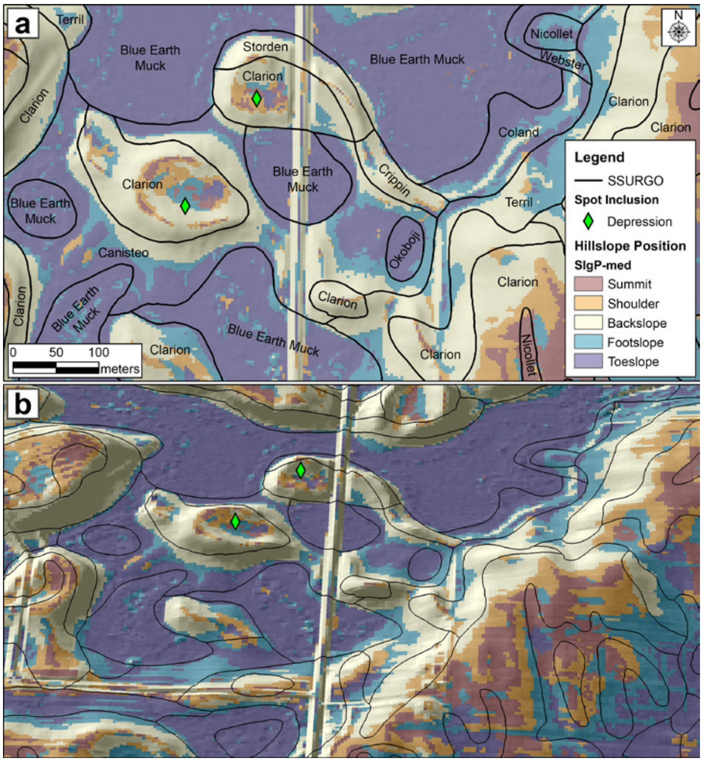

Fig. 15. Examples of depressional map unit inclusions identified by Soil Survey Staff and located within delineations of the convex Clarion map unit in Dickinson County, IA. Note the proximity of the inclusion points to isolated areas of toeslopes. In (a) plan view and (b) perspective view (relief exaggerated 3×). Also note that many of the soil map unit boundaries do not correspond to breaks in hillslope position. SlgP, slope gradient priority decision tree; SSURGO, Soil Survey Geographic dataset.

due to the combination of mapping difficulty and the perceived low return on investment for the extra mapping effort. However, applications such as environmental and ecological services (Goodchild et al., 1996; Anderson et al., 2006; Peschel et al., 2006; Clothier et al., 2011) highlight the importance of disaggregating such areas. We note that current mapping methods do not facilitate the subdividing of these areas. Using the hillslope position model, however, soils in existing Nester map units could be easily differentiated by hillslope position, and each of these positions could be examined

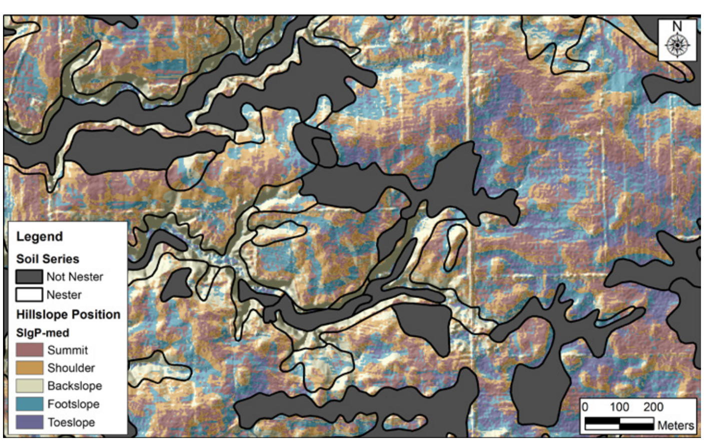

Fig. 16. Map showing areas of the Nester soil series in Ottawa County, which occurs on varying types of upland topography (Fig. 14). Application of the hillslope position model to this landscape efficiently differentiates the many different kinds of slope elements that exist within Nester soil delineations. SlgP, slope gradient priority decision tree.

to determine whether it would be best mapped out as a different series or drainage class or simply as Nester but within a different slope class. In either case, land use decisions made from a much more detailed soil map would be greatly enhanced (Fig. 16).

Opportunities for disaggregation are not limited to low relief or nonagricultural areas as discussed above. For example, the Fayette (fine-silty, mixed, superactive, mesic Typic Hapludalfs), Bassett (fine-loamy, mixed, superactive, mesic Mollic Hapludalfs), and Kenyon (fine-loamy, mixed, superactive, mesic Typic Hapludolls) soil series in Cedar County, IA are all described (Soil Survey Staff, 2013a) as occurring on interfluves and sideslopes. Figure 17 demonstrates how the model is able to identify discrete areas of summits and shoulders within existing Fayette delineations, which technically may match better with the Downs soil series. In fact, for part of an interfluve shown in Fig. 17 an area of Downs soil is delineated on the summit–shoulder within a Fayette delineation, although similar locations in the vicinity are not. Such mismapped areas can be easily spotted and the map errors rectified simply by applying our hillslope classification model.

Consistent Line Placement

Visual comparisons of boundary placement on standard, county-scale Soil Survey maps vs. slope elements identified by the hillslope position model show many areas of close agreement (Fig. 11, 15, and 17). However, many other map unit boundaries on current Soil Survey maps also deviate from the natural slope breaks determined by the model. While the delineations of the hillslope model are consistent applications of classification rules, the Soil Survey lines are subjective human interpretations and have been developed using inferior topographic data, that is, aerial photographs, many of which have extensive areas of monotonous vegetation across topographically complex landscapes. It is not unexpected that such manual methods of interpreting complex topographic information will lead to variable line placement among different mappers or even by the same mapper. Hence, we argue that application of our model provides a low-risk and cost-efficient way of identifying areas where map unit boundaries are disjunct from boundaries associated with slope elements. These types of data can be used to improve existing soil maps. For example, in Fig. 11, both the Soil Survey delineations and the hillslope position classification display generally similar landform patterns. But, in addition to showing more detail, the hillslope position classification suggests many areas where the Soil Survey delineation should be shifted, extended, or otherwise reshaped. In the higher relief of Cedar County, IA, a critical break between lowlands, backslopes, and uplands is recognizable in both the manual and digital delineations (Fig. 17). In contrast to the Soil Survey delineations, the hillslope position model identifies smaller patches of lowlands (likely due to the minimum delineation size in the Soil Survey map) and more complex shapes for dividing the upland from backslopes. Figure 15 shows similar types of differences, with the hillslope position model suggesting better line placement for separating Clarion (fine-loamy, mixed, superactive, mesic Typic Hapludolls), Storden (fine-loamy, mixed, superactive, mesic Typic Eutrudepts), and Crippin (fine-loamy, mixed, superactive, mesic Aquic Hapludolls) soils from Canisteo (fine-loamy, mixed, superactive, calcareous, mesic Typic Endoaquolls), Okoboji (fine, smectitic, mesic Cumulic Vertic Endoaquolls), and Blue Earth (fine-silty, mixed, superactive, calcareous, mesic Mollic Fluvaquents) soils. Examples such as those mentioned here are limitless.

CONCLUSIONS

We developed, calibrated, and presented a landscape classification model that reliably identifies the five standard hillslope positions using LiDAR data as the input topographic data. The use of such data for these applications is substantiated by the long history of using hillslope position in NRCS soil research and mapping. The model structure and breaks were calibrated to the experience of soil scientists in the field. The resulting hillslope position model consistently provides good agreement with soil scientists' field assessments.

The digital classification of hillslope position, as provided by the model we present here, improves on human assessment by efficiently applying rules of classification consistently and objectively across the landscape. This approach reduces the variability in such classifications due to human error, bias, and judgment, which are often introduced by interpretation of low resolution topographic and stereophotographic data. Application of this model's output can help identify areas that meet the criteria for different hillslope elements but were previously unmapped due to cartographic, base map, or resource limitations. Identification of hillslope elements of all sizes, regardless of map unit extent, presents an excellent opportunity to disaggregate and otherwise improve existing soil map units. This type of disaggregation would be best applied to topographically complex landscapes where two or three soil series vary predictably as a function of hillslope position and/or drainage class. The modeled maps of slope elements or position can be used to identify smaller, more homogenous soil areas and can help improve placement of soil map unit boundaries.

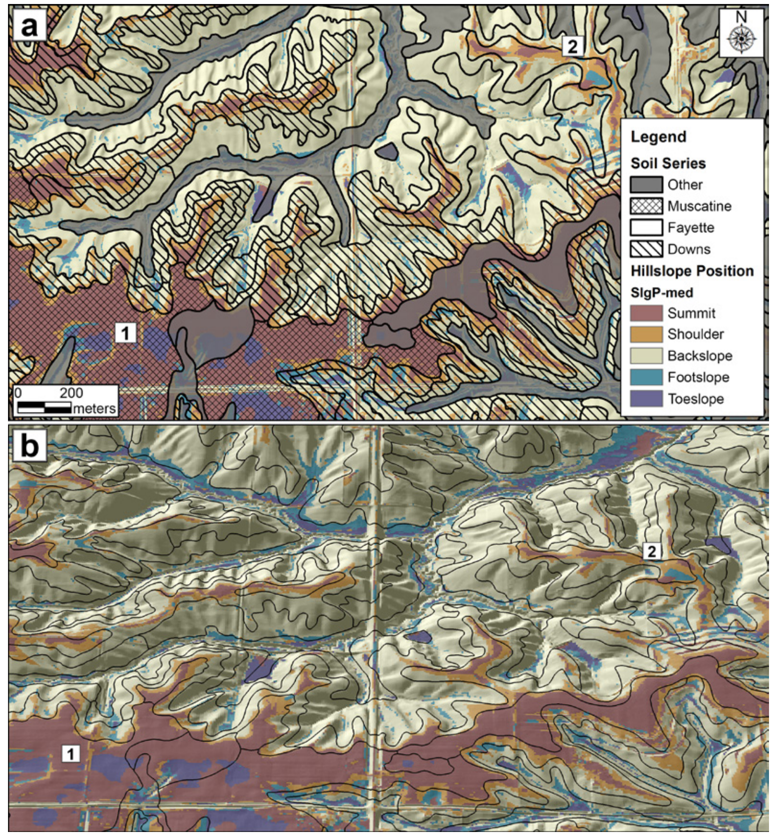

Fig. 17. Examples of a soil map from Cedar County, IA showing areas that could be disaggregated. (a) Plan view and (b) perspective view (relief exaggerated 3´). Numbers indicate matching points of reference. (1) Depressions identified by the model, potentially within the Garwin soil series, but which are mapped within the Muscatine soil series. (2) The Fayette soil series is described as occurring on interfluves and sideslopes. However, the block diagram (Fig. 12) indicates that the Downs soil series occurs on summits above the Fayette soil series, which predominantly occurs on backslopes. SlgP, slope gradient priority decision tree.

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