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Geostatistics in characterizing spatial variability of forest ecosystems

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Abstract

Forests are spatially variable due to multiple interactions among state (vegetation, species distribution, understory cover, soil, and topography) and forcing variables (climate and human) variables. In general, the spatial structure is resulted as combined effect of these external and internal variables. Geostatistical methods can aid characterizing the spatial structure of forest ecosystems. The shape and parameters (nugget, sill, range) of semivariograms provide important information on the characteristics of spatial structure. In addition, the geostatistical interpolation methods (e.g. kriging) are effective tools for constructing surface maps of variable of interest. Thus, the geostatistical methods have been used increasingly for characterizing forest spatial structure across different spatial scales for last 30 years. In this literature study, sources of spatial variability of forest ecosystems are explained and results of several geostatistical studies are discussed.

Keywords: Nugget, Range, Sill, Spatial interpolation, Spatial structure,

Özet

Ormanlar zorlayıcı (dışsal) ve etkilenen (durum) değişkenleri arasındaki çoklu etkileşimler nedeniyle uzaysal değişkenlik gösterirler. Genel olarak, uzaysal değişkenlik bu değişkenlerin ortak etkisinin bir sonucu olarak ortaya çıkmaktadır. Joeistatiksel yöntemler uzaysal yapının karakterize edilmesine yardımcı olabilmektedir. Semivaryogramın şekli ve parametreleri (nugget, sill, range) uzaysal yapı hakkında önemli bilgiler sağlar. Ayrıca, jeoistiksel enterpolasyon yöntemleri (örneğin, krigleme) ilgili değişkenin yüzey haritalarının çıkarılmasında oldukça kullanışlı araçlardır. Dolayısıyla, jeoistatistiksel yöntemler son 30 yılda ormanların uzaysal değişkenliklerinin karakterize edilmesinde artan bir şekilde kullanılmaktadır. Bu literatür çalışmasında, ormanların uzaysal değişkenliğinin başlıca kaynakları verildikten sonra, bu kaynakların bir fonksiyonu olarak ortaya çıkan uzaysal değişkenliğin karakterize edilmesinde yapılmış bazı jeoistatiksel çalışmaların sonuçları tartışılmıştır.

Anahtar kelimeler: İklim, Orman ekosistemleri, Nugget, Sill, Range, Uzaysal yapı

Introduction

Forest ecosystems vary in time and space. Spatially continuous data are important in all ecosystems including forests for decision-making. Therefore, analysis of spatial variability of forest ecosystems is needed for its thorough understanding. In addition, understanding spatial variation of forests improves our understanding of ecosystem-level processes. According to Pelissari et al. (2017), deficiency of ecological information needs to new techniques for analyzing spatial variations in forests, one of them, geostatistics is a technique for modeling and mapping.

Geostatistics was generally applied in forest research (Akhavan et al., 2010; Fox et al., 2007; Nanos et al., 2004; Palmer et al., 2010; Pelissari et al., 2014; Sales et al., 2007). The geostatistical methods are robust because the area of influence can be adjusted according to the case study needs (Torres et al., 2017). Predicting values of a variable in unsampled points allows to generate spatially continuous data (Li and Heap 2008).

Goal of geostatistics is to examine the spatial structure of the target variable and predict its values at unsampled locations. Therefore, geostatistics is an important technique that can be used to characterize spatial or temporal phenomena (Zhang, 2011). Geostatistics includes ways for analyzing the autocorrelation in spatial data. An important property of geostatistics is the semivariance, which measures spatial continuity. Use of the semivariograms needs the data supplies the real hypothesis for regional variable (Journel and Huijbregts, 1978). There have been number of studies carried out on forest ecosystems. Most of these studies were focused on carbon storage, forest biomass, growth rate and variability of trees, and forest soil quality etc. When compared with the others, geostatistics gives a powerful way to make easy of the spatial variation and interpolation quantification. In this study, geostatistical analysis of forest spatial variability as related to topography, land use, soils, and climate are mentioned and results of several studies are discussed as well.

Geostatistical measures of spatial variability in forest ecosystems

Field measurements are basic requirement in collecting information on forests. But, these measurements can be cost, time consuming and impractical in large areas (Zawadzki et al. 2005). According to Clark (1979), conventional statistics cannot completely explain the spatial variations. Therefore, geostatistical methods ensure a probabilistic structure for understanding the characteristics of the spatial distribution of forest variables (Zhang, 2011).

According to Isaak and Srivastava (1989) and Goovaerts (1997), geostatistics was improved to analyze variables, which are distributed continually in space, called "regionalized variables". The aim of geostatistics is the prediction of values of a target attribute at unsampled locations. Key steps for defining and estimating are 1) modeling of the spatial variability of data of the property by fitting of models to the experimental semivariogram, and 2) using the data with parameters of theoretical semivariogram to interpolate the target attribute in the study area (Goovaerts, 1998).

Steps of analyzing spatial pattern

1- The histograms of the data (pH in this example) are plotted and summary statistics are computed (Fig. 1). However, by this way, critical information such as spatial location of pH measurements cannot be gained (Goovaerts 1998).

2- Each values along the transect does not distribute completely random. Because close observations tend to be like. For example, h-scattergram of the pH values can be showed by plotting with observations separated by a distance of 1-m (Figure 2) (Goovaerts 1998).

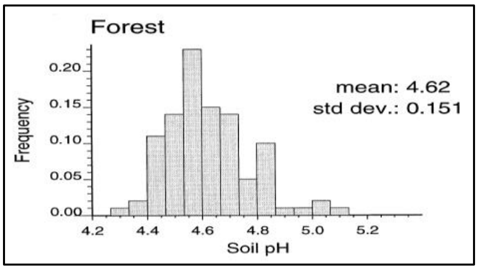

Fig. 1. Histograms of soil pH values measured in a forest plot.

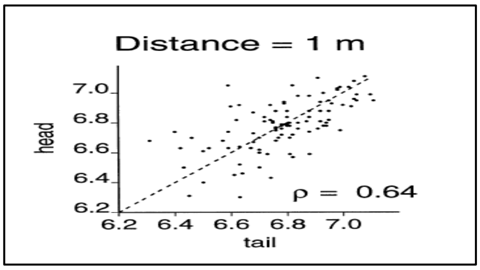

Fig.2. Scattergram of the soil pH values

3- The image of the graph shows correlations of pH values. These correlations evaluate with the linear correlation coefficient. By plotting of the estimated correlation coefficients, experimental correlogram is obtained (Fig.3).

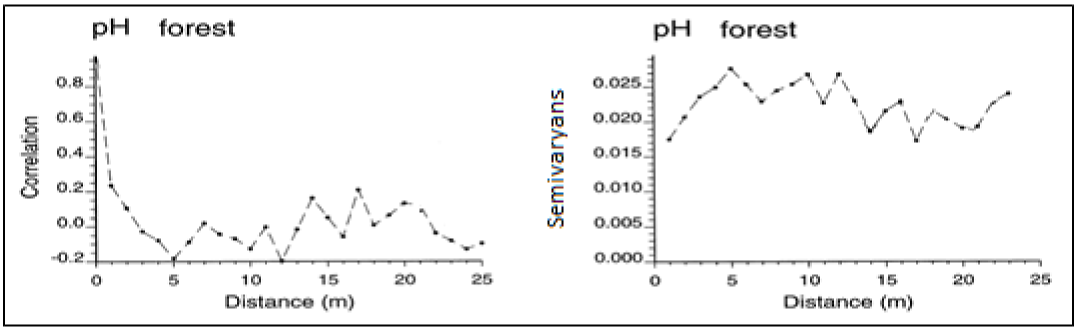

Fig. 3. Correlogram and semivariance of soil pH values measured in forest (Goovaerts 1998).

4- Spatial patterns are described with differences in data pairs. For the average of this dissimilarity, experimental semivariogram γ(h) is used. Semivariogram is half of the average squared difference between the components of every data pair (Goovaerts 1998). Semivariogram is the central tool of geostatistics and a measures spatial continuity (Zawadzki et al., 2005). The semivariogram can be predicted by Eq.(1) (Webster and Oliver, 2001).

$$\hat{\gamma}(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [z(x_i) - z(x_i + h)]^2 \qquad (1)$$

Where *γˆ(h)* is the predicted semi-variance for *N* data pairs, separated by a particular lag distance (h) $z\ (x_i)$ and $z(x_i + h)$ are the values of the variable *z* at locations of *i* and *i* + *h*.

The parameters of the semivariogram are the sill, the range, and, the nugget. Sill defines the maximum value of the semivariogram, range defines distance where the semivariogram reaches the sill, and nugget defines the y-intercept (always positive) of the semivariogram. Fig.3 (right hand side) depicts the nugget, sill, and range for pH values. The point where semivariogram intercepts the y-axis is the nugget (approximately 0.015). It's caused by measurement errors, spatial sources of variation at smaller distances than measurements are made (Journel and Huijbregts 1978). Although the variation is locally spatially structured, we can see a semivariogram as a pure nugget, depending on the sampling scale. Therefore Oliver and Webster (1986a) suggested a preliminary study to approximate the major scales of spatial variation (Fig.4). Soil pH at the unsampled locations can be interpolated with kriging or cokriging using its observations (Figure 5) (Goovaerts, 1998).

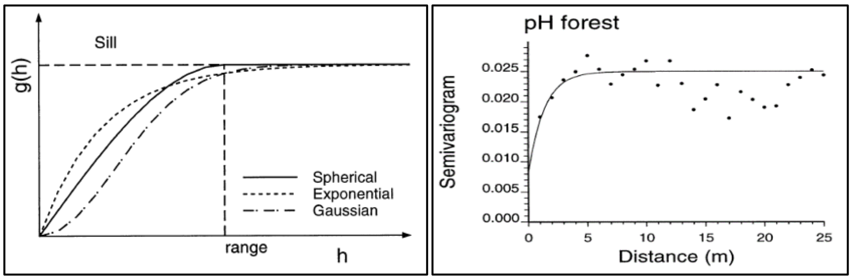

Fig. 4. Theoretical and experimental Semivariograms for soil pH in a forest (Goovaerts 1998).

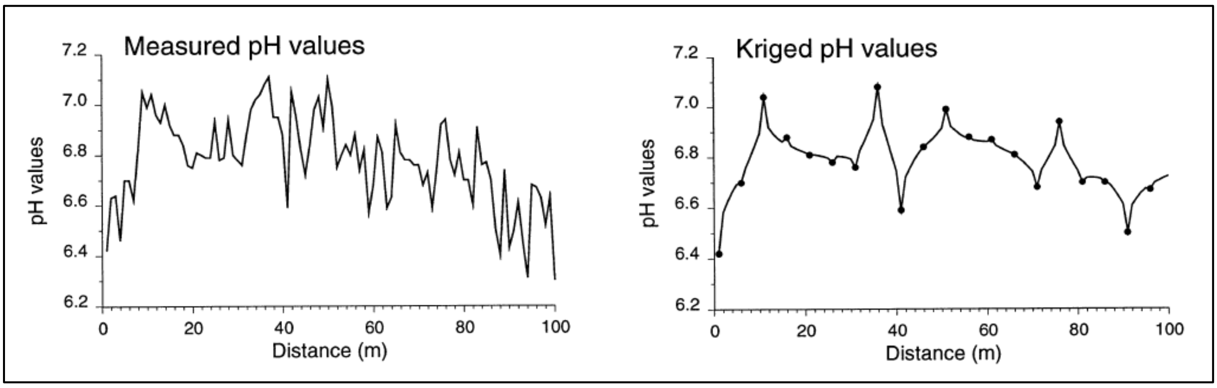

Fig. 5. Measured pH-values at left and kriged values at right

One of the earliest applications of geostatistics in forest research made by Guibal (1973) who used kriging for interpolating forest stock in a tropical forest in Gabon. He reported that kriging was more accurate than classical statistics in small areas. In addition, Mandallaz (1991) reported that geostatistics provided a natural framework for prediction technics in forest inventory studies. The species distribution and abundance patterns are effected by soils, temperature, and moisture and strength and extent of natural disturbances in forests (Whittaker, 1956; White, 1979).

Spatial variation in forest ecosystems as affected by soils

The aim of most geostatistical studies is prediction of soil properties at unsampled points and mapping for soil science (Goovaerts, 1998). For example, soil moisture, pH, and soil temperature etc. are major abiotic factors influencing degradation in forest ecosystems (Benner et al.1986; Entry et al. 1987). Wendroth et al. (1999) used geostatistics to evaluate large trends in the scale and pattern of soil properties because of the directional effect of flooding and finer-scale structure.

Forest soil’s temperature is effected by climate, topography, soil water content, and litter and canopy cover. In addition, the seasonal variation of CO_2 is effected by soil temperature (Striegl and Wickland, 1998). Schume et al. (2003) showed that differences in transpiration ratio among tree species are the key factors of spatial variation of soil water content. Spatial continuity of the water content is related with both of soil water content and drying and wetting history in forest soils. The latter can be more important especially for fine textured soils with a dynamic macropore system. Evapotranspiration is an important factor for variation (Schume et al. 2003).

Schume et al (2004) analyzed spatial variation in patterns in soil water depletion and recharge in mixed and pure forests of European beech and Norway spruce by geostatistics. They found that replenishment of soil water storage is related to crown architecture and canopy interception. Differences in plant transpiration ratio and rooting depths of tree species may have strong control on spatial and temporal depletion in the soil water storage, modification of canopy architecture change water uptake, evapotranspiration, and rain water interception. Schindlbacher et al. (2004) reported that soil water and temperature are the main factors to be considered in measurement of the emissions volumes in forests.

Soil organic carbon accumulation in forests is linked to soil parent material, topography, climate, vegetation, and time factors. Jeyanny et al. (2013) quantified the spatial variability of soil C, C:N and forest soil depth at varying topographic conditions in tropical and lowland forest. They made spatial analyses for variables using semivariograms and kriging and mapped measured and kriged values. The results showed that carbon stocks and C:N at the summit were best explained by a spherical model. They reported that spatial variability maps and C stock estimations across a catena and lowland forest would clearly aid conservation of forest ecosystem with respect to C management, suggesting that future studies should address the reliability of forest floor depth in C sequestering in relation to different forest systems.

Spatial variation in organic soil carbon stock has been related with physical, biological, and chemical processes in forest ecosystems. Kristensen et al. (2015) examined the spatial variation of organic layer carbon stocks in boreal forests. They found spherical models as the best fit at the given lag distances. They noted that the organic layer carbon stocks showed a considerably high short-range variability with spatial autocorrelation distances (0.86 up to 2.85 m) for undisturbed soils and they concluded that spherical model most accurately described the spatial structure of the analyzed soil properties.

Spatial variation in forest ecosystems as affected by topography

Topography is considered as the main abiotic factor inducing spatial variation in tropical forests on local scale, due to its effect on other properties in ecosystem (Bourgeron, 1983). Literature on grassland biogeochemistry from the 1980s revealed that topography can induce a powerful spatial variability at landscape scales (Schimel et al. 1985a; Yonker et al. 1988). Variation of soil properties within a relatively uniform climatic region may also be resulted from topographic heterogeneity (Brubaker et al. 1993). Topography can be used to estimate live biomass in central Amazonia (Castilho et al. 1983). Ecological processes may control the timing of disturbance across a landscape, while topography determines their spatial pattern (Swanson et al. 1988).

Forest biomass is not the same on a landscape due to differences in physiological conditions such as soil and topography. In general, greater forest biomass corresponds to more fertile soils, independent of species composition as more resources available for plant growth in those soils. However, Silva et al. (2002) did not found any topographic effect on forest growth rate in central Amazonia. Establishing relations between topography and biomass is hard since topography combines soil type (Chauvel et al. 1987), canopy openness (Robert, 2003), and soil water availability (Daws et al. 2002).

Topography influences some forest dynamics (Gale and Barfod, 1999; Bellingham and Tanner, 2000) and nutrient cycling (Luizao et al. 2004). Topography has been associated with drainage regimes and soil properties are correlated with tree species distribution in a forest (Bourgeron, 1983; Johnston, 1992). Beaty and Taylor (2001) reported that slope aspect and position induced considerable variation in forest composition. They compared fire regime characteristics at different topographies and found that fire regime parameters are different in slope aspect, slope position, and elevation.

Bořůvka et al. (2007) investigated acid soils of forests in mountainous areas of the Czech Republic. Spatial autocorrelations of O and B horizons was analyzed using cross-variograms. Application of geostatistics let to define the spatial structure of main stand factors. They noted that surface horizons had higher sensitivity to forcing factors (external disturbances) such as acid deposition, liming, and grass expansion.

Spatial variation in forest ecosystems as affected by vegetation

Spatial arrangement of forest, woodland, riparian, and meadow vegetation types suggest that topographic features such as slope aspect and elevation are primary determinants of the local vegetation patterns (Hadley, 1994). Forest management can significantly affect diversity and spatial patterning of understory vegetation. Each forest stand type has a characteristic combination of understory composition, diversity, and spatial patterning of communities (Scheller and Mladenoff, 2002).

Variation of soils can influence the distribution and abundance of plant species, resulting in important consequences for ecosystem-level processes (Gallardo, 2003). Goodland and Pollard (1973) reported that a powerful correlation existed between vegetation structure (height, basal area and density) and nutrient contents of soils in the cerrado vegetation of Brazil. In bare soils, physical properties describe a substantial percentage of the variability in soil water content (Wendroth et al. 1999), while the condition under vegetation cover is different as vegetation controls pattern in soil water content due to differences in evapotranspiration (Western et al. 1998). Mature forest consumes more water than most agricultural crops, resulting in their greater influence on soil water content variability in forests. In a mixed forest stand, influence of vegetation on soil water content variability can be even greater.

Rainfall is an important factor, which is affect by many factors such as canopy structure, tree spacing, wind, rainfall intensity, and evaporation. Canopy structure affects spatial variation of rainfall interception due to differences in gap fraction, horizontal and vertical distribution of leaves, and species composition. Therefore, canopy structure is used in most rainfall interception models as an important influencing factor. He et al. (2013) analyzed spatial variability of canopy interception and related factors, and the minimum number and locations of collectors using statistical techniques. They used the semi-variogram to calculate the parameters of spatial heterogeneity (Isaak and Srivastava, 1989). They found that the spatial variation of canopy interception had a significant positive relationship with PAI (Plant Area Index), but not with LAI (Leaf Area Index). They also found that the mean of collectors, which were located at the edge of the canopy was higher than those within canopy.

Spatial variation in forest ecosystems as affected by climate

Forests are affected by climate due to long life-span of trees. The forest trees are difficultly adapted to unusual variations in climate (Lindner et al. 2010). Tree growth rate is not only depends on the photosynthesis but also on other factors such as soil nutrient availability (Hungate et al. 2003; Luo et al. 2004). When the atmospheric CO_2 increased, stomata are closed partially to decrease water loss by transpiration (Field et al. 1995; Picon et al. 1996).

Changes in the chemistry of atmosphere including tropospheric and ground-level concentrations of ozone can result in increased tree drought stress (McLaughlin et al. 2007) and reduced tree biomass (Wittig et al. 2008). In addition, due to the industrial activities, atmospheric nitrogen deposition has become one of the major factors influencing forest growth over the last decades (Magnani et al. 2007; Kahle et al. 2008).

According to Weber and Flannigan (1997), weather is closely related to forest fires. Weather variables such as temperature, precipitation, wind speed and direction and atmospheric moisture are the principal agents of naturally caused forest fires. Spatial variation of forests is highly correlated with fire regime, which controls distribution, migration, and extinction of species (Matyssek et al. 2006). Tree biomasses of tropical forests are more spatially variable (Laurance et al. 1999; Chave et al. 2003). In many aspects, the complex humid tropical vegetation is an indicator of the spatial and temporal variability in environmental conditions. However, this variation has been documented poorly

(Houghton 2005). Most studies recognized differences in the aboveground biomass in the Amazons forest (Houghton 2001). Nevertheless, studies on the variation in carbon stocks within a single forest type are not adequate, yet (Castilho et al. 2006). Climate changes and the fire regime will alter carbon and nitrogen cycling, and nutrient budgets, which in turn affect spatial variation of forest ecosystems.

Discussion

Geostatistical methods are frequently used for analyzing forests and their use has been increased rapidly for the last decades. Studies carried out using geostatistics in forest research include seed adaptation, species distribution, forest classification, topography, and soil conditions. Measurements in large forests are expensive, time consuming, and impractical. Therefore, the use of geostatistical methods in forest research is practical and numerous of results obtained to date are encouraging. For example, St-Onge and Cavayas (1995) used high-resolution images for evaluating effect of tree size and density on the spatial structure of forest stands. They showed that the directional semivariograms were useful for analyzing spatial variability of their forests. Van der Meer (1996) used a nonparametric geostatistics (indicator kriging) for calcite-dolomite mineral mapping in a forest. They noted that this method can be an effective tool in forest studies if the reflectance spectra of the classified species type are known adequately and data with adequate resolution are used.

Woodcock et al. (1988a) evaluated relations between spatial properties of forests and their maps. They reported that the sill is associated with the rate of the objects area; the range is associated with the dimension of the objects; the shape of the semivariogram and the geostatistical range are more closely associated to the space of objects than to their size; the shape of a semivariogram is associated with the overall variance and decreased spatial resolution results in a smaller sill and greater geostatistical range, and in faster rise of the semivariogram height at the distance of the first lag as well. Bruniquel-Pinel and Gastellu-Etchegorry (1998) found that the sill and the oscillation amplitude of semivariograms rise with the increased LAI in visible band. On the other hand, Colombo et al. (2003) analyzed the spatial variability of LAI for five vegetation types. They reported that geostatistically interpolated data strengthened correlation between LAI and SVI (spectral vegetation indices) and geostatistics helped developing the LAI–SVI correlations. Zawadzki et al. (2005) reported that geostatistic techniques make great information about RS images. They noted that when remote sensing values do not used, kriging is a method to combine values of vegetation samples.

Kriging interpolates rainfall better than conventional methods (Tabios and Salas, 1985; Phillips et al., 1992). However, Dirks et al. (1998) reported that sampling density and data resolution are important for better results. Borga and Vizzaccaro (1997) evaluated kriging and multiquadratic surface fitting at different measured densities and they found similar results. Creutin et al. (1988) and Azimi-Zonooz et al. (1989) used cokriging for merging raingage and radar-rainfall data. In the same way, Hevesi et al. (1992a, b) used cokriging, to incorporate elevation into the mapping of rainfall and they found a correlation coefficient of 0.75 between them. Daly et al. (1994) estimated rainfall versus elevation using, ordinary cokriging. They concluded that prediction capacity of the different algorithms is associated with the strength of the correlation between rainfall and elevation.

Goovaerts (1997) studied incorporating elevation into the spatial interpolation of rainfall by geostatistical approaches. He showed that the contribution of the elevation to the prediction accuracy of rainfall depends on patterns of spatial continuity for rainfall and topography as well. This is valid especially when the cross semivariogram and the semivariogram of the elevation variable have a small relative nugget (Fig. 6). Goovaerts (1997) concluded that elevation data can be used in cokriging of rainfall, if the nugget effect is small. In addition, he noted that further research should be conducted to understand relation of elevation to the spatial variability displayed by rainfall.

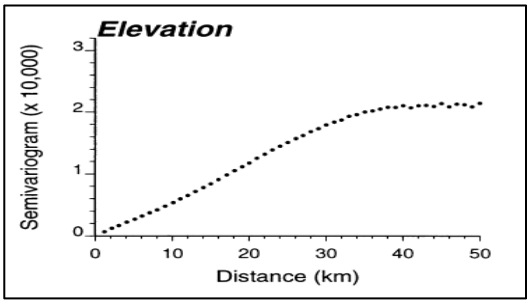

Fig. 6 Experimental semivariogram of elevation

Søe and Buchmann (2005) mapped soil respiration rates by ordinary block kriging using an exponential semivariance in a natural unmanaged highly heterogeneous beech forest. Their results showed significant effects of tree roots and forest structure on soil CO_2 fluxes, indicating that the spatial variation in soil respiration could be explained by the spatial variation of gross primary production. On the other hand, Kosugi et al. (2007) evaluated soil respiration rate using a geostatistical analysis and noted that there was a negative spatial relationship between soil respiration rate and soil water content in a tropical forest. Jost et al. (2005) analyzed the effect of tree species composition on soil water storage (SWS) at the forest stand scale in a mixed stand of Norway spruce and European beech in Austria. They compared spatio-temporal patterns in vegetation and SWS and they noted that that there was a good relation between predicted soil water storage and sudden changes in SWS with kriging

Most resent geostatistical studies have focused on a few soil properties in forest ecosystems. However, more research is needed for an adequate understanding of forest soils. Therefore, it was noted that geostatistical analysis is a strong mean to understand spatial variations of forest characteristics across multiple scales (Sauer et al., 2006). For example, Yavitt et al. (2009) reported that there is no adequate information on spatial heterogeneity of tropical forest soils. They investigated spatial heterogeneity for pH and nutrient including trace elements in tropical moist forest in Panama. Random, exponential, spherical, gaussian, linear, and power functions were found as best fit models in their studies. Their results provided important information for further research in this field. However, they concluded that soil chemical properties are very variable due to their small scale. According to Condit (1995) and Losos and Leigh (2004), more research on geostatistics is needed in tropical forests, because most of the tropical forests were studied in a small scales.

Wang et al. (2007) investigated the spatial data for soil moisture as related to topography to understand their mutual effect on N forms in a subtropical forest in China. They reported that the soil NH4+ and NO_3 contents were similar with different forest conditions. Their results further showed that N mineralization and nitrification showed negative correlation with topographic position.

Jeyanny et al. (2013) analyzed spatial variability of soil carbon, carbon and nitrogen ratio, and forest floor depth by kriging analyses in tropical and lowland forests with different topography. They concluded that spatial structure of soil C showed differences in forest with different topography. In addition, their maps showed spatial clustering and acceptable interpolated values and short to moderate effective range for C, which was less than 125.2 m for all areas. In other studies, soil C was found to exhibit relatively longer effective range (Kravchenko et al. 2006, Law et al. 2009). Zhang and McGrath (2004) reported that longer effective range for soil C was common as large spatial variations in C was evident.

It was reported that forest floor depth is highly variable due to topography, vegetation distribution, soil temperature, moisture, and decomposition rates (Jeyanny et al. 2013). They found a short effective range in their study areas, especially at the side slope which registered an effective range of 8.6 m. Based on their short effective range, they recommend that minimum sampling interval for forest floor depth should not be greater than 10 m for geospatial analysis. Generally, variograms of the toe slope had sill values close to the sample variance, implying that a fixed variance was present

(Rossi et al. 2009). Silver et al. (1994) reported that spatial variations of soil properties related to plant species and basal area.

Spatial variability in soil organic carbon stocks in forest have been related with a series of physical, biophysical, biological, and chemical processes, such as climate, soil type, tree species composition, stand age, and topography (Kristensen et al. 2015). Kristensen et al. (2015) computed spatial properties from the combination of grid and variable lag distance observations and they reported that spherical models yielded the best fit in Boreal forests. They found that the organic layer carbon stocks indicate large short-range variability. They also noted that even there are high differences between soil variables; there is a high correlation between horizon thickness and organic layer (horizon) carbon. Others (Bens et al. 2006; Liski 1995; Penne et al. 2010) reported that the organic layer carbon was high in location closer to tree stems. Similarly, Liski (1995) reported higher organic carbon contents and organic horizon variability in the vicinity of Scots pine stems and Hansson et al. (2011) found that organic layer carbon stock and neighboring basal area have positively correlated in younger spruce and pine stands.

Rossi et al. (2009) evaluated spatial distribution of soil organic carbon in tropical forests. They analyzed OC variability in five forests using conventional statistical methods and geostatistics. Spherical model was fitted to experimental variograms, suggesting a typical spatial behavior. However, these researchers found no spatial structure for pine plantation, described by a pure nugget model, suggesting that the values beyond the smallest sampling distance were independent one to another, and this further indicated that the mean of the soil carbon content may represent soil carbon across the field at the current sampling resolution.

Overall, information on spatial pattern of forest properties is important in developing strategies for forest management. Geostatistics proved beneficial for evaluation of forest inventories in various conditions. For successful geostatistical analyses at process scale (Zhang et al. 2004), spatial variability should be accurately analyzed. Some geostatistical researches show that spatial parameters are scale-dependent (Schume et al. 2003). It can be concluded that research is still needed for developing an adequate understanding on spatial structure and its relation to biotic and abiotic factors in different forests across multiple scales. In this regard, studies should be conducted to evaluate multiple interactions and feedbacks among components of forest ecosystems across different scales of time and space.

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