Topographic Controls on Soil Nutrient Variations in a Silvopasture System

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ABSTRACT

Topography plays a crucial role in spatial distribution of nutrients in soils; however, studies to quantify topographic influence on soil nutrient distribution from a silvopasture system are mostly lacking. To address this question, a 4.3-ha silvopasture site in northwest Arkansas was selected and a total of 51 topsoil (0–15 cm thickness) samples were collected and analyzed for primary (total N [TN], P, K), secondary (Ca, Mg, S), and micronutrients (Fe, Zn, Cu, Mn, B, Na). Topographic information was acquired from 12 terrain attributes derived from a 1-m digital elevation model. The prediction model was based on random forest. Results showed TN, S, and P were best predicted, whereas Cu, Ca, and Mn had the lowest prediction performance. Levels of S, Ca, Zn, Fe, and TN increased with SAGA wetness index, valley depth, flow accumulation, and multi-resolution valley bottom flatness index. Normalized height and slope height were positively related to Na but negatively to B and Cu distribution. Aspect had a positive influence on P and Mg concentrations. Based on terrain attributes, the study site could be divided into four topographic functional units (TFU), namely A, B, C, and D; TFU A had the highest nutrients present, whereas TFU B had the lowest P, K, Zn, Cu, Fe, and Ca but highest Na content. However, Mn, Mg, and B did not vary among TFUs. This study affirmed topographic influences on soil nutrient distribution, and the resulting continuous soil nutrient maps are useful for fine-tuning production systems through optimum nutrient and pasture management.

Abbreviations: CART, Classification and Regression Trees; CCC, cubic clustering criterion; DEM, digital elevation model; DSM, digital soil mapping; FlowAccum, flow accumulation; GPS, global positioning system; LiDAR, light detection and ranging; LSFactor, slope-length factor; MidSlope, mid-slope position; MRRTF, multi-resolution ridge top flatness index; MRVBF, multi-resolution valley bottom flatness index; NormHt, normalized height; PCA, principal component analysis; R², coefficient of determination; RF, random forest; RMSE, root mean square error; SAGAWI, system for automated geoscientific analysis wetness index; SlopeHt, slope height; SlopePer, slope percent; TFU, topographic functional unit; TN, total nitrogen; ρc, Lin’s concordance correlation coefficient; ValleyDep, valley depth; VDistChn, altitude above channel network.

Core Ideas

- Topographic variation influenced soil nutrient distribution in a silvopasture system.
- High-resolution digital maps of soil nutrients were generated.
- Terrain attributes identified topographic functional units as management zones.
- Level of soil nutrients in topographic functional units were different.

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while keeping the initial concept intact, and the model is called **scorpan model** (McBratney et al., 2003):

\[ s = f(s, e, o, r, p, a, n) + \varepsilon \]

The "scorpan" is the mnemonic for Jenny's equation (letters in it stand for soil, climate, organism, relief, parent material, age, and geographical location). The approach by McBratney et al. (2003) is more quantitative as it considers an error component (\( \varepsilon \)) as an integral part of the model, and incorporates geographical location as a factor to describe the development and distribution of soils. In both models, topography has been considered as one of the main factors because of its critical role in soil formation, development, and in the (re)distribution of soils, especially at landscape-scales. Several studies have explained the topographic controls over soil variations (e.g., de Oliveira et al., 2014; Florinsky et al., 2002; Moore et al., 1993; Raghubanshi, 1992; Seibert et al., 2007; Silveira et al., 2013). The fundamental role topography plays is that it routes and characterizes the flow of water and energy across landscapes contributing to catenary soil development and variations in soil property distribution (Hook and Burke, 2000; Milne, 1936; Moore et al., 1993). Therefore, a successful soil–landscape model relies on how well it captures topographic variations and assesses the soil–topographic relationship; the latter can be quantified through empirical as well as inference models (e.g., Adhikari et al., 2013; McBratney et al., 2003; Moore et al., 1993; Silveira et al., 2013; Zhu et al., 1997).

Variation in topography is studied using terrain attributes such as elevation, slope aspect, slope gradient, curvatures, topographic wetness index, landscape position, height above channels, and so forth, which can be derived from a digital elevation model (DEM) through digital terrain analysis (Wilson and Gallant, 2000). Based on the information from terrain attributes, landscapes can be classified into more homogenous terrain units or landform elements (de Bruin and Stein, 1998; Irvin et al., 1997), and soil attributes in each unit can then be inferred through soil–landscape relationships corresponding to soil functional similarities (Moore et al., 1993). Such a classification of continuous terrain data can be done following fuzzy set concepts (Zadeh, 1965) and by using fuzzy clustering algorithms (Bezdek et al., 1984). de Bruin and Stein (1998) have successfully applied fuzzy clustering of the terrain attributes to identify terrain spatial patterns to be used in soil mapping. In a more extensive form, these typical terrain units in the landscape can be identified as terrons (Carré and McBratney, 2005) or terrir (Barham, 2003) that are usually differentiated based on terrain, soil properties, and micro-climate, and are also associated with socio–economic and cultural values in the production of an agriculture commodity. A recent study from Australia identified and mapped soil terrons in a wine growing areas and matched terrons with different grape varieties (Malone et al., 2014).

There is a wealth of literature about the use of terrain attributes in mapping soil attributes across spatial scales (e.g., Adhikari et al., 2013; Gessler et al., 2000; McKenzie and Ryan, 1999; Moore et al., 1993; Wang et al., 2018). Some studies have shown that the spatial distribution of soil nutrients are influenced by elevation, slope, and landscape positions, by soil use and management (Wang et al., 2009; Zhang et al., 2011), and by variations in microtopography such as surface roughness and tortuosity (Moser et al., 2009). Even under a uniform management, hill slope position determined the spatial–temporal variations in soil C, N, and P distribution in a citrus orchard (Wangshiong et al., 2013). Different geospatial techniques are used to quantify the spatial relationship between soils and the terrain attributes, and digital soil mapping (DSM) (McBratney et al., 2003)—a novel approach in soil mapping—describes such tools and techniques in soil mapping and in environmental applications (Boetinger et al., 2010; Lagacherie et al., 2007). Among DSM techniques available, multivariate machine learning techniques such as tree-based learners are common (Heung et al., 2016). Random forest (RF) (Breiman, 2001) is one of the tree-based learners that has been successfully used in mapping soil properties with a higher prediction performance (Bui et al., 2006; Grimm et al., 2008; Hengl et al., 2015; Ließ et al., 2012; Ramcharan et al., 2018). In RF predictions, instead of developing a single decision tree, multiple trees are trained, and the results are obtained as an ensemble of individual trees (Breiman, 2001). Each tree is trained with randomly selected bootstrap samples, and the splitting is made with a subset of predictors that are also selected randomly.

Silvopasture systems are reportedly beneficial to soil quality due to manure additions, and can increase biomass production, carbon sequestration, and other ecosystem services and environmental benefits compared with monocropping systems (Cardinael et al., 2017; Jose, 2009; Jose and Bardhan, 2012; Pinho et al., 2012; Place et al., 2002; Schroeder, 1993). Silvopasture systems are being evaluated in northwest Arkansas, as the soils are relatively shallow and have low inherent nutrient availability. These soils cannot support high value crops, including cereals and grains and are mostly used as pasture and grazing lands. Assessment and mapping of soil nutrient status in such systems can allow land managers to fine-tune their fertilizer inputs for better management decisions and improved economic and environmental returns. Although, investigating soil nutrient variations as influenced by topography is common in different land-use management systems, studies quantifying the spatial relationship between soil nutrients and terrain attributes in a silvopasture system are limited and relationships poorly understood. Especially in areas where silvopasture land management systems are common, quantifying terrain influence on soil nutrient status in these systems is important and can contribute to overall farm benefits through best management practices. The objectives of this study are (i) to predict and map soil nutrient variations in a silvopasture system using RF techniques; (ii) to quantify the influence of terrain attributes on soil nutrient variations; (iii) to generate a topographic functional unit map for improved management decisions; and (iv) to compare soil nutrient status across topographic functional units.

**MATERIALS AND METHODS**

**Site Description**

The study was conducted in a silvopasture research site (Fig. 1) at the University of Arkansas Agricultural Research and Extension Center located in Fayetteville, AR (36°5′ N; 94°10′ W). The site was established in 1999 from an idle, ungrazed pasture to a silvopasture system to evaluate nutrient cycling through plant–soil–ground water continuum representative of northwest Arkansas (Sauer et al., 2015), which covers an area of about 4.3 ha. It consists of 16 east–west oriented tree rows of which the southern six rows were planted with pecan (*Carya illinoinensis* (Wangen.) K. Koch), and the five north-most rows with northern red oak (*Quercus rubra* L.).
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The remaining five rows in the middle have sections of three tree species, sycamore (Platanus occidentalis L.), cottonwood (Populus deltoides W. Bartram ex Marshall), and pine trees (Pinus strobus L.) planted east to west. Orchardgrass (Dactylis glomerata L.) and a big bluestem (Andropogon gerardii Vitman)—dominated native grass mix were seeded in alleys during 2015. Most soils in the study area are mapped as Captina silt loam (fine-silty, siliceous, active, mesic Typic Fragiudults) with some Pickwick silt loam (fine-silty, siliceous, active, mesic Glossic Fragiudults) and Johnsburg silt loam (fine-silty, mixed, active, mesic, Aquic Fragiudults) toward the north, and small areas of Nixa cherty silt loam (loamy-skeletal, siliceous, active, mesic Glossic Fragiudults) and Johnsburg silt loam (fine-silty, mixed, active, mesic, Aquic Fragiudults) along the central–west and southeast margins, respectively (Harper et al., 1969). The elevation of the surface ranges between 378 to 386 m asl where the upper half of the site is higher than mean elevation of 382 m. The site receives an annual precipitation of about 1217 mm and has average ambient temperatures of 13.7°C.

**Soil Sampling and Laboratory Analysis**

A total of 51 topsoil (0–15 cm thickness) samples from alleys between tree rows were collected where sampling locations were identified using a purposive stratified design based on topographic position in the study site (high, low, and medium elevations) and randomly selected within each elevation strata. Samples were air-dried, ground, and passed through a 2-mm sieve before they were analyzed for primary (N, P, K), secondary (Ca, Mg, S), and micronutrients (Fe, Na, Mn, Zn, Cu, and B) in the soil laboratory of USDA-ARS, Poultry Production and Product Safety Research Unit, Fayetteville, AR. Total N concentration (g kg⁻¹) was determined by high-temperature combustion using a VarioMax CN analyzer (Elementar Americas, Mt. Laurel, NJ). Mehlich-3 concentrations (mg kg⁻¹) of P, K, Ca, Mg, S and micronutrients (Fe, Na, Mn, Zn, Cu, and B) were determined using a 1:10 soil mass:extractant solution volume ratio and analyzed by inductively coupled argon-plasma spectrometry (ICP, Agilent Technologies, Santa Clara, CA). Geographical coordinates of each sampling site were recorded using a hand-held Global Positioning System (GPS) unit.

**Topographic Information**

Topographic information of the study site was gathered from a bare earth DEM derived from Light Detection and Ranging (LiDAR) technology. A DEM of 1 × 1 m grid spacing was downloaded from the USDA-Geospatial Data Gateway site (https://datagateway.nrcs.usda.gov) and was used to extract 12 terrain attributes within SAGAGIS (Conrad et al., 2015) and ArcGIS platforms (ESRI, 2014). The spatial distribution pattern of terrain attributes is shown in Fig. 2 and their general statistics with description in Table 1. It was observed that the area toward the north-east corner and the central-west had a higher surface elevation, higher slope height (SlopeHt), and higher altitude above channel network (VDistChn) than the rest of the area. In general, areas with a higher elevation and slope had lower indices for system for automated geoscientific analysis wetness index (SAGAWI), multi-resolution valley bottom flatness index (MRVBF), and valley depth (ValleyDep). A channel like depression or convergent site running north–south through the middle of the study area was observed with maximum FlowAccum, SAGAWI, and MRVBF indices.

**Modeling Approach**

Figure 3 shows a schematic representation of the overall prediction approach adopted in this study. For each point observation, information on the terrain attributes was extracted through the intersection in ArcGIS and a correlation among soil nutrients and terrain attributes was generated in the JMP statistical program (SAS Institute, 2016). Because the aim was to capture as much topographic variation as possible with respect to soil nutrient variations, all 13 terrain attributes were used as predictors of nutrient distribution. As a prediction model, RF (Breiman, 2001), an ensemble learning method, was chosen to quantify the spatial relationship among soil nutrients and terrain attributes. Random forest is a non-parametric Classification and Regression Trees (CART) technique where the model performance is improved by employing many predictive trees that are split based on a randomly chosen predictor subset. Before model calibration, 75% of the point data were selected for model training (Training set) with the remaining 25% for model validation (Test set). The RF algorithm adopted was the randomForest package and was run in R environment (R Development Core Team, 2008). The input parameters were set as: number of trees to build (ntree) equal to500, minimum data at each terminal node, node size equal to 1, and the number of variables that are randomly sampled at each split (mtry) was set to 4. The function varImpPlot was applied to identify important variables and quantify its statistical importance using the %IncMSE index based on out-of-bag samples for each prediction. This function ranks the importance of each variable based on the increase in prediction error when the variable is removed from the set of covariates (Liaw and Wiener, 2002). Once the model was calibrated, it was applied to the whole set of terrain attributes covering the entire study area and a prediction map for each soil nutrient was derived.

**Legend**

- Soil sample location
- Transect X1–X2
- Transect Y1–Y2

**Tree Transsects**

- Cottonwood
- Pine
- Sycamore
- Oak
- Pecans

**Elevation (m)**

- 302
- 378

Fig. 1. Study area and soil sampling locations overlaid on top of the digital elevation model. The two transects across the field for topographic and soil nutrient surface profile analysis are X1–X2 and Y1–Y2.
Fig. 2. Map of terrain attributes extracted from the digital elevation model (grid size: 1 x 1 m). FlowAccum, flow accumulation; LSFactor, slope-length factor; MidSlope, mid-slope position; MRRTF, multi-resolution ridge top flatness index; MRVBF, multi-resolution valley bottom flatness index; NormHt, normalized height; SlopePer, slope percent; SlopeHt, slope height; SAGAWI, system for automated geoscientific analysis wetness index; ValleyDep, valley depth; VDistChn, altitude above channel network.

Fig. 3. Schematic representation of the modeling approach adopted in this study.
The clustering analysis was performed in JMP software (SAS Institute, 2016) using 7 factors from the PCs of 13 terrain attributes as inputs. The procedure included defining the number of clusters or seeds by assigning each observation to the closest cluster where the centroid and reassigning the observations to new cluster and the procedure continued iteratively until the clusters are stable.

To identify the optimum number of TFUs, a Cubic Clustering Criterion (CCC) for each class was calculated and the class with the highest CCC was selected as the optimum number of TFUs as representative of the study area. Although the resulting map was derived from machine learning technique, it would indeed be functional with respect to soil–landscape model because it considered topographic variation in a landscape as inputs. After the TFUs were identified, a general statistic of soil nutrients in each TFU was obtained by the zonal statistics tool in ArcGIS and the results were compared within and among TFUs. Use of CCC to identify optimum number of clusters is common and has successfully been used to identify potential soil profile horizons (Adhikari et al., 2016). The CCC compares the $R^2$ of clusters with the $R^2$ of a uniformly distributed set of points with the highest CCC value for the most optimal cluster set. The CCC can be computed from the observed $R^2$:

$$\text{CCC} = \ln \left[ \frac{1 - E(R^2)}{1 - R^2} \right] \sqrt{\frac{np}{2}} \left[ 0.001 + E(R^2) \right]^{2}$$

where $E(R^2)$ the expected value of $R^2$ derived from extensive simulations, $n$ the number of observations, and $p^*$ the between cluster variation.

### Prediction Model Evaluation

The performance of random forest model to predict soil nutrient distribution was evaluated on both training and test data sets. For the training dataset, a leave-one-out procedure was followed,
whereas the test dataset not being used for model calibration provided a pseudo-independent validation. Predicted and observed values for each observation were used to calculate validation indices: coefficient of determination ($R^2$), Lin's concordance correlation coefficient ($\rho_c$), root mean square error (RMSE), and bias or mean error of prediction. In soil attributes predictions, a model with a higher value of $R^2$, and $\rho_c$, a lower RMSE, and bias close to zero is generally perceived as a better model in terms of prediction performance.

$$R^2 = \frac{\sum_{i=1}^{n} (\text{pred}_i - \text{obs}_i)^2}{\sum_{i=1}^{n} (\text{obs}_i - \text{obs})^2}$$

$$\rho_c = \frac{2\rho \sigma_{\text{pred}} \sigma_{\text{obs}}}{\sigma_{\text{pred}}^2 + \sigma_{\text{obs}}^2 + (\text{pred}_i - \text{obs}_i)^2}$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (\text{obs}_i - \text{pred}_i)^2}$$

$$\text{bias} = \frac{1}{n} \sum_{i=1}^{n} (\text{pred}_i - \text{obs}_i)$$

where $\text{obs}_i$ and $\text{pred}_i$ are the mean of the observed and predicted values of soil nutrients at $i$-th locations of $n$ number of observations, $\rho$ is the correlation coefficient between observations and predictions, $\sigma$ and $\sigma'$ are standard deviation and corresponding variances, $R^2$ is a coefficient of determination, $\rho_c$ is Lin's concordance correlation coefficient, RMSE is a root means square error, and bias is the mean error of prediction.

**RESULTS**

**Terrain Attributes and Soil Nutrients**

Of the terrain attributes, flow accumulation (FlowAccum) had a maximum variation (CV = 560%) followed by VDistChn (CV = 154%) and surface elevation (Elevation) was the least variable (<1% CV) (Table 1). SlopeHt and MRRRTF had a comparable CV of about 93%, which was higher than the rest of the attributes except for FlowAccum and VDistChn. The mean values for SAGA WI, MRVBF, and ValleyDep indices were 4.1, 2.0, and 1.1 with corresponding SD of 1.1, 1.2, and 0.6, respectively. VDistChn ranged between 0 and 3.6 m with a mean of 0.4. Mean elevation and slope were 382 m and 3.4%, and the maximum slope-length was about 3 m (Table 1).

Overall, TN and Ca had comparable means; however, the distribution of TN values was less variable (CV = 17.4%) than Ca, that was also slightly negatively skewed (Table 2). Among all nutrients, Na had the highest CV (88.8%) followed by P (61.7%), and by K (49.2%), whereas TN had the lowest CV. Average Fe and Mg content were about 141.8 mg kg$^{-1}$ (±33.8) and 60.1 mg kg$^{-1}$ (±14.8) with corresponding CVs of 27.4 and 24.7%, respectively.

Among the nutrients, TN was negatively correlated with slope-length factor (LSFactor) ($r = -0.38, p = 0.005$) and ValleyDep ($r = -0.35, p = 0.009$), but was positively correlated with MRVBF ($r = 0.37, p = 0.009$) and SAGAWI ($r = 0.42, p = 0.003$). Similarly, Elevation, slope percent (SlopePer), and SlopeHt had a negative correlation but mid-slope position (MidSlope), multi-resolution ridge top flatness index (MRRTF), and FlowAccum had a positive correlation with TN. All elements had a positive correlation with SAGAWI and MRVBF, except for Na and Mn, which had a weak negative correlation with MRVBF. Almost all elements were negatively influenced by increased Elevation and SlopePer except for P, Mg, and Zn, which had a weak positive correlation with Elevation. Distribution of Na was positively influenced by increasing MRRTF, normalized height (NormHt), SlopeHt, and VDistChn but it had a negative correlation with LSFactor, ValleyDep, MRVBF, and FlowAccum. Similarly, a decreasing value of Ca was observed with increasing Elevation, NormHt, SlopePer, SlopeHt, and VDistChn but increased with ValleyDep, SAGAWI, MRVBF, and FlowAccum. Distribution of S increased with SAGAWI, MRVBF, FlowAccum, and MidSlope but decreased with SlopePer and LSFactor. Iron, on the other hand, was highly positively influenced with SAGAWI and MRVBF but had a negative correlation with SlopePer, SlopeHt, LSFactor, NormHt, and Elevation. A negative correlation of Cu and B was observed with NormHt, SlopeHt, and SlopePer, but the distribution was positively correlated by SAGAWI, MRVBF, and ValleyDep.

For X1–X2 transect, minimum values of SlopeHt and NormHt were observed at distance between 90 and 110 m from the origin where a maximum index for SAGAWI, MRVBF, and ValleyDep were observed. That is the distance at which X1–X2 transect met a channel or depression, and where soils have a higher potential of remaining moist compared with the rest of the area. Higher indices for SAGAWI, MRVBF, and ValleyDep indicate high moisture potential. Similarly, with increasing Elevation along

<table>
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<th>Parameter</th>
<th>TN</th>
<th>Ca</th>
<th>P</th>
<th>K</th>
<th>Mg</th>
<th>S</th>
<th>Na</th>
<th>Fe</th>
<th>Mn</th>
<th>Zn</th>
<th>Cu</th>
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<td>60.1</td>
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<td>61.7</td>
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<td>52.0</td>
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† SD, standard deviation; CV, coefficient of variation; IQ-Range, inter quartile range; TN, total nitrogen.
the Y1–Y2 transect, a decreasing trend in SAGA WI and MRVBF were observed. So, based on the results from Table 1 and Fig. 4, we observed that Elevation itself did not explain much of the underlying variation; however, use of terrain attributes could capture a great amount of topographic variation in the study area.

**Map of Soil Nutrients**

Spatial distribution of soil nutrients in the study area is shown in Fig. 5, and its general statistics in Table 3. Predicted TN ranged from 1.2 to 2.1 g kg\(^{-1}\) with a mean value of 1.6 g kg\(^{-1}\). Average predicted P was about 45 g kg\(^{-1}\) and that for K was 95 g kg\(^{-1}\). Of the predicted micronutrients, mean Fe was found to be 142 mg kg\(^{-1}\), Zn was 4.5 mg kg\(^{-1}\), and Cu was 2.0 mg kg\(^{-1}\) (Table 3). Sodium showed the highest CV and Mn showed the lowest CV. Phosphorus, K, and B shared a comparable CV of about 25%. Similarly, average Ca and S were 1505 and 8.7 mg kg\(^{-1}\), respectively, with a CV of 15%.

Distribution of all nutrients showed spatial patterns and trends except for Mn, the distribution of which did not follow a specific trend. In general, the southernmost part of the study area had higher concentrations of nutrients than the rest of the study area. Almost all nutrients had higher concentrations in the low relief areas within the field, illustrating some signature of the convergent flow zone in the middle except for Na, which increased with elevation and SlopeHt. Of the secondary nutrients, Ca and S were more concentrated along the mid channel, whereas a higher value of Mg occurred in the eastern half of the study area, which also contained higher P levels. Most of the study area had K levels lower than its predicted mean (95 g kg\(^{-1}\)). Similarly, a lower concentration of Fe and Zn were found in the west half, whereas Cu and B were mostly concentrated in the middle of the study area. The predicted range for B was very low (0.3 mg kg\(^{-1}\)); however, its distribution showed a strong pattern across the study area. Boron concentration was higher along the mid-channel and toward the southern part. The majority of the study area had a higher concentration of Ca, Fe, and Cu and its distribution mostly followed the pattern of NormHt and SlopeHt. Similarly, the distribution of S followed the pattern of SAGA WI and MRVBF. Total N, on the other hand, followed a general pattern of LSFactor, SAGA WI, and MRVBF.

**Important Terrain Attributes**

The distribution of predicted soil nutrients indicated the influence of topography as their distribution followed some terrain attribute patterns. Figure 6 shows the results of the analysis of variable importance calculated for TN, P, K, Ca, Mg, and Fe as
examples. Of the 13 terrain attributes, distribution of TN was greatly influenced by ValleyDep, LSFactor, SlopeHt, and SAGAWI, among others, with higher %IncMSE. The model identified Aspect, SAGAWI, NormHt, and SlopePer as main contributing factors for the distribution of P. Similarly, SlopeHt, NormHt, ValleyDep, and SAGAWI were considered as the main terrain attributes for K and Ca distribution in the study area. For Mg, Fe, S, and Zn distribution, SAGAWI, SlopePer, LSFactor, and Aspect were the main determinants, whereas Cu and B were mostly related to SlopePer, SlopeHt, and NormHt. Results indicated that SAGAWI, ValleyDep, and slope related attributes such as SlopePer, LSFactor, and SlopeHt were among the top terrain attributes influencing spatial distribution patterns of soil nutrients in the study area.

**Prediction Performance**

Prediction model performance results based on validation indices are listed in Table 4. For the training data, $R^2$ values ranged from 0.81 to 0.93, $\rho_c$ from 0.76 to 0.89, and RMSE ranged from 0.04 to 139. The prediction model for P had the highest $R^2$ followed by Mg and Zn, both sharing an $R^2$ of 0.91. Magnesium had the highest (0.89) and K had the lowest (0.76) $\rho_c$ of prediction. Models for K and Na were highly positively biased, whereas Ca, Mg, Fe, and Mn models were negatively biased. For the test dataset, a maximum $R^2$ of 0.25 was recorded for TN followed by S and P with corresponding $R^2$ of 0.23 and 0.15, respectively. Likewise, TN also shared a maximum $\rho_c$ of 0.45 followed by S with $\rho_c = 0.38$. Prediction of Ca and Mg had lower $R^2$ and higher RMSE and higher bias.
Table 3. Summary statistics of soil nutrients based on predicted raster maps (n = 65,212 pixels; 238 rows by 276 columns).†

<table>
<thead>
<tr>
<th>Parameter</th>
<th>TN</th>
<th>Ca</th>
<th>P</th>
<th>K</th>
<th>Mg</th>
<th>S</th>
<th>Na</th>
<th>Fe</th>
<th>Mn</th>
<th>Zn</th>
<th>Cu</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimum</td>
<td>1.3</td>
<td>963.4</td>
<td>20.3</td>
<td>65.1</td>
<td>46.4</td>
<td>6.8</td>
<td>12.9</td>
<td>77.6</td>
<td>122.6</td>
<td>2.6</td>
<td>0.9</td>
<td>0.1</td>
</tr>
<tr>
<td>Maximum</td>
<td>2.1</td>
<td>2045.8</td>
<td>72.1</td>
<td>185.6</td>
<td>78.6</td>
<td>10.9</td>
<td>87.6</td>
<td>182.3</td>
<td>191.3</td>
<td>6.9</td>
<td>3.2</td>
<td>0.4</td>
</tr>
<tr>
<td>Mean</td>
<td>1.6</td>
<td>1505.9</td>
<td>45.3</td>
<td>93.5</td>
<td>60.6</td>
<td>8.7</td>
<td>45.7</td>
<td>142.3</td>
<td>148.6</td>
<td>4.5</td>
<td>2.0</td>
<td>0.2</td>
</tr>
<tr>
<td>SD</td>
<td>0.2</td>
<td>225.9</td>
<td>10.7</td>
<td>23.6</td>
<td>6.5</td>
<td>0.7</td>
<td>21.0</td>
<td>21.0</td>
<td>10.8</td>
<td>0.8</td>
<td>0.4</td>
<td>0.1</td>
</tr>
<tr>
<td>CV, %</td>
<td>10</td>
<td>15</td>
<td>24</td>
<td>25</td>
<td>11</td>
<td>8</td>
<td>46</td>
<td>15</td>
<td>7</td>
<td>18</td>
<td>20</td>
<td>25</td>
</tr>
</tbody>
</table>

† SD, standard deviation; CV, coefficient of variation; TN, total nitrogen.

Table 4. Validation results for training and test data. Total number of samples (n) = 51.

<table>
<thead>
<tr>
<th>Soil nutrient</th>
<th>Training data (75%)</th>
<th>Test data (25%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$R^2$</td>
<td>$\rho_c$</td>
</tr>
<tr>
<td>Total N</td>
<td>0.89</td>
<td>0.87</td>
</tr>
<tr>
<td>P</td>
<td>0.93</td>
<td>0.86</td>
</tr>
<tr>
<td>K</td>
<td>0.81</td>
<td>0.76</td>
</tr>
<tr>
<td>Ca</td>
<td>0.90</td>
<td>0.88</td>
</tr>
<tr>
<td>Mg</td>
<td>0.91</td>
<td>0.89</td>
</tr>
<tr>
<td>S</td>
<td>0.83</td>
<td>0.77</td>
</tr>
<tr>
<td>Na</td>
<td>0.87</td>
<td>0.84</td>
</tr>
<tr>
<td>Fe</td>
<td>0.90</td>
<td>0.88</td>
</tr>
<tr>
<td>Mn</td>
<td>0.89</td>
<td>0.81</td>
</tr>
<tr>
<td>Zn</td>
<td>0.91</td>
<td>0.86</td>
</tr>
<tr>
<td>Cu</td>
<td>0.90</td>
<td>0.86</td>
</tr>
<tr>
<td>B</td>
<td>0.90</td>
<td>0.86</td>
</tr>
</tbody>
</table>

Fig. 6. Variable importance of terrain attributes in the prediction of soil nutrients. FlowAccum, flow accumulation; LSFactor, slope length factor; MidSlope, mid-slope position; MRRTF, multi-resolution ridge top flatness index; MRVBF, multi-resolution valley bottom flatness index; NormHt, normalized height; SlopePercent; SlopeHt, slope height; SAGAWI, system for automated geoscientific analysis wetness index; ValleyDep, valley depth; VDistChn, altitude above channel network.
Topographic Functional Units

Delineation of TFUs started with principal component analysis of terrain attributes used as predictors in soil nutrients mapping. Of the 13 PCs identified, 12 PCs had a statistical significance on terrain variations (Barlette test, p value < 0.001), but only 7 PCs had an eigenvalue > 1, explaining nearly 95% of the total variation. Figure 7A illustrates the 13 terrain attributes in the first two PC axis that explained about 59% of the total variation. Terrain attributes such as NormHt, SlopeHt, VDistChn, and Elevation were grouped together, projecting in the same direction with comparable vector length and were closer to positive 1, indicating a similar and greater positive influence of these attributes for PC1. On the other hand, ValleyDep and FlowAccum both had a negative influence where the latter had a lower impact because of its shorter vector length. After a varimax rotation of these PC scores during a Factor analysis, we observed that Elevation, NormHt, SlopeHt, and VDistChn had a high and a positive loading for Factor 1, whereas MRVBF, SAGAWI, and ValleyDep had a negative loading (Table 5). Factor 2 had a maximum loading from SlopePer and Factor 3 from MidSlope. For the last two factors (Factors 6 and 7), Aspect and FlowAccum had a maximum impact. Some factors, for example Factor 2, were highly but negatively influenced by MRVBF and SAGAWI. These results suggest that all the terrain attributes played a role in explaining variations in the study area, and including these variables in cluster analysis would benefit in the delineation of functional units that show similar functionalities within zones and behave differently between the zones.

The result of clustering analysis is shown in Fig. 7B, where the potential number of clusters are plotted against CCC. Cluster 5 had a maximum positive CCC suggesting that the study area could be divided into five optimal zones or TFUs, such that each TFU would share similar soil–landscape functions than the neighboring TFUs. Although CCC suggested five optimal zones in the study area, one of the zones had a small spatial coverage (<65 m² area), and thus it was incorporated into the neighboring zones through majority filter in ArcGIS. The corresponding map of the TFU is shown in Fig. 8. We observed that TFU B represents an area with higher values of Elevation, SlopePer, SlopeHt, NormHt, and VDistChn, indicating the dryer part of the study area. On the other hand, TFU A was within a high convergence zone where soils would potentially remain moist due to higher indices of SAGAWI, ValleyDep, MRVBF, and FlowAccum. Moreover, CV of all terrain attributes in TFUs revealed that TFU A and TFU D were more variable than TFU B and TFU C; TFU B had a minimum CV for Elevation, SlopeHt, and VDistChn but maximum CV for MRVBF and ValleyDep [Fig. 11A].

Table 5. Factor loading after varimax rotation of the principle components. Seven factors explained nearly 95% of the total variation.

<table>
<thead>
<tr>
<th>Terrain attributes</th>
<th>Factor 1</th>
<th>Factor 2</th>
<th>Factor 3</th>
<th>Factor 4</th>
<th>Factor 5</th>
<th>Factor 6</th>
<th>Factor 7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aspect</td>
<td>-0.04</td>
<td>-0.07</td>
<td>0.02</td>
<td>0.00</td>
<td>0.05</td>
<td>0.99</td>
<td>0.01</td>
</tr>
<tr>
<td>Elevation</td>
<td>0.85</td>
<td>0.19</td>
<td>-0.15</td>
<td>-0.11</td>
<td>-0.12</td>
<td>-0.01</td>
<td>-0.04</td>
</tr>
<tr>
<td>FlowAccum</td>
<td>-0.07</td>
<td>-0.06</td>
<td>0.06</td>
<td>-0.08</td>
<td>0.05</td>
<td>0.01</td>
<td>0.99</td>
</tr>
<tr>
<td>LSFactor</td>
<td>0.05</td>
<td>0.79</td>
<td>-0.04</td>
<td>-0.40</td>
<td>0.30</td>
<td>0.00</td>
<td>0.04</td>
</tr>
<tr>
<td>MidSlope</td>
<td>-0.05</td>
<td>-0.13</td>
<td>0.97</td>
<td>0.05</td>
<td>0.10</td>
<td>0.02</td>
<td>0.06</td>
</tr>
<tr>
<td>MRRTF</td>
<td>0.02</td>
<td>-0.22</td>
<td>0.04</td>
<td>0.94</td>
<td>-0.03</td>
<td>0.00</td>
<td>-0.08</td>
</tr>
<tr>
<td>MRVBF</td>
<td>-0.46</td>
<td>-0.69</td>
<td>0.35</td>
<td>-0.25</td>
<td>0.01</td>
<td>0.05</td>
<td>0.05</td>
</tr>
<tr>
<td>NormHt</td>
<td>0.86</td>
<td>0.22</td>
<td>-0.17</td>
<td>0.08</td>
<td>-0.33</td>
<td>-0.08</td>
<td>-0.04</td>
</tr>
<tr>
<td>SlopePer</td>
<td>0.21</td>
<td>0.89</td>
<td>0.00</td>
<td>-0.17</td>
<td>-0.22</td>
<td>-0.07</td>
<td>-0.08</td>
</tr>
<tr>
<td>SlopeHt</td>
<td>0.90</td>
<td>0.15</td>
<td>0.00</td>
<td>0.07</td>
<td>0.03</td>
<td>-0.05</td>
<td>-0.03</td>
</tr>
<tr>
<td>SAGAWI</td>
<td>-0.59</td>
<td>-0.60</td>
<td>0.24</td>
<td>0.11</td>
<td>0.27</td>
<td>0.12</td>
<td>0.07</td>
</tr>
<tr>
<td>ValleyDep</td>
<td>-0.41</td>
<td>-0.05</td>
<td>0.13</td>
<td>-0.06</td>
<td>0.88</td>
<td>0.06</td>
<td>0.06</td>
</tr>
<tr>
<td>VDistChn</td>
<td>0.91</td>
<td>0.06</td>
<td>0.16</td>
<td>0.01</td>
<td>-0.21</td>
<td>0.05</td>
<td>-0.03</td>
</tr>
</tbody>
</table>

† FlowAccum, flow accumulation; LSFactor, slope length factor; MidSlope, mid-slope position; MRRTF, multi-resolution ridge top flatness index; MRVBF, multi-resolution valley bottom flatness index; NormHt, normalized height; SlopePer, slope percent; SlopeHt, slope height; SAGAWI, system for automated geoscientific analysis wetness index; ValleyDep, valley depth; VDistChn, altitude above channel network.
soil nutrients in topographic functional units

Soil nutrient distribution in different TFUs is shown in Fig. 9. Among all TFUs, TFU B had the lowest and TFU A had the highest levels of almost all soil nutrients; TFU C held a lower level of TN, Mg, S, and Na. The highest level of Na was found in TFU B. We observed that the distribution of Mn and Mg in all TFUs, and all elements between TFU C and TFU D were not significantly different. However, the distribution of P, K, Fe, S, Zn, Cu, TN, and Ca between TFU A and TFU B; K, Cu, TN, and Ca between TFU B and TFU C; and Fe between TFU D and TFU A were significantly different (p < 0.05).

DISCUSSION

Soil Nutrients and Topography

Surface elevation of the study area didn’t show much variation (CV < 1%), but the terrain attributes derived from the DEM provided a lot more information about the topography, verifying the beneficial use of terrain attributes to understand local terrain diversity. The maximum CV of FlowAccum and VDistChn illustrated the existence of highly diverse hydrology and moisture distribution pattern in the study area as it quantifies the number of upland cells draining to a given cell, and the vertical distance for a cell to its nearest channel, respectively. The relationship between terrain attributes and landscape hydrological processes has long been reported by (Moore et al., 1991). Overall, a higher concentration of almost all nutrients was found along the convergent zones in the study area, recognizing a dominant terrain signature in nutrient variations. Convergent zones as represented by higher indices of FlowAccum, SAGAWI, MRVBF, and ValleyDep are areas that have a high probability of receiving upland flow and are potentially more moist compared with the rest of the area (Moore et al., 1993; Schaeztl and Anderson, 2005), thus contributing to accumulation of elements such as Ca, S, and Fe through surface runoff. The distribution of Cu and B followed a similar pattern and could possibly be explained with the similar phenomena in the landscape as aforementioned. However, those areas had lower concentration of Na, a higher value of which was observed in potentially drier parts of the study area. Profile graphs of nutrient distribution revealed that at a distance between 80 m to 120 m from the origin of transect X1–X2, a higher concentration of almost all elements was observed (Fig. 10), with this area having a maximum wetness potential (Fig. 2). Similarly, concentration of P, Na, K, and Mg increased slightly at a distance between 120 and 140 m along the transect where NormHt, MidSlope, and SlopeHt had higher values. The distribution of Mg and P was also influenced by the Aspect of the terrain; however, P was equally influenced by SAGAWI, which had a minimum influence on Mg. These results further reinforce the impact of topography on the distribution of soil nutrients as the former determines the flow of water and energy across the landscape, contributing to spatial variations across the study area. The distribution of TN and Fe seemed to be fluctuating along the transect with a concentration value ranging between 1.5 to 1.8 g kg\(^{-1}\) and 110 to 155 mg kg\(^{-1}\), respectively. SlopeHt and LSFactor were among the terrain attributes that influenced the distribution of these two elements. On the other hand, distribution of Mn was mainly influenced by FlowAccum and ValleyDep even though its distribution showed a more random pattern.

Influence of Management

The distribution of nutrients in the study area might have also been influenced by management. The study site was established from a pasture through intensive site preparation and fertilization. According to Sauer et al. (2015), the eastern half of the study site received 3.9 to 6.7 Mg ha\(^{-1}\) fresh poultry litter, whereas the
The western portion received only 50 to 76 kg ha\(^{-1}\) N as NH\(_4\)NO\(_3\) mineral fertilized annually. The western portion also received an application of P and K fertilizer, as their levels were found to be below optimum for forage growth (Sauer et al., 2015). This indicated that the soils in the western half had always minimum P and K levels that are consistent with our findings. Furthermore, application of a high amount of fresh poultry litter in the eastern half continuously for 5 to 6 yr might have elevated P, K, Ca, Mg, Zn, and Cu levels (e.g., Kingery et al., 1994; Netthisinghe et al., 2014; Tewolde et al., 2011). Studies have shown that continuous applications of manure could increase P availability in soils due to organic matter dominating the adsorption sites where P could be adsorbed (Eghball et al., 1996; Guppy et al., 2005; Kingery et al., 1994). Apart from the pedogenetic source of these nutrients in the study area, the primary source could also be related to management, especially the use of mineral fertilizers, and poultry litter. Poultry litter is reported to have significant amounts of Fe, Cu, Zn, and Mn (Stephenson et al., 1990) and its frequent application can increase N, soil organic matter, and P (Kingery et al., 1994; Sainju et al., 2010). The source of N in the study area could be from decomposed plants and N fertilizer applications.

**Topographic Functional Units and Soil Nutrient Elements**

The study area was divided into four distinct TFUs considering terrain information as input to fuzzy classification using clustering algorithms. Use of fuzzy classification to delineate potential landform units based on terrain attributes has long been proven to be a promising technique that could be used as an alternative to manual delineation (Irvin et al., 1997). As reported in de Bruin and Stein (1998), use of a similar technique could improve conventional soil–landscape modeling, especially in the identification of distinct soil–landscape units that could hold a high degree of association between soil property and terrain characteristics. Benefits of using fuzzy sets in the classification of soil units associated with terrain and lithological variations have also been reported in Odeh et al. (1992). The TFUs identified in this study were distinct in terms of terrain attributes they represent and were believed to be functioning differently as the soil moisture and energy distribution across the landscape might have a unique response to terrain characteristics in each unit. This uniqueness in terrain functionality creates a niche for a specific soil–landscape process to occur, developing a group of individual soils that are

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**Fig. 10.** Surface profile graph of soil nutrients across X1–X2 transect. Profiles are derived from the predicted maps of soil nutrients.
more homogeneous within the unit and are different between them leading to overall soil variations (Odeh et al., 1992). Our findings further verified that TFUs that only considered terrain attributes as inputs were able to capture the major differences in the distribution of soil nutrients. Although there might be some influence of other environmental factors in the spatial distribution of nutrients in the study area, quantification of such influence was beyond the scope of this study. We observed that the TFU B had the lowest concentration of all nutrients, whereas TFU A had the highest. The TFU A mostly represented areas with a potentially high moisture status reflected by the higher values of SAGAWI, MRVBV, and ValleyDep as compared with TFU B, which mostly covered potentially drier areas with higher values of SlopeHt, NormHt, and LSFactor (Fig. 11B), as well as the highest values for Elevation and VDistChn. A maximum concentration of Na was found in TFU B and lower concentration in TFU A. Due to a higher solubility and hygroscopic nature of Na, it would dissolve faster and leave the system leading to relatively lower Na levels in areas with high moisture. As reported by Richardson et al. (1992), however, the same depression areas can switch from accumulating Na to depleting it depending on the amount of precipitation. Therefore, concentration of Na in a landscape is very much dependent on soil moisture and how water moves across the landscape that is governed by terrain attributes (Moore et al., 1991).

### Implications of the Study

This study mapped the spatial distribution of soil nutrients in a silvopasture site and identified topography as a driver of such variation. A better understanding of nutrient distribution status in a silvopasture system would improve management decisions to maximize biomass yield and minimize environmental impacts (Shrestha and Alavalapati, 2004). The maps generated in this study can be used to identify nutrient risk areas (Blicher-Mathiesen et al., 2014) that have optimum forage and tree production potentials and can be linked to preferential animal grazing (Hoogendoorn et al., 2016) as it relates to hydrology, forage quality, and ultimately spatial soil nutrient variability. For example, lower concentrations of Ca and TN in the field could lead to deficiencies that affect forage production and animal grazing pressure. Similarly, recognizing TFUs as potential zones for site-specific management would provide economic as well as environmental benefits through resource optimizations and fine-tuning farm practices in the silvopasture system. As an example, addition of fertilizers in the wet areas or TFU A in our study site may not be economical or environmentally advised due to denitrification potentials and susceptibility to losses.

### CONCLUSION

This study quantified the topographic relationship with soil nutrient measurements and mapped its spatial distribution in a silvopasture site in northwest Arkansas. Fifty-one topsoil samples were used to build a prediction model based on random forest algorithms where 13 terrain attributes were employed as predictors for soil nutrient mapping. Model performance was evaluated and contributing variables in the prediction were identified. Terrain attributes were used to delineate a topographic functional unit map by running k-mean clustering algorithms on factors of principal components with eigenvalue > 1, and soil nutrient variations among TFUs were compared. Based on the results, we concluded the following:

- The study area offered well-structured topographic variation as captured by 13 terrain attributes.
- TN, S, and P were best predicted, whereas Cu, Ca, and Mn had the lowest prediction performance.
- Spatial distribution of soil nutrients was influenced by terrain attributes at varying degrees. For example, TN was influenced more by LSFactor, ValleyDep, and SlopeHt than by MidSlope and MRRTF.
- Levels of S, Ca, Zn, Fe, and TN increased with SAGAWI, ValleyDep, FlowAccum, and MRVBV. NormHt and SlopeHt positively related to Na but negatively to B and Cu. Aspect had a positive influence on P and Mg concentration.
- Most of the study area had TN and K levels lower than the overall average. The eastern half of the study area had more P and Mg than the western half.
- The distribution of Mn approached random; however, it was slightly influenced by FlowAccum and ValleyDep.
- Based on topographic variations, the study area could be divided into four TFUs; TFU B had the lowest and TFU A had the highest levels of almost all soil nutrients present. There was a significant difference in the nutrient levels among and between the TFUs.
• This study only considered topography as a driving factor of soil nutrient variations in the study area. However, it might be possible that the source and nature of distribution of these nutrients could also be influenced by site management.

• This study mapped soil nutrients from the soil surface (0–15 cm thickness). However, soil nutrient movement with depth was not elaborated in this study and could potentially be further studied to provide a more thorough understanding of the dynamicity of nutrients and their interaction with soil landscapes and management practices.

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