Spatial Prediction of Some Biological Forest Variables by Terrain Analysis –the Kheiroud-Kenar Forest, North of Iran

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Abstract:
This research conducted to evaluate spatial pattern of some biological variables (mean diameter, density, richness index and bio-diversity index) of forest by linear regression models using terrain analysis in the Kheiroud-Kenar forest located at the Nowshahr, north of Iran. To obtain these parameters, sampling was performed on a systematic grid (250× 400 m) in 193 plots with one ha area. Density and mean diameter were computed at each plot. The richness index in each plot was estimated by extraction of species number. The biodiversity of each plot was calculated using Simpson index. The primary topographic attributes (slope, elevation, aspect, profile curvature and plan curvature) and compound or secondary attributes (wetness index, stream power index, solar radiation and LS factor) were estimated by DEM model. The multiple linear regression models by stepwise method were fitted between topographic attributes and biological variables of forest. The developed models were validated using some additional data (60 plots); and mean error (ME) and root mean square error (RMSE) were calculated to verify unbiased and accurate predictions. The result of this research indicated that richness index show a significant ($r= 0.81$, $p<0.05$) relationship with elevation, profile curvature, LS factor and aspect. The biodiversity index in the examined forest showed a significant ($r= 0.71$, $p<0.05$) with elevation, LS factor, slope and stream power index. The mean diameter and density also revealed the significant relationships with topographic attributes. The results showed that forest variables in the given area could be predicted about 50-60 % of variation by these linear models. These models can be used to predict spatial pattern for adjacent forest with similar conditions (such as management and geology) properties using DEM models and without no measurement or sampling.

1. INTRODUCTION

Forests of Iran with an area about 12.4 million hectare comprise 7.4% of the country's area. These forests have various geographic conditions, producing different forests of various tree and shrub species and production capacity in different edapho- climatic conditions (FAO, 2002). Among five large vegetation regions in throughout Iran, the most important vegetation region according to density, canopy cover and diversity, is the Hyrcanian (Caspian) region that covers an area of 1,925,125 ha, extending throughout the south coast of the Caspian Sea in the northern part of the country. The Hyrcanian vegetation zone is a green belt stretching over the northern slopes of the Alborz mountain ranges (Sageb-talebi et al., 2003). It has a high production capacity due to humid temperate climate and suitable soil. Hyrcanian forests extend for 800 km in length. These natural mixed-hardwood forests have rich diversity based on tree species. Species such as beech (*Fagus orientalis*), hornbeam (*Carpinus betelus*), alder (*Alnus glutinosa*), oak (*Quercus castaneafolia*), maple (*Acer velotonia*), ironwood (*Parotia persica*) are the main species in these forests (Sageb-talebi et al., 2003).

Conservation and protection of these forests are a major duty for the government of Iran. The spatial prediction and mapping of quantitative criteria and parameters of forest such as diversity, richness, mean of diameter and density of trees has major importance to forest managers for the evaluation of forest resources and scheduling the future treatments (Nanos and Montero, 2002). In the best way, they should be extracted and mapped in over whole forest area but, in the current way, they are obtained or estimated trough sampling methods which mapping of these parameters isn't spatially careful due to much distances of samples and to be light the sampling networks.

By the way, quantifying of forest parameters and mapping of them through field study is also time-consuming and cost-intensive. Seeking the suitable methods for mapping and spatial prediction of parameters was the most important investigation by researchers. Many methods have been proposed for quantifying forest parameters. They can be subdivided into broad categories: non-spatial and spatial methods. Spatial methods can be further distinguished as those using spatial indices on the one hand and those on spatial statistical techniques on the other (Kint *et al* 2000). Different models have been used for predict biological properties of forest based on minimum limiting factors, remote sensing technique, generalized linear models and artificial neural network (ANN). The methods are varied in accuracy and costs for sampling and measurements. Franklin *et al.* (2000) showed that spatial pattern of different species within landscape in south California was related to water balances and subsequently this factor could be controlled by topographic indices like elevation, slope, aspect and others. In other hand, Plant growth can be control by soil properties, water accumulation, and solar radiation. Furthermore, these properties could be affected by topographic attributes.

Many researches showed that landform factor is effective on the movement and accumulation of water, sediments and other components (More et al., 1988). In addition, landform is effective on the spatial distribution of lights, heat, water and nutrient elements for photosynthesis of vegetation (Mc key, 1996; Linaker, 1992; Tarboton, 2003).

FAO (1997) introduced the index of potential biomass density index (PBDI) for prediction of forest biomes so that topography is one of the related factors on the PBDI.

Wheatley and et al (2000) are used an automated land cover mapping using Landsat-TM images and topographic attributes. Mackey and et al (2000) are applied the terrain analysis for tracing and recognition of three forest species in the Tanderbee, Canada. They also are used solar radiation, wetness index and elevation as ancillary data on their study and could accurately map the spatial distribution of species.

An overview on the these results and researches, it would be find that the terrain analysis weren't since considered and applied to predict forest biological parameters such as density, diameters, richness and bio-diversity indices in a landscape scale. This study presents and investigates applicability of terrain analysis to predict and quantify some forest parameters in the kheyroud-kenar forest at the north of Iran.

2. MATERIALS

2.1 Study area:

The study area is located in the educational and experimental forest of Tehran University in the north of Iran between 51°33'12"E and 51°39'56" E longitude and 36°32'08" N and 36°36'45 5" N latitude. This forest has been subdivided into seven districts. However, the study has only been performed in three districts (Patom, Namkhaneh and Gorazbon respectively) with about 3000 hectares area (Fig. 1). Altitude ranges from 50 to 1350 meters. Regarding different aspects and altitude zones, a variety of forest types have established.

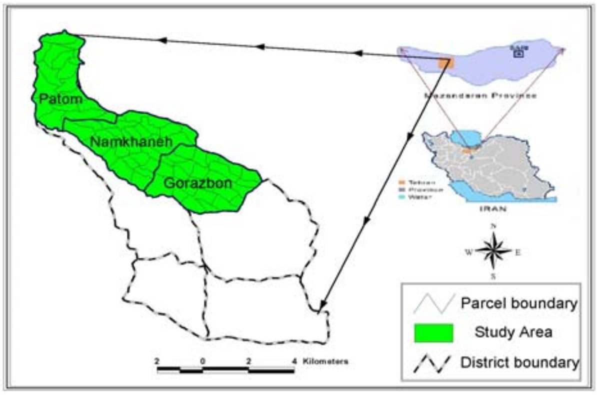


Figure1. Location of the study area at the research forest of Tehran University, north of Iran

2.2. Data

The square sample plots were distributed systematically throughout 3000 hectares study area in size of 10000 m2 (1 hectare). The diameter of trees with the DBHs (diameter at the breast height) greater than 12.5 cm were measured in each plot and the kind of species were noted for all trees. The 193 plots were measured in the non-protection section of the study area (Figure 2).

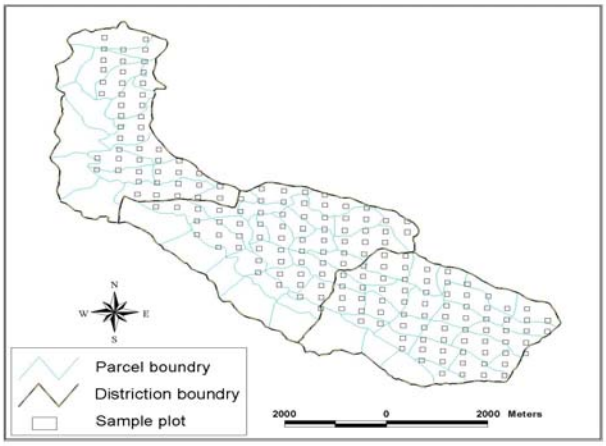


Figure 2: Systematic sample network with square sample plots

2.3. Methods:

2.3.1. Biological forest parameters:

The frequency or density and mean DBHs which are important biological factors for forest managers and silvicultures to apply some treatments on forest. The density of trees that shows the number of trees in each hectare was computed in each sample plots. The minimum, maximum and mean density on each one-hectare plot was obtained 15, 501 and 232 respectively. Also, the mean diameter in breast height of trees in each plot was computed using information of DBHs. The mean, maximum and mean was computed 21.89, 59.41 and 36.09 respectively.

The richness index is another important factor that shows the sustainability and stability of forests. It is evaluated by numbering of different trees and shrubs in each given area. To compute the trees and shrubs richness in each plot, the given species number was numbered. In this study, the maximum, minimum and mean richness in whole plots was 11, 3 and 6.5 respectively. This shows that the study area has a medium situation compared to a natural hardwood forest.

The bio-diversity is also important factor that shows diversity and stability degree of forest. It is determined by the diversity indexes such as Simpson index that use the number of trees and shrubs species occurred in each hectare. In study area, it was calculated using Simpson equation:

$$1\text{-}D = 1-\Sigma\,(Pi)^2 \qquad \textbf{[1]}$$

Where **1-D** is diversity based on Simpson index and **Pi** is the ratio of frequency of given species in hectare.

2.3.2. Primary topographic parameters:

In the Hyrcanian forests, it was known and certified (Asadollahi, 1987, FAO 1997, Shataee and Darvishsefat, 2004) that the topography elements such as aspect, slop and elevation are affected on the forest characters, so that they can be used to predict spatial pattern of some biological forest elements. The primary topographic elements such as aspect, slop and elevation can be directly extracted from an accurate digital elevation model (DEM). A proper digital elevation model with 30 meters resolution was generated using 10 meters contour elevation lines. To make these parameters, mainly the differential filters with a 3*3 kernel were applied on the DEM. The differential filters were applied on DEM in two directions X and Y with following equations:

$$f_{yy}=\partial^2 Z/\partial y^2 \qquad f_{xy}=\partial^2 Z/\partial x\partial y \qquad F_{xx}=\partial^2 Z/\partial x^2 \qquad f_y=\partial Z/\partial y \qquad f_{yy}=\partial^2 Z/\partial y^2$$

$$P=f_x^2+f_y^2 \qquad q=p+1 \qquad [2]$$

Computing of topographic parameters i.e. slop in degree (β) (figure 3b), slope aspect (Φ) (figure 3c), plane curvature (ω) (figure 3d) and profile curvature (φ) were accomplished using following formula:

$$\beta=\arctan(p1/2) \qquad [3]$$

$$\varphi=180-\arctan(f_y/f_x)+90(d_x/\left|f_x\right|) \qquad [4]$$

$$\Phi= (f_{xy}+f2_x+2f_{xy}f_xf_y+f_yf2y)q(3/2) \qquad [5]$$

$$\omega=(f_{xy}f2_x-2f_{xy}f_xf_y+f_yf2_y)/p(3/2) \qquad [6]$$

2.3.3. Secondary related topographic parameters:

However, some secondary and related to topographic parameters such as wetness index (W), stream power index (Ω) and sediment transportation index (Γ) could be also derived from composing of primary elements. These parameters are mainly used in special process such as water and sediment transportation at the forest area.

Wetness index: this index contains spatial distribution of soil moisture in landscape length unit that was computed by following formula (figure 3g):

$$W=Ln(A_s/\tan\beta) \qquad [7]$$

Where **As** is given area of watershed (m2) and **β** is slop in degree (More et al., 1991)

Stream power index: this index is presented as erosion power of surface streams and was computed by following formula (More et al., 1991). See figure 3f.

$$\Omega = A_s \tan\beta \qquad [8]$$

Sediment transportation index:
The index that presents sediment and erosion processes as well as impact of slop on erosion was obtained using following formula (figure 3e). More and Wilson (1992) expressed that this index is equal with length slop (LS) factor in USLE erosion estimation model.

$$\Gamma=(A_s/22.13)^m(\sin\beta/0.0896)^n \qquad [9]$$

Where m and n are fixed parameters and equal with 0.6 and 1.3, respectively (More et al., 1991).

Solar radiation:
The factor that is affected on the illumination and resultantly on the growth of vegetation was computed using latitude and percentage of cloudy (actual sunny times) for study area (figure 3h).

2.4. Statistical model and validation:

After computing and generation of primary and secondary indexes, multiple linear regression models by stepwise method were fitted between topographic attributes and forest biological variables using SAS program. To create models, 2/3 plots (133 plots) were used and the rest (60 plots) were used for validation of the models. The mean error (ME) and root mean square error (RMSe) of results were calculated to verify unbiased and accurate predictions by following formula:

$$ME= \Sigma[Z^*(si)-Z(si)]/n \qquad [10]$$

$$RMSE= \{\Sigma[Z^*(si)-Z(si)]^2/n\}^{1/2} \qquad [11]$$

Where Z*(si) is estimated rate, Z (si) is actual rate for variables and n is the number of observations.

3. RESULTS AND DISCUSSION

Table 1 shows the statistical information of biological forest variables in 193 sample plots at the study area. As the table shows, to be close mean and mode of information as well as skew ness showed that the forest variables used in this study were statistically normal.

Table 1: Statistical attributes of forest biological indexes in the study area

Index	Min.	Max.	Mean	Median	Standard deviation	Coefficient variation	skew ness
Richness	3	11	6.44	6	1.56	0.24	0.33
Diversity	1.08	5.27	2.25	2.19	0.77	0.34	0.89
Density	15	501	232	214	80.38	0.34	0.73
Mean diameter	21.8	59.4	36.09	36.25	6.19	0.28	0.39

Figure 3 shows the results of primary and secondary topography parameters computed by mentioned formula and using DEM. These elements were created as raster maps with 30*30 meters resolution. Using GIS and DEM and terrain analysis studies, statistical information of topographic parameters including slop, aspect, profile curvature, plane curvature, LS factor, stream power index and other parameters were extracted in 193 plots. Table 2 show statistic attributes of topography parameter in plots.

Table 2: statistical attributes of topographic parameters in 193 sample plots

Parameters	Min	Max	Mean	Median	Standard deviation	Coefficient variation	skew ness
Elevation (m)	84	1328	969.5	1065	288.5	0.29	-1
Aspect (º)	0	357	210.2	217	92.14	0.44	-0.79
Slop (%)	1	89	25.9	24	15.18	0.59	1
LS factor	0.09	65.86	15.41	12.99	11.36	0.73	1.01
Plane curvature	0	0.01	0.001	0	0.001	0.99	0.37
Profile curvature	0	0.01	0.001	0	0.001	0.86	0.65
Stream power index	0.4	3132.2	129.3	59.3	88.8	0.68	0.89
Wetness index	4.98	11.49	7.18	6.96	1.19	0.16	0.98
Solar radiation	859.4	2214	1863.2	1964.5	294.96	0.15	-1

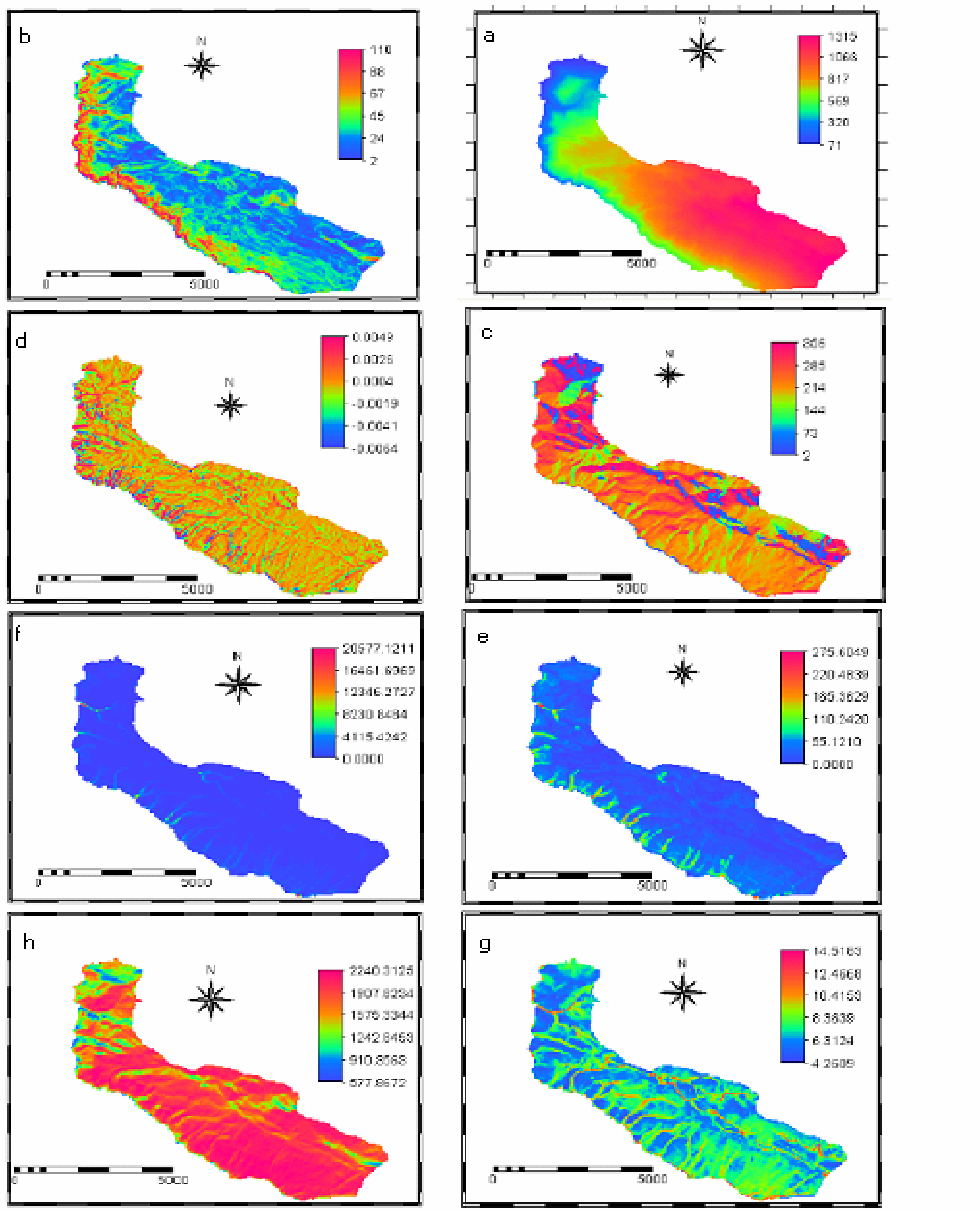
Using multiple linear regression analysis, the best models were fitted for four forest variables in $p<0.05$ (table 3). The result of this research indicated that richness index show a significant ($r= 0.81$, $p<0.05$) relationship with elevation, profile curvature, LS factor and aspect. The bio-diversity index in the examined forest showed a significant ($r= 0.71$, $p<0.05$) with elevation, LS factor, slope and stream power index. The mean diameter and density also revealed the significant relationships with topographic attributes.

Table 3: the best multiple linear regression models estimated for study area

Validation index (n=60)		R^2	Regression models
ME	RMSe		
-0.01	0.12	0.67**	Rich = 9.12-0.003Elev + 306.58Proc + 0.022LS-0.002Asp
-0.05	0.02	0.51**	Div = 2.48+0.058LS-0.001Strm -0.02Slp+ 0.03Elev
0.03	1.52	0.55**	Dens = 26.44+ 0.091Solar+ 1.283Slp+7065Proc
0.01	0.06	0.63**	Diam = 40.138+0.008Elev-0.005Slp-0.127LS-697.42Plac
*abbreviations: Rich =Richness, Elev =Elevation, Proc = Profile curvature, LS= LS factor, Asp =Aspect, Strm = Stream power, Slp =Slop, Solar =Solar radiation, Plac = Plane curvature, Diam =Mean diameter, Dens =Density, Div =diversity			

The R^2 determination coefficients show that created models could express forest variables acceptable. However, with a more closed sample network (low distance between plots) and high-resolution digital elevation model may be find the better models compared with studied models.

Figure 3: the primary topographic parameters and secondary
related variables extracted from DEM.



The results of validation of models showed that ME rates of models were close to zero. It is means that estimation by models was unbiased. The low RMSe in table 3 shown those estimated results were accurate and acceptable. Although in this study the forest biological parameters could be acceptable predicted in an unique geology structure, however, the land form in the study area have no high diversity in according to slope, profile curvature, aspect and different relief. The low coefficient variations (C.V.) in table 2 show and certify those. This causes that the results of the study can not be creditable on other sites with different landforms.

In other hand, different maternal materials lead to produce different soil characteristics and at the results, they are affected on the growth of forest species and differentiated on forest biological variables. So, the results of the study are validated only on sites with similar soil materials. Mackey and et al. (2000) are also emphasized that their created model is not validated for other sites in Canada with different geology structure those are studied.

4. CONCLUSION

Overall results from this study showed that topography and its related parameters can be affected on the forest biological variables. Using these parameters to predict spatial distribution and their rates can be help to forest managers where due to problems in accessibility, gathering information trough current fielding ways is time consuming and cost-intensive. The results of this study showed that forest variables in the given area could be predicted about 50-60 % of variation by these linear models. These models can be used to predict spatial pattern for adjacent forest with similar conditions (such as management and geology) properties using DEM models and without no measurement or sampling. These models can be used as spatial decision systems to predict forest situations and trends. In overall, results suggested that terrain analysis integrated with other techniques such as remote sensing data, might be more effective to predict biological variables in forests with minimum costs of measurement and acceptable accuracy.

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