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Soil–landscape modeling across a physiographic region: Topographic patterns and model transportability

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Abstract

Soil–landscape modeling techniques have been developed as a quantitative method to predict patterns of soil properties from observed patterns in soil-forming factors. However, transportability of these models to unsampled landscapes is unknown. Our objective was to develop quantitative soil–landscape models for multiple study sites and examine the similarity of these quantitative models, and therefore the similarity of soil–landscape relationships among areas with similar soils. We collected high-resolution digital elevation models (DEM) for six study sites across the Pennyroyal physiographic region of Kentucky, and for each study site used terrain attributes derived from the DEM to collect discrete soil samples using a stratified random sampling design for morphological, physical, and chemical characterization. For three of these sites we examined the inherent differences in terrain attributes among sites, and developed quantitative soil–landscape models that predict the spatial patterns in A-horizon depth, surface soil organic carbon content, and surface sand and silt content. The other three sites were used to test the transportability of these models. Terrain attribute distributions differ significantly among study sites, with regional terrain attributes (upslope contributing area, topographic wetness index) being more similar among fields than local terrain attributes (slope gradient, slope curvature). Predictive models explained from 28% to 67% of the variation in soil properties. The terrain attributes that best predicted soil variability were similar across all three fields used for model development, with slope gradient, elevation, slope curvature, and upslope contributing area appearing in most of the models. However, applying models from one field to other fields within the same physiographic region produced inconsistent results. In general, prediction quality decreased with distance from the site of model development. Further sampling, modeling, and validation at additional field sites are required to properly establish model transportability.

Keywords: Terrain analysis; Soil–landscape model; Spatial variability; Regional scale

1. Introduction

Soil–landscape modeling provides a quantitative approach to analyzing and predicting the spatial distribution of soil properties based on the variability of environmental correlates, particularly topographic and hydrologic parameters (Moore et al., 1991; McSweeney et al., 1994). Methods normally involve (i) characterization of the local physiographic domain through analysis of digital elevation model (DEM) data, (ii) collection of georeferenced soil samples and compiling desired soil property data, and (iii) development of explicit, quantitative, and usually simple empirical models (McSweeney et al., 1994). This approach provides a means to quantify the spatial distribution of

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soil properties by relying on the variability of correlated proxy variables that are easier to collect at a higher resolution than sampling and measuring soil properties directly.

Soil–landscape modeling has been successfully applied to predict soil variability at the site or hillslope scale, commonly focusing on study areas less than 100 ha in size (Moore et al., 1993a; Thompson et al., 1997; Gessler et al., 2000; Chaplot et al., 2000, 2001; Thompson et al., 2001; Park et al., 2001; Florinsky et al., 2002). These studies have demonstrated that combinations of one to five terrain attributes derived from a DEM can explain 20% to 88% of the variation in selected soil properties. These and similar studies are predicated on the catena concept (Milne, 1935), which suggests that topographically associated soil profiles are repeated across certain landscapes. They have evolved from Jenny's (1941) model of soil formation where, at the landscape scale, topography is the primary factor controlling soil variability.

There are various perceived benefits to predicting soil variability using a soil–landscape modeling approach. An important advantage is that it can reduce the need for extensive field sampling and costly laboratory analysis by minimizing the number of samples needed to generate spatial predictions (Chaplot et al., 2001). Linear regression is the most widely used method used in soil–landscape modeling efforts (Walker et al., 1968; Pennock et al., 1987; Moore et al., 1993a; Gessler et al., 1995, 2000; Chaplot et al., 2000; Park et al., 2001). This preference for multiple linear regression techniques stems from their simplicity, ease of use, computational efficiency, and straightforward interpretation (Hastie et al., 2001). Multiple linear regression is particularly suited for prediction of quantitative soil attributes. However, other methods, such as tree models, generalized linear models, generalized additive models, and artificial neural networks, can provide greater predictive power and the capability of handling nonlinear or qualitative data. Geostatistical methods, which have also been widely used to predict soil spatial variability, have also been used for soil–landscape modeling purposes by incorporating terrain information through co-kriging (Odeh et al., 1994) or kriging with external drift (Bourennane et al., 1996).

Terrain data has been used to model soil variability for a wide array of applications. Moore et al. (1993b) and Bell et al. (1995) were early to demonstrate the application of terrain analysis and soil–landscape modeling in precision agriculture. Soil organic C (SOC) storage and dynamics have frequently been the focus of soil–landscape modeling efforts (Arrouays et al., 1995, 1998; Bell et al., 2000; Chaplot et al., 2001; Abnee et al., 2004a,b; Terra et al., 2004; Thompson and Kolka, 2005). Hydric and hydromorphic soil delineation (Thompson et al., 1997; Chaplot et al., 2000), net primary productivity (Gessler et al., 2000), soil drainage class (Bell et al., 1992, 1994), and soil water dynamics (Chamran et al., 2002) have also been successfully modeled.

The results of these many studies illustrate that the empirical relationships between soil properties and terrain attributes are somewhat unique to each soil property and each soil-forming environment. A common conclusion among many studies is that the models that were developed may not be valid for landscapes removed from the original study site (Moore et al., 1993a; Gessler et al., 1995; Thompson et al., 1997), but it is not clear how transportable these models may be to nearby areas with similar soil-forming environments. In other landscapes, model coefficients, model variables, and/or model structure may change. Lagacherie and Voltz (2000) speculated that, especially over large areas, predictive capabilities are limited because relationships between soil properties and landscape attributes are nonlinear or unknown. This is especially important if other soil-forming factors change, such as differing parent materials or variations in climate. However, this lack of transportability has never been fully or explicitly tested by developing and validating models for fields from similar landscapes.

Several authors (Bell et al., 1992, 1994; Thompson et al., 1997; Chaplot et al., 2000; Thompson and Kolka, 2005) have employed an independent data set (collected from the same study site and not used in model development) to validate their models. Chaplot et al. (2003) have provided the most rigorous test of model transportability across a region. They developed a model to predict the spatial distribution of a soil color index related to hydromorphic soil properties for a single hillslope. Then, to validate this model, they collected unique validation data sets from different landscapes far removed from the site where the data used to develop their soil–landscape model were collected. Both coefficients of correlation (r) between the hydromorphic index and terrain attributes and coefficients of correlation between observed and predicted values of the hydromorphic index were statistically significant at most of the validation sites. However, the magnitude of these correlations decreased the further removed from the model development site.

To fully exploit the benefits of soil–landscape modeling, it is necessary to understand the transportability of soil–landscape models to study sites beyond where these models were developed. Our objectives were: (i) to generate quantitative soil–landscape models that predict the variability in multiple soil properties (A-horizon depth, sand content, silt content, and organic matter content) for multiple fields in the Crider–Pembroke soil association in the Pennyroyal physiographic region of Kentucky; and (ii) to examine the similarity of these quantitative models, and therefore the similarity of soil–landscape relationships across the Pennyroyal physiographic region.

2. Materials and methods

2.1. Study sites

The Commonwealth of Kentucky in eastern USA is divided into five major physiographic regions. One of the largest and most agriculturally important is the Pennyroyal region (Fig. 1). The Pennyroyal is underlain by limestone bedrock, which influences both the soils and topography of the region. Common soils throughout the region are Crider (fine-silty, mixed, active, mesic Typic Paleudalfs) and Pembroke (fine-silty, mixed, active, mesic Mollic Paleudalfs).

The Pennyroyal is the limestone capped portion of the Mississippian Plateaus region of Kentucky, the remainder of which is generally capped with sandstone (McFarlan, 1950). The Mississippian Plateaus is the largest region in Kentucky, covering about 30% of the state, and the Pennyroyal constitutes 60–65% of the Mississippian Plateaus region (Bailey et al., 1970). The limestone residuum of the Pennyroyal is covered by a mantle of loess, with loess thickness decreasing from west to east.

The Pennyroyal's land area is dominated by agriculture, with 60% to 90% of the surface under row crops and pasture as one moves from east to west. Row-crop land area rises from 30% to 75%, from east to west, within the physiographic region (Bailey et al., 1970). The region experiences frequent short-term droughts (Ligon et al., 1967). This, as well as the fact that the region's soils are highly erodible, has caused wide adoption of no-tillage soil management in the Pennyroyal's row-cropped fields (Phillips et al., 1980).

Topography changes across Pennyroyal region. In the western Pennyroyal, rolling, karstic topography dominates, with a partially closed drainage system. In the eastern Pennyroyal, distinct upland interfluves are bounded by short steep sideslopes. In the central Pennyroyal, longer but gentler slopes are found with secondary depressions superimposed upon them, such that drainage in still open.

One agricultural field site was selected in the eastern, central, and western Pennyroyal (Fig. 1) to be used for model development. A second field site in each area was selected for model testing. The second field in the

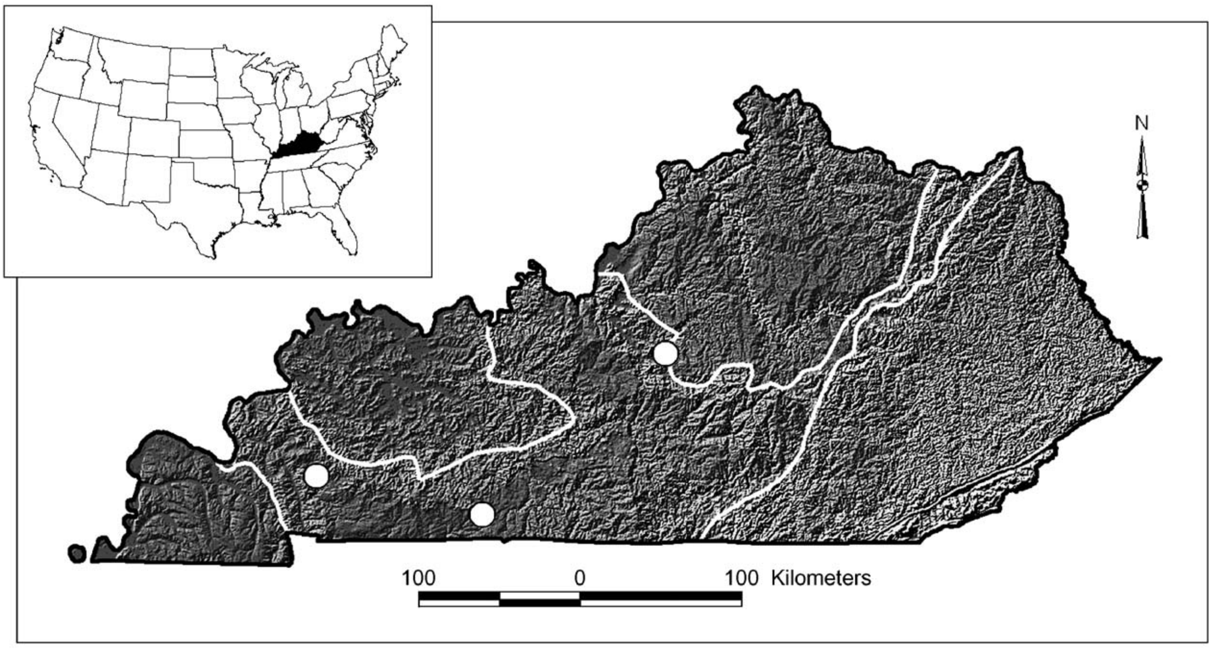

Fig. 1. Locations of three study sites across the Pennyroyal region of Kentucky. Analytical hillshade derived from NED 30-m DEM data (Source: US Geologic Survey).

western and central Pennyroyal was adjacent to the first field. In the eastern Pennyroyal the second field was 2.5 km from the first field. All chosen fields had a history of at least 8 years of no-tillage row-crop (corn, wheat and soybean) agriculture. Most had a history of 10 years of this kind of agriculture. The criteria used to identify and select the study sites were that, in addition to the history of no-tillage row-crop agriculture, the fields be dominated by Crider and/or Pembroke soils in upland positions and that there be willing and cooperative land managers. Each of the six field sites was located mostly or entirely within Crider or Pembroke map units. In the east and west, the field boundaries are within an area mapped as Crider silt loam (Humphrey et al., 1966; Kelley and Craddock, 1991). In the central Pennyroyal, fields are mapped as Pembroke silt loam and Pembroke silty clay loam (Mitchell, 1985).

2.2. DEM generation

We collected elevation data at each site using a dual-frequency real-time kinematic global positioning system (GPS) with one GPS receiver serving as a stationary reference and a second GPS receiver mounted on an ATV to record elevation values (height accuracy ±0.05 m, horizontal accuracy ±0.02 m). Over the entire area of each field, surface elevation measurements were taken every 7 m along transects spaced approximately 7 m apart. We used ANUDEM (Hutchinson, 1995) to interpolate a 10-m horizontal resolution and 0.1-m vertical resolution DEM. ANUDEM uses an iterative finite difference interpolation technique, and has the benefits of removing spurious pits and imposing a drainage network consistent with the original data (Hutchinson, 1989).

2.3. Terrain analysis

Terrain attributes were calculated using ArcGIS (Version 9.0, Environmental Systems Research Institute, Inc., Redlands, CA, USA). Terrain attributes included elevation (Z, meters), slope gradient (S, percent), profile (down slope) curvature (K_p, m m^{-1}), contour (cross-slope) curvature (K_c, m m^{-1}), total curvature (K, m m^{-1}), tangential curvature (K_t, cm m^{-1}), upslope length (L, meters), specific catchment area (A_s, m^2 m^{-1}), topographic wetness index (TWI), stream power index (SPI), and terrain characterization index (TCI). The distribution of A_s is positively skewed, so all comparisons and modeling were performed with $\ln(A_s)$. Tangential curvature, a measure of local flow convergence or divergence, is a secondary terrain attribute calculated as the product of contour curvature and slope gradient ($K_t = K_c \times S$). The topographic wetness index, a predictor of zones of soil saturation, is the ratio of specific catchment area to slope gradient ($\mathrm{TWI} = \ln(A_s/S)$) (Wilson and Gallant, 2000). The stream power index, a measure of runoff erosivity, is the product of specific catchment area and slope gradient ($\mathrm{SPI} = \ln(A_s \times S)$) (Wilson and Gallant, 2000). The terrain characterization index is described by Park et al. (2001) as an estimate of transport capacity, and is calculated as the product of total curvature and the log of specific catchment area ($\mathrm{TCI} = \ln(A_s) \times K$). The values for these terrain attributes were extracted for all sample locations by assigning the terrain attribute values from the nearest cell of the DEM.

2.4. Soil sampling

We used a stratified random sampling strategy to collect 30 intact soil cores at each study site, with TWI (as calculated from the DEM from each field) as the grouping variable. The TWI data for each field were grouped into three TWI classes (with classes established so that approximately one-third of the field was in each class) and ten sample locations were selected at random from within each of these classes. Soils were sampled to a depth of approximately 1 m using 5-cm diameter core. For each core a detailed morphological description was made (Soil Survey Division Staff, 1993), including depth and color of major horizons (A, AB, B). These horizons were identified based on color, structure, and texture. The A horizons showed the darkest color, the B horizon had a lighter, redder color. The AB horizons, if present, were characterized by slightly lighter color than A but darker and browner than the B horizons.

Subsequently, the cores were subdivided into 10-cm increments and all subsamples were analyzed for particle size distribution by the pipette method (Gee and Bauder, 1986), and organic matter by dry combustion (Nelson and Sommers, 1996). In fields under no-tillage management, this 10 cm depth is the depth of soil sampling recommended for purposes of chemical and physical analyses that themselves would be the basis of soil nutrient management recommendations (Thom et al., 2003). Only the 0–10 cm data are considered in our analysis.

2.5. Terrain attribute comparison

Considering the similarities and differences among the landscapes across the Pennyroyal region, we examined differences in the DEM and derived terrain attributes among the three fields from across the region. Quantile–quantile (Q–Q) plots were used to qualitatively compare terrain attribute cumulative distribution functions (cdf). The two-sample Kolmogorov–Smirnov goodness-of-fit test was used to quantitatively compare terrain attribute cdf.

2.6. Soil–landscape modeling

The soil variables we analyzed were A-horizon depth, surface sand content, surface silt content, and surface organic matter content. The surface data were taken from the 0–10 cm sample from each of the soil cores. Simple exploratory data analysis was used to elucidate terrain attributes that appeared to control variability in soil properties at each study site. We calculated the correlation coefficients between soil properties and the various terrain attributes calculated from the DEM.

Stepwise linear regression (Neter et al., 1989) and regression trees were used to identify variables related to the selected soil properties, and then robust linear regression (Rousseeuw and Leroy, 1987) was used to develop models. Model R^2 values were adjusted to account for sample number and number of variables present in the model. Models were tested against the assumptions of linear regression analysis (Neter et al., 1989): lack of multicollinearity, equal error variance (no heteroscedasticity), and normal and random residuals.

Models were developed individually for each of the three initial field sites, as well as a combined model that incorporated all 90 soil observations from across three fields. After establishing the best possible model for each of the four soil properties at a given field, the models were applied to the data from the other five fields as a measure of transportability of the models. We used simple regression analysis (observed vs. predicted), mean error (ME), and root mean square error (RMSE) to assess the ability of a soil–landscape model from one field to predict soil variability in the other fields within the region.

3. Results and discussion

3.1. Terrain attribute comparisons

Both Q–Q plots (Fig. 3) and Kolmogorov–Smirnov goodness-of-fit test results indicate that calculated terrain attributes (Table 1) differ significantly among all fields. This is expected because the sites were selected to represent the full range in terrain variability across this physiographic region. All differences are statistically significant; P values from Kolmogorov–Smirnov goodness-of-fit tests are <0.001 for

Table 1

Summary statistics for terrain attributes and soil properties for each of the three study sites used for model development from the western, central, and eastern Pennyroyal region of Kentucky

Property	East				Central				West			
	Minimum	Mean	Maximum	Standard deviation	Minimum	Mean	Maximum	Standard deviation	Minimum	Mean	Maximum	Standard deviation
Terrain attributes												
Z (m)	224	238	244	4.51	195	200	204	2.40	148	154	160	2.47
S (%)	0.0	3.0	13.4	1.88	0.0	2.1	5.3	1.13	0.0	3.0	7.7	1.40
K (m m^{-1})	−2.50	0.14	1.75	0.38	−0.47	−0.01	0.77	0.17	−1.21	0.00	1.20	0.29
K_p (m m^{-1})	−1.63	−0.11	0.98	0.25	−0.57	0.00	0.28	0.10	−0.73	−0.01	0.72	0.17
K_c (m m^{-1})	−1.56	0.03	1.10	0.20	−0.28	−0.01	0.50	0.10	−1.08	−0.01	0.74	0.18
K_t (cm m^{-1})	−6.97	0.12	9.09	0.77	−0.95	−0.03	0.79	0.24	−2.63	−0.07	2.43	0.58
ln(A_s)	0.0	2.5	8.5	1.88	0.0	3.0	8.6	1.88	0.0	2.8	8.5	1.87
SPI	0.0	1.6	7.2	1.43	0.0	2.2	8.4	1.61	0.0	1.8	8.3	1.49
TWI	0.0	1.7	7.5	1.43	0.0	1.8	5.2	1.26	0.0	1.9	6.1	1.38
TCI	−18.1	0.0	5.1	1.34	−2.7	−0.2	1.4	0.54	−6.8	−0.4	1.8	1.00
Soil properties												
AHD (cm)	2	15.6	35	7.47	7	16.1	35	6.14	4.5	13.7	36	7.65
Sand (%)	6.3	11.2	19.2	3.26	7.4	17.0	32.0	6.08	2.0	6.2	23.5	4.41
Silt (%)	63.6	71.1	76.6	3.61	41.9	63.5	75.2	9.13	68.7	78.3	83.2	3.56
OM (%)	2.2	3.0	6.0	0.79	1.7	2.3	2.8	0.35	1.3	2.3	3.5	0.59

Terrain attribute statistics calculated from entire DEM data set for each field. Soil property statistics calculated from soil core samples (n=30) collected in each field.

AHD=A-horizon depth.

comparisons between all terrain attributes from all fields. The greatest differences are seen in local terrain attributes, such as slope gradient (Fig. 3a) and profile curvature (Fig. 3b), as well as the other curvatures and the secondary terrain attributes calculated using curvature (tangential curvature, TCI). The slope gradients are steepest in the east (Table 1, Fig. 3a), which is the influence of the more incised landscape, with steep slopes heading down into the drainages outside the field boundaries (Fig. 2c). The overall relief is also greater in the eastern Pennyroyal (Table 1).

Slope curvatures are also more extreme in the east (Fig. 3b), with both more concave and convex curvatures compared to the landscapes of the central and western Pennyroyal. Slope curvatures, however, were greater in the west compared to the central Pennyroyal (Fig. 3b), presumably because of the high density of depressional features in the field of the western Pennyroyal (Fig. 2a). These differences in slope gradient and slope curvature as you travel from east to west across the Pennyroyal region mimic some of the changes seen in terrain attributes of a single landscape as the resolution of the DEM used to represent that landscape is decreased. With decreasing resolution the landscape features tend to become smoothed, with less steep slope gradients and less extreme slope curvatures (Wolock and Price, 1994; Zhang and Montgomery, 1994; Thieken et al., 1999; Thompson et al., 2001). The variations in landscape configuration across the Pennyroyal region appear as a spatial analog for this phenomenon, with steeper slope gradients and greater curvatures in the eastern Pennyroyal and flatter slopes and less curvature in the central and western Pennyroyal. This is seen in the DEM data across the Pennyroyal region (Fig. 1) and can be discerned in the DEM for the fields from each region (Fig. 2). The eastern Pennyroyal is more incised, with steeper slopes and greater curvatures because of the narrow interfluves. The central Pennyroyal has some incision, but the interfluves are broader, flatter, and have closed depressions superimposed upon them. In the western Pennyroyal, drainage is predominantly closed, with a regional slope toward more widely spaced surface drainage systems, but much of the surface drainage is depression-focused.

The least differences are seen in regional terrain attributes, such as upslope contributing area (Table 1, Fig. 3c) and the secondary terrain attributes calculated using A_s (TWI, SPI). The distribution of upslope contributing area values is similar among the three sites, particularly at the low end of the distribution. Differences are seen in the highest values. Maximum upslope contributing areas are lower in the western Pennyroyal compared to the eastern and central parts of the region. The closed drainage pattern leads to a more distributed pattern of surface flow accumulation and lower upslope contributing area values in these smaller depressions. Maximum upslope contributing area values for the field in the eastern Pennyroyal are not significantly greater than those from the field in the central Pennyroyal because the deeply incised areas with high accumulated flow are not part of the production area and were not included in the topographic survey (Fig. 2c).

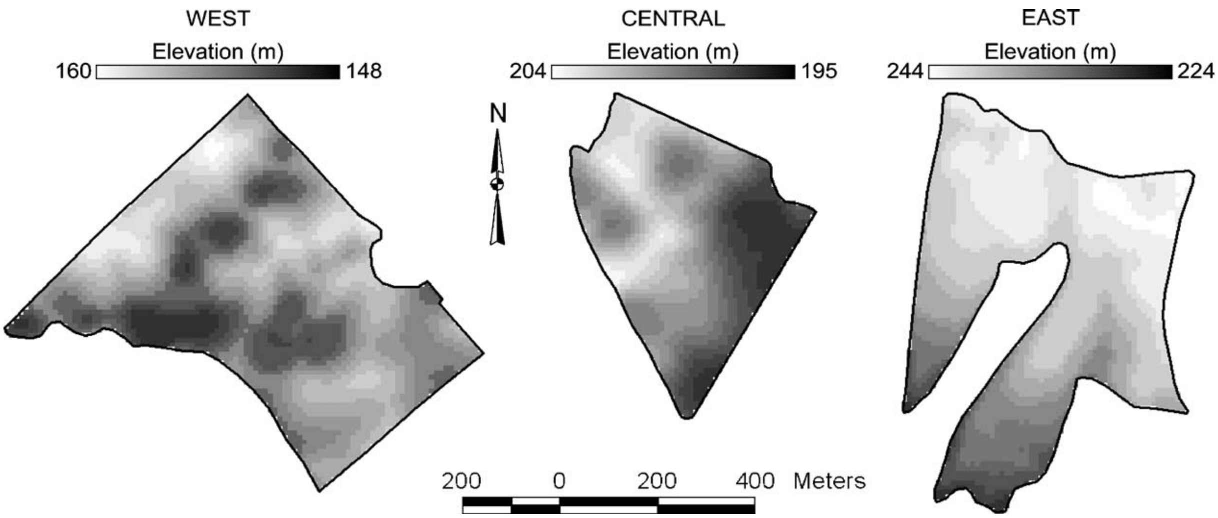

Fig. 2. Relief maps of three study sites used for model development from the western, central, and eastern Pennyroyal region of Kentucky.

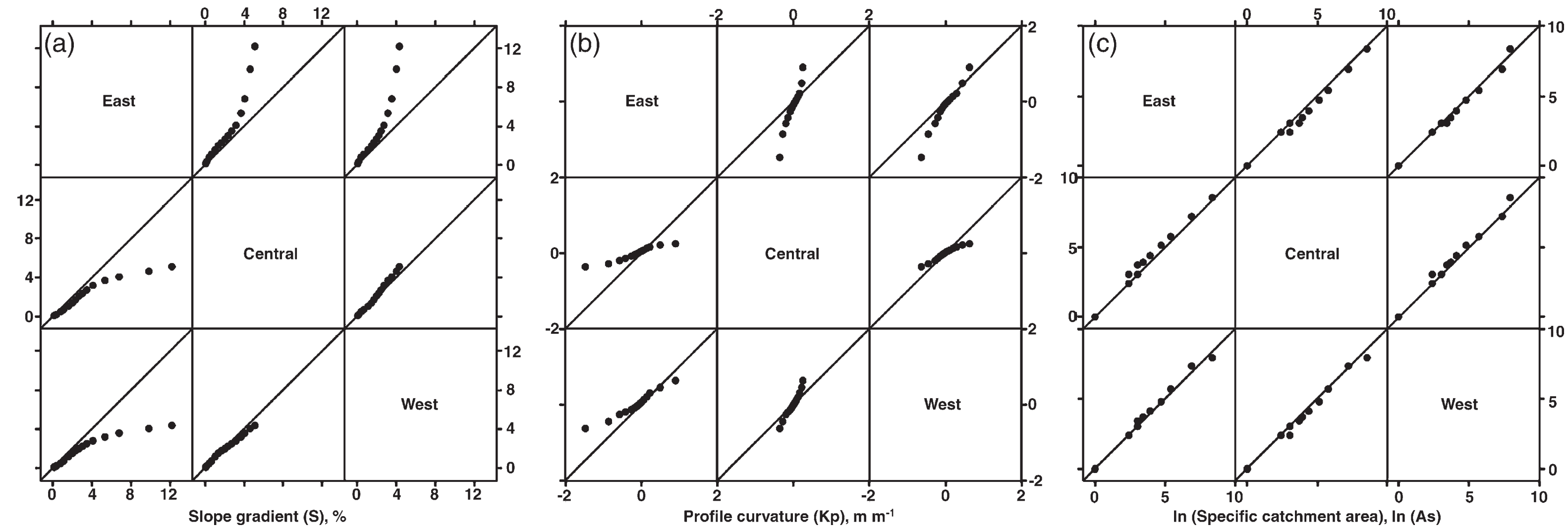

Fig. 3. Q–Q plots comparing terrain attributes calculated from three field sites across the Pennyroyal region of Kentucky: (a) slope gradient, (b) profile curvature, and (c) upslope contributing area.

Table 2
Terrain attributes with statistically significant ($P \leq 0.05$) coefficients of correlation with selected soil properties for three field sites used for model development across the Pennyroyal region of Kentucky

Field	A-horizon depth	Sand content	Silt content	OM
Elevation (Z), m				
East	+	−	+	−
Central				
West		−	+	
Slope gradient (S), %				
East	−		−	−
Central		+	−	
West				
Total curvature (K), m m^{-1}				
East		+	−	
Central		−	+	
West		−	−	
Profile curvature (K_p), m m^{-1}				
East		+		+
Central		+	−	
West		+	−	
Contour curvature (K_c), m m^{-1}				
East				+
Central			+	
West		−		−
Specific catchment area (A_s), m^2 m^{-1}				
East		+		+
Central			−	
West		+		+
Terrain characterization index (TCI)				
East		−	+	−
Central		−	+	
West		−		−

Positive and negative signs indicate the direction of the relationship.

3.2. Soil–landscape relationships

Despite these significant statistical differences in the distribution of terrain attributes among the sites, some of the relationships between terrain attributes and selected soil properties are similar across all three fields (Table 2). For each soil property we examined there were one or more terrain attributes that showed significant statistical correlations in at least two of the three fields (Table 2). Across the three fields there were up to nine terrain attributes that individually accounted for a significant amount of the variability in sand content, silt content, and organic matter content (Table 2). Furthermore, several terrain attributes were consistently reliable predictors of soil property variability, including elevation (six statistically significant correlations), slope gradient (four), total curvature (six), profile curvature (six), upslope contributing area (five), and TCI (seven). For each of these terrain attributes, when correlated with the same soil property across at least two of the three fields, the sign of this correlation was consistent (e.g., TCI has a negative correlation with sand content in all three fields) (Table 2).

Many of these soil–landscape relationships are similar to those found in other landscapes. As slope gradient increases, A-horizon depth tends to decrease (Pennock et al., 1987; Moore et al., 1993a; Gessler et al., 2000; Park et al., 2001; Thompson et al., 2001) and sand content tends to increase (Moore et al., 1993a). Park et al. (2001) found TCI to have a significant negative correlation with A-horizon depth and loess thickness, presumably an indicator of greater erosion and topsoil loss from summit and shoulder locations with positive TCI and less soil loss or even deposition at footslope and toeslope positions, which have negative TCI. In these Pennyroyal landscapes positive TCI values are associated with lower sand content and higher silt content (Table 2), similarly indicating the influence of erosion of silty (loess-derived) topsoil on surface soil texture.

3.3. Soil–landscape modeling

Empirical models using selected terrain attributes explain 28% to 67% of the variation in selected soil properties (Table 3). However, statistically significant

Table 3
Soil–landscape models and adjusted coefficients of multiple determination (adj R^2) for prediction of selected soil properties at three field sites across the Pennyroyal region of Kentucky

Field	Intercept	Z	S	K_p	K_c	ln(A_s)	TCI	adj R^2
A-horizon depth								
East	13.4	0.53	−1.3	–	–	−1.0	–	0.44
Central	19.1	–	−2.1	–	–	–	–	0.28
West	–	–	–					N/A
Sand content								
East	15.3	0.41	0.48	–	–	–	−0.56	0.67
Central	11.8	–	3.1	21.6	–	−0.58	–	0.63
West	4.7	−0.31	0.79	5.9	–	–	–	0.49
Silt content								
East	70.7	0.30	−1.2	–	–	–	0.57	0.46
Central	69.6	0.66	−2.5	–	–	–	9.8	0.58
West	71.0	0.71	–	6.3	–	0.96	–	0.33
Organic matter content								
East	3.6	0.072	0.11	–	–	–	−0.23	0.47
Central	–	–	–	–	–	–	–	N/A
West	1.7	–	0.14	–	2.2	–	–	0.43

models could not be developed for all four soil properties at all three sites. Additionally, attempts to develop an overall model using all data from all three fields could not produce any statistically significant relationships. The terrain attributes that best predicted soil variability in the selected soil properties were similar across all three fields (Table 3). Slope gradient was an important predictor, being present in nine of the ten models we developed. Elevation was also in seven of ten models. TCI, a secondary terrain attribute that is the product of total curvature and upslope contributing area, occurred in four of the ten models. However, a curvature (profile or contour) and/or upslope contributing area were individually present in five of the remaining six models. These differences in the models are likely due the significant correlations between the various terrain attributes (Table 4). There are no significant correlations between elevation or slope gradient and the other terrain attributes (Table 4), so they are included in most of the models. However, because the curvatures and TCI are highly correlated (Table 4), the individual models may slightly favor one measure of curvature over another (Table 3).

The signs of the coefficients in the regression equations were consistent when the same terrain attribute appeared in the more than one of the equations for the same soil property. The values of these coefficients, however, differed.

The most predictable soil property among the three fields was sand content, with silt content also having relatively high model R^2 values (Table 3). For a given field, the models of sand content and silt content are similar in terms of included variables, although the sign of the coefficients were opposite. In fact, for the field in the eastern Pennyroyal the regression models for all four soil properties had almost identical terrain attribute combinations, with elevation, slope gradient, and TCI in three of the four, and elevation, slope gradient, and upslope contributing area in the model for A-horizon depth. Moore et al. (1993a) also found that models for A-horizon depth, sand content, and silt content for the same field had similar model variables, differing only in their coefficients. Others (Gessler et al., 2000; Park et al., 2001) have identified models with similar structure when modeling multiple soil properties for the same field.

3.4. Model transportability

The value of these soil–landscape models is predicated on the ability to use them to predict soil variability at sites removed from the location where they were developed. We applied the models we developed for each soil property in one field to the other two fields to examine model transportability. Based on simple correlation coefficients (Table 5) several of the models are able to explain soil variability in fields in other parts of the Pennyroyal region. For example, the model for sand content developed at the field in the western Pennyroyal had an r of 0.78 when applied to the field in the eastern Pennyroyal. Several models had statistically significant r values for at least two of the three fields, but only the models for sand content from the eastern and western Pennyroyal had statistically significant r values for all three fields (Table 5). Both models show similarities in the selected variables and even in the magnitude of the coefficients. Both models indicate that (in the east and west fields) as slope gradient increases so does the sand content. This is presumably related to erosion processes that removed silt particles. Similarly, both models indicate that as elevation increases, sand content is lower. We attribute this to the presence of more stable landscape areas at the higher elevations in these fields, such that more of the silty loess mantle

Table 4
Statistically significant ($P \leq 0.05$) coefficients of correlation between selected terrain attributes from soil core samples ($n = 90$) collected among all three field sites used for model development across the Pennyroyal region of Kentucky

Terrain attribute	Z	S	K	K_p	K_c	K_t	L	$\ln(A_s)$	TWI	SPI
S	ns*									
K	ns	ns								
K_p	ns	ns	−0.92							
K_c	ns	ns	0.93	−0.71						
K_t	ns	ns	0.86	−0.68	0.91					
L	ns	ns	−0.57	0.52	−0.54	−0.38				
$\ln(A_s)$	ns	ns	−0.62	0.53	−0.61	−0.43	0.82			
TWI	ns	ns	−0.62	0.55	−0.59	−0.40	0.87	0.97		
SPI	ns	ns	−0.53	0.43	−0.54	−0.38	0.67	0.92	0.83	
TCI	ns	ns	0.81	−0.80	0.71	0.65	−0.69	−0.49	−0.55	−0.36

* Not significant ($P > 0.05$).

Table 5
Correlation coefficients (r), mean errors (ME), and root mean square errors (RMSE) between observed and predicted values of selected soil properties at three field sites used for model development across the Pennyroyal region of Kentucky when predicted using soil–landscape models developed at each of the three field sites

Field	East			Central			West		
Model	r	ME	RMSE	r	ME	RMSE	r	ME	RMSE
A-horizon depth									
East	0.53**	−0.64	6.29	0.16	−6.06	8.81	0.09	−4.24	9.01
Central	0.47**	−1.98	6.88	0.26	−0.82	5.93	−0.03	−0.74	8.40
West	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Sand content									
East	0.82***	−0.51	1.92	0.39*	−2.18	6.02	0.65***	8.37	9.07
Central	0.34	−10.71	50.89	0.54**	−6.83	12.34	0.46*	5.21	33.40
West	0.78***	−9.16	9.38	0.56**	−12.07	13.18	0.61***	−0.91	3.64
Silt content									
East	0.70***	0.66	2.61	0.70***	5.89	9.97	0.24	−9.72	10.37
Central	0.49**	−1.63	22.73	0.74***	−0.03	6.01	0.35	−18.64	22.34
West	0.48**	13.36	13.75	0.02	13.26	16.15	0.62***	−0.03	2.73
Organic matter content									
East	0.83***	−0.11	0.45	0.00	1.31	1.38	0.54**	1.29	1.39
Central	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
West	0.53**	−0.99	1.20	0.01	−0.30	0.58	0.62***	−0.15	0.48

* Significant at the 0.05 level.
** Significant at the 0.01 level.
*** Significant at the 0.001 level.

remains. The similarities between models indicate that although the models were developed empirically, the relations seem to be related to underlying processes, particularly erosion.

Because the east field shows the steepest slopes, we would expect slope gradient to affect many of the measured surface properties. Slope gradient affects water movement at the soil surface, which will control water infiltration, soil water content, erosion, and, as a consequence determine OM content and A-horizon depth. This was evident in our results. All but one of the statistically significant regression models for this field select slope gradient (S). In the Pennyroyal region, elevation (Z) may be related to thickness of the loess material. Higher elevations indicate thicker loess cover and/or less erosion, as a result, silt content and A-horizon thickness will be greater. These relationships were also observed in the studied fields, Elevation was always positively correlated to silt and A-horizon depth (Table 2). We were able to observe that, across this physiographic region, certain terrain attributes were more generally valuable for predicting the spatial variability of soil surface properties (e.g., S, Z with A-horizon depth, silt and sand content), there were other terrain attribute relationships that were more field specific (e.g. A_s, K_p).

The ME and RMSE values give an additional indication of how well the models predict soil variability. As expected, ME and RMSE values tended to be lowest for the fields where the individual models were developed (Table 5). The models developed for the site in the central Pennyroyal seem to be least transportable, with particularly high ME and RMSE values when used to model sand and silt contents in the fields of the eastern and western Pennyroyal. For all four soil properties predicted using the model from the eastern site, the RMSE values increase from east to west as the models are applied to more distant landscapes. This is similar to trends observed by Chaplot et al. (2003), as prediction quality decreased with distance from the site of model development.

When the models (Table 3) were applied to the three validation fields the calculated ME and RMSE values (Table 6) are significantly higher. Correlations between observed and predicted soil property values were not statistically significant in most cases, with the best results seen in the western Pennyroyal (Table 6). The models developed for the eastern Pennyroyal were better at predicting soil property variability, and the models developed for the central Pennyroyal were the poorest (Table 6). While none of the correlations were statistically significant, the models to predict A-horizon

Table 6
Correlation coefficients (r), mean errors (ME), and root mean square errors (RMSE) between observed and predicted values of selected soil properties at three field sites used for model validation across the Pennyroyal region of Kentucky when predicted using soil–landscape models developed at each of the three field sites

Field	East			Central			West		
Model	r	ME	RMSE	r	ME	RMSE	r	ME	RMSE
A-horizon depth									
East	0.12	5.63	7.94	−0.25	−7.15	10.00	−0.02	−6.69	9.16
Central	0.14	3.20	5.86	0.17	−0.92	5.74	0.04	−1.78	6.11
West	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Sand content									
East	0.11	−1.49	3.52	0.21	−1.02	5.74	0.57**	10.02	10.08
Central	0.30	−5.98	39.95	0.20	−4.98	8.67	0.21	6.46	11.70
West	0.34	−10.17	10.54	0.16	−10.95	12.34	0.39*	0.57	1.39
Silt content									
East	0.41*	3.56	6.25	0.10	3.07	5.73	0.42*	−8.06	8.79
Central	0.20	0.84	12.99	0.14	−0.67	6.73	−0.29	−12.52	14.85
West	−0.22	15.91	17.39	0.13	9.29	10.63	0.09	1.21	4.27
Organic matter content									
East	0.28	0.19	0.65	0.22	1.41	1.47	0.01	1.46	1.55
Central	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
West	0.36	−0.53	0.81	0.20	−0.30	0.50	0.27	0.05	0.43

* Significant at the 0.05 level.
** Significant at the 0.01 level.

depth produced the lowest RMSE values relative to the actual range of the data (21–48% of the range in AHD). Models for sand content produced the highest RMSE values relative to the actual range of the data (24–323%). These results for the validation sites are in strong contrast to the more favorable results observed in the fields used for model development (Table 5), and suggest that the transportability of these soil–landscape models may be limited.

4. Conclusions

Landscapes differ across the Pennyroyal region of Kentucky, and these observable differences were confirmed by statistical comparison of the DEM-derived terrain attributes from representative field sites from the eastern, central, and western Pennyroyal. However, these differences in terrain attributes appear to be systematic, with changes in terrain attribute distributions from east to west that mimic the changes in terrain attribute distributions that occur when the DEM resolution for an individual landscape is decreased: lower slope gradients, reduced slope curvatures, smaller upslope contributing areas. Despite these differences, the soil-forming environments across the Pennyroyal region are similar with respect to climate, historical vegetation, and parent materials, which is reflected in that terrain attributes that are most related to the spatial variability in soil properties such as A-horizon depth, sand content, silt content, and organic matter content are similar across the fields we examined across the region.

Relationships between terrain attributes and selected soil properties indicated some similarities between fields in the Pennyroyal region. Across the Pennyroyal physiographic region, topographic patterns and soil properties are highly variable, however, for relatively static surface soil characteristics such as surface texture our modeling approach may hold some promise. The regression models we developed are somewhat specific to the distinct characteristics of each field. However, certain terrain attributes, such as slope gradient, show up consistently across most of the models, suggesting that it is associated with major surface processes occurring in all the fields (e.g. erosion, organic matter accumulation). The rationale is that soil-forming factors and soil management have had a similar effect on the landscape processes responsible for variability in surface properties. The fields sampled for this study have been under similar agricultural management for eight to ten years. However, less recent differences in management may have contributed to the observed differences in soil–landscape relationships and models across the region. For example, over the last 10 years, spatial variability in organic matter content of the upper 10 cm of soil may have been diminished by the adoption of no-tillage agricultural practices, thus limiting the effectiveness of these models. It is possible that landscapes that have experienced greater amounts of erosional soil redistribution may show more significant relationships to terrain characteristics. Furthermore, it is likely that relationships between terrain attributes and surface soil properties will differ under different management practices. This is a topic that should be explored in further research.

A soil–landscape modeling approach provides a framework for assessing soil variability among similar soil-forming environments. Across the Pennyroyal region of Kentucky, the empirical soil–landscape models we developed had similar structure among the field sites. Across all sites, steeper slopes were associated with thinner A horizons, higher sand content, and lower silt content. Positive TCI values (footslopes and toeslopes) similarly had higher silt and lower sand content. These results are the first step in an attempt to improve quantitative, regional, field-scale soil mapping. It is necessary to extend this sampling, modeling, and validation to additional field sites. It may, however, be necessary to collect a greater number of soil core samples from each field to improve model reliability. It would also be useful to examine additional soil properties as well as data that integrate information from greater soil depths.

At the field scale, topography (and its derivatives) is the primary factor influencing soil variability—either directly or indirectly. Other soil-forming factors (climate, organisms, parent materials) are essentially uniform across the fields. Other measures of soil variability, such as remotely sensed data or geophysical measures, may have helped explain some of the observed soil variability. However our goal was to develop simple and interpretable predictive models using variables (DEM-derived terrain attributes) that are now or will soon be readily available for most land managers.

The errors in predicted soil attributes when models developed for one part of the region are applied in another tend to consistently be overpredictions or underpredictions (e.g., predicted organic matter content in the central and western Pennyroyal using the model from the eastern Pennyroyal is a minimum of 0.5% higher at all sample points). We hypothesize that, because model variables are similar but with different coefficients, there may be scaling factors that can be applied to model coefficients or model results that will scale the model results appropriately. Identification of such scaling factors would require analysis of additional field sites from across the Pennyroyal region. Also, because of the issues related to scale, particularly the observed changes in topographic complexity, relief, and drainage characteristics across the Pennyroyal region, it may be necessary to test DEM of different horizontal resolution to identify the optimum DEM resolution for field-scale modeling in these landscapes. It is possible that this optimum resolution also changes across the region.

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