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Estimating the biomass production of three rangeland species using geo-statistic techniques, Taleghan, Iran

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Abstract

The study area of the current study is located in Taleghan region, Iran;enclosing about 54 hectares. What is argued here, is estimating the amount of biomass production of some rangeland species by making use of geo-statistical techniques. Random systematic sampling design was applied with 100 quadrats of one square meter area in two phases. In the first phase, random starting point located in the *Phlomis-Astragalus*,25 quadrates were drawn parallel to the slope and another 25 quadrates perpendicular to the slope, keeping regular 10-meter distances in between. In the second phase also, another 50 quadrates were drawn. For each quadrat, biomass of the species and GPS locations were recorded (discarding the quadrates lacking the species of interest). The corresponding variogram for the 100 quadrates was plotted in the next step and showed a low level of homogeneity for the recorded biomasses. Using the OrdinaryKriging and by analyzing the obtained variogram, the amount of biomass of *Astragalusgossipinu, Bromustomentellus*and*Agropyronsibiricum*was determined for the quadrates delimiting one square meter. In the obtained variogram, the random variance was high implying a poor representation of the biomass production for the species. Accordingly, the geo-statistic techniques based on analyzing variograms and by applying *Kriging* method are not the appropriate way to perform such studies.

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Introduction

One of the most significant current discussions in range management is knowing the amount of production and biomass. Since on the one hand, gathering reliable information in this context is time and capital consuming and on the other hand the acreage of Iran's rangelands is so vast but money and time are both limited, taking the advantage of state-of-the-art techniques instead of the obsolete methods is worth considering.

One of the statistical methods being applied in the rangeland science is the spatial analysis on the basis of the *kriging -geostatistic techniques* centered on the notion of spatial variability, first introduced by Matheron in 1965. This integrated approach could be applied in the estimation of herbaceous biomass. Sokan& Oden (1978) carried out a research on the level of bio- resources exploiting geo-statistical analysis. Results suggested that the spatial correlation analysis of this type of data is well consistent with what is actually happening in the field. Zimmerman & Zimmerman (1991) made an attempt to predict spatial variability of plant biomass by applying the Kriging method which ended with acceptable results for the species under study. In an effort to use geo-statistics for the estimation of the available forage in the prairies under controlled grazing in western Mexico, Conan *et al* (1992) found that the accuracy of the estimates depends heavily on the level of biomass homogeneity. Rossi *et al* (1992) studied the spatial correlation of vegetative ecological characteristics using Kriging and concluded that the capacity of interpolation of this method is greatly dependent on the ecological homogeneity and the species of close ecological demands will have closer estimations. Maravalias (1996) in a site of clumpy vegetation structur with close distances showed that the geostatistics (Kriging) is able to estimate biomass with acceptable accuracy. The author introduced a model to approximate the production amount in short distances capable of interpreting the spatial variability in the distance unit. Gunnarson *et al.* (1998) determined the efficiency of the Kriging interpolation methods in estimating the acreage of age-classified forest stands and found that in the homogeneous needle-leave stands this method is verifiable (Akhavan, 2006). Goovarets (1999) stated that geostatistic techniques are of proper practicality in forming a model to approximate the rangeland species' distribution in the studied area. It was shown by Carroll and Pearson (2000) that geostatistics is quiet capable of determine the decrease of vegetative biomass production in volume. Holmes and colleagues (2007) proposed a model for approximating rangeland species production and distribution in western rangelands of New South Wels, Australia via the Kriging method. In the pages that follow, the possibility of using the Kriging interpolation method to estimate the biomass production of three rangeland species will be presented.

Material and methods

Study area

The studied area, located to the north of Taleghan, spans between 50 43 19 and 50 53 20 eastern longitude and 36 05 58 to 36 11 22 northern latitude. The region's area reaches up to 54 hectares and its elevation ranges from 1800 to 3500 m a.s.l. Since a great part of the area has remained intact from human disturbances, its variability for vegetative biomass quality could be used to make a correlation between the measure of distance and the amount of biomass content which is a perquisite in performing an interpolation in Kriging method. Of the vast gamut of plant composition in the area and given the importance and role of the species, *Astragalusgossipinus*was selected because of its industrial use while *tomentellus* and *Agropyronsibiricum*were chosen for their role in providing forage to the local livestock.

Study and Sampling Design

Dwelling on the fact that the capability of geostatistics in estimating variables draws heavily on the existence of a spatial correlation in a short distance, the first quadrat was laid randomly and the following ones (perpendicular to the slope) were placed systematically with the fixed distance of 10 meters in between. (Moghadam, 2001). In order to reach a better distribution for the sampling quadrats and maintaining the maximum level of homogeneity, the sampling plots were divided into two groups of 50 quadrats. This was arranged in four sub-phases with 25 quadrats parallel to the slope and another 25 quadrates perpendicular to the slope in each, and holding the same procedure for the other 50 plots.

Geostatistics can also be characterized for their sensitivity to the samples with spatial correlation. Here, a relationship is made between the dependent variables, called the spatial structure of variables. The variogram function is given as eq. 1.

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} \left[Z(xi) - Z(xi+h)\right]^2$$

Here, $\gamma(h)$ represents variogram value, N denotes paired samples, h shows distance, x stands for variables and z shows the variable value.

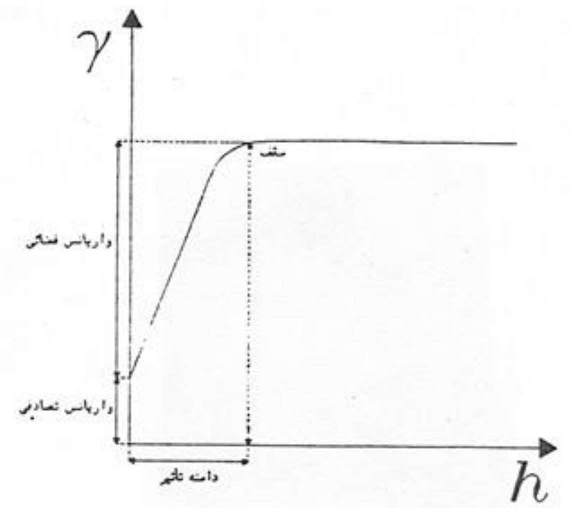

Fig. 2. Theoretical Variogram.

The random variance is the result of the bias in sampling procedure and causes the variogram not to begin from the origin of coordinate. The lower goes the random variance, the higher reaches the level of precision in sampling procedure. Capability of the variogram in approximating the correlation between samples is communicated through its effective range. Outside of this range, the variogram levels off which deteriorate the spatial correlation between variables. For those variables with the same longitude and latitude in the UTM coordination system, the intercept must be equal to zero but in effect there was a remarkable random variance. Hence, the estimated values have to be tested for the goodness of fit.

The range of the proposed models for the theoretical variogram is vast, however could be categorized into two groups of No-thresholds (linear and parabolic) and threshold-based (spherical, exponential, Gaussian, and nested structures). In this study the value of the normalized theoretical variogram was obtained via GS+ software. Next, based on the Residual Sum of Squares (RSS) and Correlation Coefficient (R^2), a proper model was selected among Linear, spherical, exponential and Gaussian. The overall formula obtained for the Kriging method, like other estimators, is defined as eq. 2 as given.

$$Z^*(xi) = \sum_{i=1}^{n} \lambda i \,.\, z(xi)$$

Where z*(xi) shows the estimated variable, λ_i shows the importance or weight of the i*th* sample and z(xi) denotes the observed value for the variable. This type of the Kriging model is called linear because it is a linear combination of n values. The reliability of this type of estimation is allowable as long as the distribution of z values is normalized. Validation process of the model follows OmittedIntermittent andStage Estimate of these variables using the Kriging method.

Results

Variography

In the beginning, data were analyzed for normality. Table 1 show that original raw data are not normal, therefore data have been normalized using data transformation (taking logarithm). Table 2 shows experimental variogram based on normalized data.

Table 1. Inventory of raw data (before conversion).

Range	Maximum	Minimum	Variance	Median	Mean

240	260	20	2889.59	129.5	140.73

Table 2. Experimental variogram characteristics of data after conversion (taking logarithm).

Model	Nugget effect (gr/m²)	Roof $\frac{Sill}{Co+C_1}$ (gr/m²)	Range Parameter	Effective range	$\frac{C}{Co+C}$	Correlation coefficient (r²)	Residual sum of squares (RSS)	Lag (m)
Linear	4.57	4.57	39817.71	39817.81	0.618	0	101	1000

According to table 2 and 3, the nugget effect of variogram and variogram roof is equal (4.57) and is very high too. It implies that there is a very weak space structure among data. Despite high effective range (39817.81), high nugget effect forms a small part of the total variance by variogram and most part of it has been described via random and non-structured part.

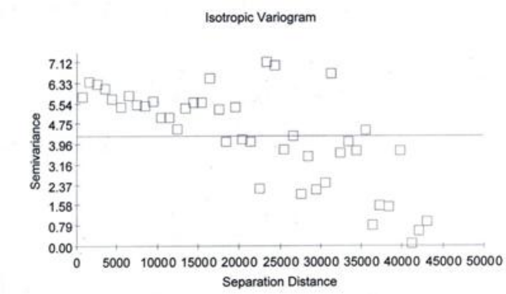

Fig. 3. Isotropic variogram of observed data for biomass (gr/m2).

Kriging

OrdinaryKriging interpolation was conducted within 100m² network via GS⁺ software (Fig 4 and 5).

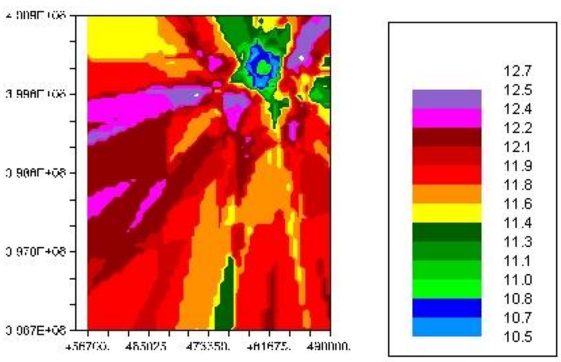

Fig. 4. kriging Map for estimating biomass (scale, 1:44500).

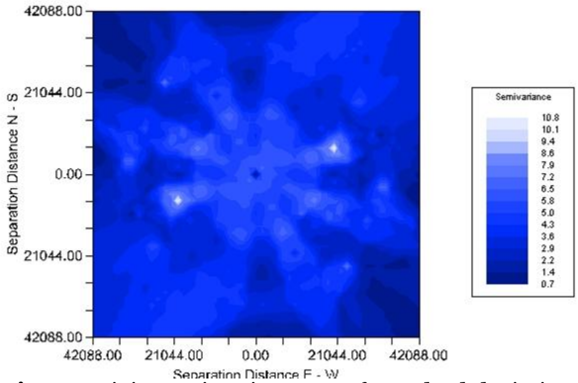

Fig. 5. Kriging estimating map of standard deviation for production variable in studied region.

Model validation

The mean absolute error (MAE), mean bias error (MBE) and mean square standard deviation ratio (MSDR) were used. Standard deviation (error rate) was estimated by using MAE and MBE. Tendency of amounts to zero is indicating low deviation of estimating values in comparison to actual values. On the other hand, MSDR values tend to one number whichrepresents a small difference between variances or difference between experimental and theoretical variogram. Table 3 shows these values.

Table 3. Presented data for mean absolute error, mean bias error and mean square standard deviation ratio.

Mean Absolute Error (gr/m2)	Mean Bias Error (gr/m2)	Mean Square Standard Deviation Ratio
550.24	-1.96	550.24

Considering to presented data in table 3, the values of MAE and MBE have a high distance from zero number. This indicate that high amount of nugget effect prevent estimating actual biomass in weak structure of data for kriging model. High amount of MSDR is indicating high difference between variance of Kriging and variance of calculated values in experimental and theoretical variogram that presented in figure 6. There is high difference between estimated values and actual values.

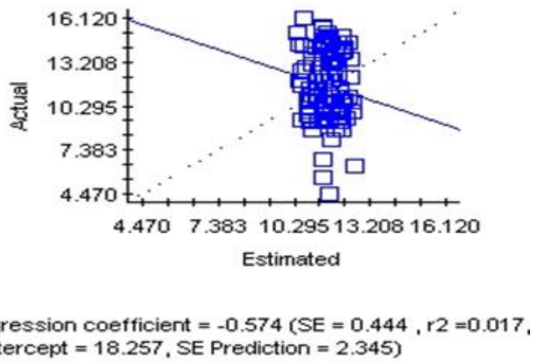

Fig. 6. Comparison between estimated and measured values of biomass in three rangeland species.

Discussion and conclusion

Obtained all information by kriging interpolation are depending on overall structure of variogram especially amount of nugget effect. In variogram related to kriging estimation model, nugget effect has a high value due to absence of homogeneity among biomass amounts in Bromustomentellus, Astragalusgossypinus and Agropyronsibiricum in investigated different distances. Geostatistics capability for estimation is low Because its ability is depending on spatial variability of environmental variables and this homogeneity properties doesn't not exist in collected data (high nugget effect indicating this matter). High nugget effect in obtained variogram can be due to existence of overgrazing and degradation in some of studied region.

Existence of bias in estimated data by kriging interpolation is related to weak structure of variogram and high of nugget effect amount (low correlation coefficient between actual and estimating values confirm this matter, P=0.05).

Random distribution of biomass in the study area (due to disregarding utilization season, rangeland capacity and different topography) causes high variability of biomass in the sampling distance and creating non homogeneity among data and this is another reason for lack of efficiency of geostatistics in estimating biomass of species in study region. It seems classified-based sampling method with on environment homogeneity and good classification of data using satellite images and aerial photos cause homogeneity among data and decreased spatial variability of data. Subsequently,nugget effect decreased and geostatistics capabilityincreased. The results of this research are consistent with Conan *et al* (1992), Maravelias *et al* (1996) and Gunnarsson (1998) in estimation of biomass of broadleaf forest trees. Sokal and Oden (1978), Rossi *et al* (1992) and Jost*et al* (1993) used Kriging interpolation for estimation of biomass of needle-leave forest trees and found contradictory results with what has been reported here. Geostatistics in micro scale will have better results than application of ordinary statistical methods such as multivariate regression. These scales are ranging effect of data and the condition of high environment homogeneity considering to ecologic factors including distribution, topography and soil properties. Area selection and suitable numbers of data are effective in application of this method.

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