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PREDICTIVE MODELING OF SOIL AND PLANT DISTRIBUTIONS: A REVIEW

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ABSTRACT: Predictive modeling of plant species' distributions based on their relationship with environmental variables is important for a range of management activities. Examples include management of threatened species and communities, risk assessment of non-native species in new environments and the estimation of the magnitude of biological responses to environmental changes. Variability is one of the intrinsic characteristics of the soil properties. Within an ecosystem, soil properties have vast spatial variations which mainly arise from factors and processes of pedogenesis and land use. Spatial variability in the soil is natural, but understanding these changes, particularly in agricultural lands for planning and management is inevitable. Soil properties change with time and space of the small scales to large scales, which are influenced by intrinsic properties (such as soil parent materials) and non-inherent characteristics (such as management, fertilizer and crop rotation). To plants predictive mapping, it is necessary to prepare the maps of all affective factors of models. Geostatistics is a useful tool for analyzing the structure of spatial variability, interpolating between point observations and creating the map of interpolated values with an associated error map. In this paper, we are focusing on the spatial variation of plant diversity with respect to soil and environmental impacts.
KEYWORDS: Geostatistics, soil properties, Plant diversity, Regression models

INTRODUCTION - DEFINITIONS AND BASIC CONCEPTS

Geostatistics is a subset of statistics specialized in analysis and interpretation of geographically referenced data [18, 21, 36, 50]. In other words, geostatistics comprises statistical techniques that are adjusted to spatial data. One of the main uses of geostatistics is to predict values of a sampled variable over the whole area of interest, which is referred to as spatial prediction or spatial interpolation.

Note that there is a small difference between the two because prediction can imply both interpolation and extrapolation [21]. An important distinction between geostatistical and conventional mapping of environmental variables is that the geostatistical prediction is based on application of quantitative, statistical techniques. Unlike the traditional approaches to mapping, which rely on the use of empirical knowledge, in the case of geostatistical mapping we completely rely on the actual measurements and (semi-) automated algorithms. Although this sounds as if the spatial prediction is done purely by a computer program, the analysts have many options to choose whether to use linear or non-linear models, whether to consider spatial position or not, whether to transform or use the original data, whether to consider multicolinearity effects or not. So it is also an expert-based system in a way. In summary, geostatistical mapping can be defined as analytical production of maps by using field observations, auxiliary information and a computer program that calculates values at locations of interest [21].

Ideally, variability of environmental variables is determined by a finite set of inputs and they exactly follow some known physical law. If the algorithm (formula) is known, the values of the target variables can be predicted exactly. In reality, the relationship between the feature of interest and physical environment is so complex that it cannot be modelled exactly [21]. This is because we either do not exactly know: (a) the final list of inputs into the model, (b) the rules (formulas) required to derive the output from the inputs and (c) the significance of the random component in the system. So the only possibility is that we can try to estimate a model by using the actual field measurements of the target variable [21].

Environmental variables are quantitative or descriptive measures of different environmental features. Environmental variables can belong to different domains, ranging from biology (distribution of species and biodiversity measures), soil science (soil properties and types), vegetation science (plant species and communities, land cover types), climatology (climatic variables at surface and beneath/above), hydrology (water quantities and conditions) and similar [21]. They are commonly collected through field sampling (supported by remote sensing), which are then used to produce maps *showing their distribution in an area. Such accurate and up-to-date maps of environmental features represent a crucial input to spatial planning, decision making, land evaluation or land degradation assessment [21].*

In the case of plants and animals, geostatistical mapping becomes much more complicated. Here, we deal with distinct physical objects (individuals), often immeasurable in quantity. In addition, animal species change their location dynamically, often in unpredictable directions and with unpredictable spatial patterns (non-linear trajectories), which asks for high sampling density in both space and time domains [21].

In vegetation mapping, most commonly field observations of the plant occurrence (ranging from 0 to 100%) are recorded (Figure 1). In addition to mapping of temporary distribution of species, biologists aim at developing statistical models to define optimal ecological conditions for a certain species. This is often referred to as habitat mapping and can be also dealt with geostatistics. Occurrence of species or habitat conditions can also be presented as continuous fields, i.e. using raster maps [21].

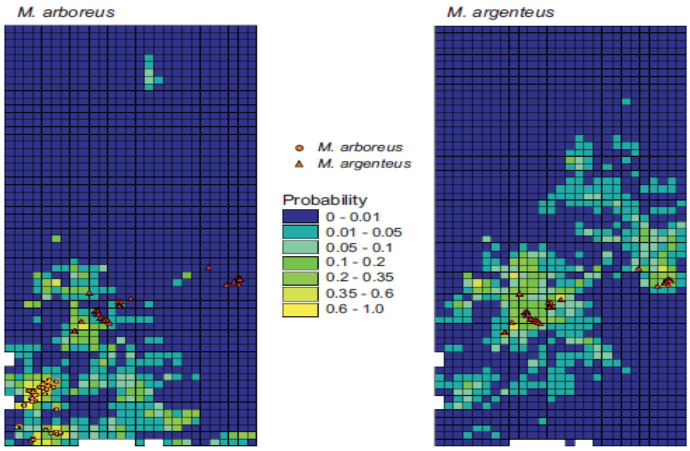

Figure 1. Example of a geostatistical mapping of occurrence of sister (plant) species (After [27] and [21])

DISTRIBUTION OF PLANT SPECIES - REGRESSION MODELS

The analysis of species-environment relationship has always been a central issue in ecology [52]. Climate in combination with other environmental factors has been much used to explain the main vegetation patterns around the world. The quantification of such species– environment relationships represents the core of predictive geographical modeling in ecology [52]. These models are generally based on various hypotheses as to how environmental factors control the distribution of species and communities [2]. Regression methods relate species response to single or multiple environmental predictors. These methods include frequently used approaches such as logistic regression [22], generalized additive modeling [20], and classification and regression tree [8]. Guisan and Zimmermann [19] presented a comprehensive review and classified the methods into two categories: (1) regression-based methods; and (2) environmental envelope methods. Logistic regression is a frequently used regression method for modelling species distributions [19, 41]. This is a particular case of Generalised Linear Models [29].

Generalised Linear Models (GLM) has been recognized in ecology for some time as having great advantages for dealing with data with different error structures particularly presence/absence data that is the common type of data available for spatial modelling of species distributions [35,41]. In the other hands, logistic regression is one of the methods that can predict the probability of occurrence of each plant species related to site condition factors [52]. Ecologists believe that the relationships between plant species and environmental factors are non-linear [30].

Function of logistic regression is a sigmoid curve. This method has been used by Wu and Huffer [51], Bio et al [5], Austin et al [3], Carter et al [10], Zare Chahouki and Zare Chahouki [52], for predictive species modeling. Based on obtained predictive models for each species (through LR method) related predictive maps will be prepared in GIS (Figure 2). Logistic regression

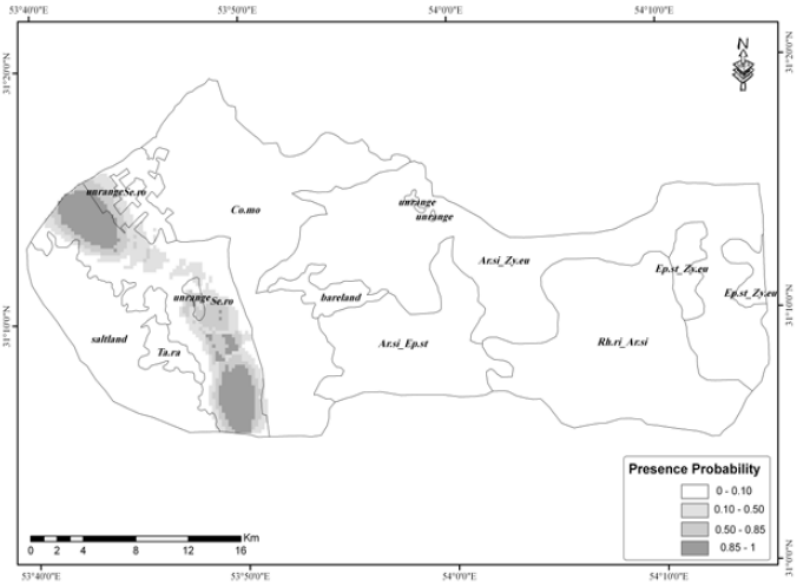

Figure 2. Predicted map of vegetation types provided by logistic regression (Example from [52])

(LR) is a kind of generalized linear model (GLM) suitable for analysis when response data are binary. It uses a logit link to describe the relationship between the response and the linear sum of the predictor variables [31]. This is accomplished by applying the following regression equation, in which presence/absence of an object is transformed into a continuous probability y ranging from 0 to 1.

Values close to 1 represent high probability of presence, whereas values close to 0 represent high probability of absence. In order to discrete y into presence and absence, a posterior threshold is assigned. Occurrence probability of each plant species is calculated with respect to the combined effect of site conditions with the following equations:

$$Y = \frac{\exp(LP)}{(1+\exp(LP))} = \frac{\exp(b_0 + b_1x_1 + b_2x_2 + \ldots + b_nx_n)}{1+\exp(b_0 + b_1x_1 + b_2x_2 + \ldots + b_nx_n)} \tag{1}$$

or

$$Y = \frac{1}{1+e^{-(b_0+b_1x_1+b_2x_2+\ldots+b_nx_n)}} \tag{2}$$

where: Y is the probability; x_n is explanatory variable; b_0 is the constant; and exp is an exponential function.

MULTI-SPECTRAL SATELLITE IMAGE CLASSIFICATION

One approach to describing the spatial patterns of plant diversity in landscape mosaics consists of accounting for the diversity within and between particular habitats that could be considered homogeneous communities [24]. On the one hand, plant diversity is estimated inside each of these habitats. On the other, the dissimilarity (or complementarity) between such habitats is also estimated. The most commonly employed measures for estimating the diversity of species in a community are those related to species richness (i.e., the number of species present in an area) and measures based on species frequencies or abundance, including Shannon and Simpson indices [24]. One of the main problems in comparing the number of species among communities is that species richness is not independent of the sample size. The number of species increases with the size of the area sampled. Therefore, to make comparable the number of species among different habitat types, it is necessary to employ the same sampling effort in every one of them [24].

Another problem in measuring biological diversity is presented by the difficulties and effort required for sampling large areas of densely forested landscapes, particularly when access to some particular sites is difficult, which is the case of most tropical forests [14, 15]. However, combining ground surveys with the support from remote sensing image analysis has proven to be a very useful tool for solving the numerous practical problems involved in this type of undertaking [24]. So, multi-spectral satellite images can be used for identifying and mapping land cover classes (Figure 3).

Such classes can be taken, in a broad sense, as being equivalent to habitats. Mapping such classes offers several advantages in the assessment of biodiversity over the landscape. First, the diversity within the mapped classes can be assessed relatively easy through field measurements. Second, land cover classes could be sufficiently linked to species composition and abundance in those particular areas over the landscape [24, 34].

SPATIAL VARIABILITY OF PLANT DIVERSITY

The spatial distribution of species can be estimated through several approaches. One of the most common approaches is to assess species diversity based on the average values of computed diversity indices, as obtained from the diversity measurements within vegetation or land cover classes [25]. In this method, the mapped classes are viewed as habitats and the diversity within those classes is assessed through field samples. Then, species composition and abundance are both referred to such mapped classes [25].

Researchers and practitioners have used vegetation or land cover classes to analyze the spatial distribution of plant species [25, 47] of animal species [32] or they have considered both, plant and animal species [14, 15].

This approach implicitly uses the mean values of classes as spatial interpolators by assigning the average

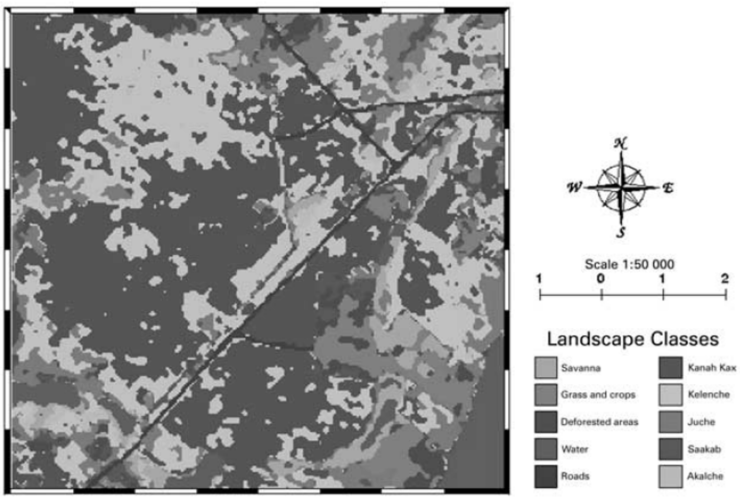

Figure 3. Land cover map showing the six vegetation types mapped from a supervised classification (Prepared by [24)

values of the diversity indices measured at different locations to the entire area covered by those classes [6, 46].

Figure 4 showing the proportion of variance (semivariance) found at increasing distances of paired soil samples (lag distances). The random model is expected when soil properties are randomly distributed. The spherical model is expected when soil properties show spatial autocorrelation over a range (Ao) and independence beyond that distance. Total variance is the sum of the variation explained by the spatial model (C) and the variation found at a scale finer than the field sampling (nugget variance Co).

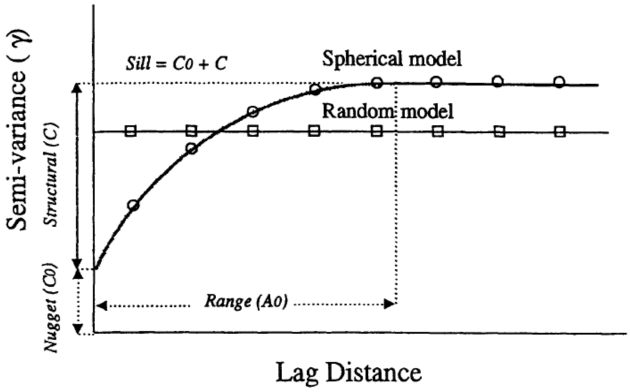

Figure 4. Schematic diagram of a semi-variogram

One of the main concerns of this approach, aside from the simplification of having a single mean value predicting all non-measured points within each class, is that it assumes independence of the samples, i.e. it does not account for spatial dependence and auto-correlation. Yet, species composition is often influenced, at any given location, by the structure of species at surrounding locations, due to contagious biotic processes such as growth, reproduction, mortality, etc. [28]. In such cases, it is reasonable to assume that the values of diversity from points closer together are often more similar than those farther apart. Therefore, the assumption of spatial independence of samples is not realistic due to the presence of spatial autocorrelation [25].

Geostatistical techniques are useful in providing estimates of sampled attributes at unsampled locations from sparse information [7]. These methods are based on knowledge of the spatial structure of the phenomenon, which is obtained through spatial autocorrelation or auto-covariance functions, such as semi-variograms (Figure 4).

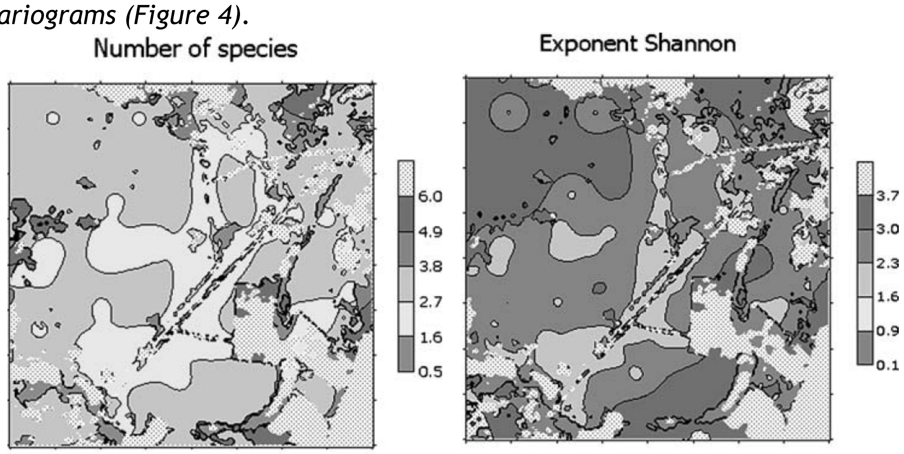

Figure 5. Standard deviation maps of estimates of number of species and exponent Shannon using geostatistics (Example from [25])

Estimating values between measured points follows the semivariogram estimation, based on the degree of spatial autocorrelation or covariance found in the data [25]. Geostatistical techniques have been useful for characterizing the spatial distribution and mapping of soil properties [9] and of climatic data [38]. They have been also applied to ecological studies such as in the prediction of forest volume [48], or the characterization of the spatial structure of vegetation communities [25] (Figure 5).

SPATIAL VARIABILITY OF SOIL PROPERTIES AND PATTERNS OF MINERALS AVAILABILITY

Within an ecosystem, soil properties have vast spatial variations which mainly arise from factors and processes of pedogenesis and land use [42]. Environmental heterogeneity is often essential for the coexistence of species [17]. Numerous researchers have proposed a positive correlation between environmental variability and species richness (for example [11]). In plant communities, this correlation may be explained, at least partially, by variation in below ground resources. Variation of soil resources at the individual scale is likely to affect the local distribution and abundance of plant species and the performance of individual organisms and, therefore, to have important consequences for both communities structure and ecosystem level processes [17, 43].

Soil properties can vary dramatically within plant communities [40]. Soil pH, organic matter content, and assorted mineral element concentrations have been shown to vary in some communities by an order of magnitude at spatial scales of 5 m or less (e.g. [44]), and in a number of cases this variation has appeared to be associated with changes in plant species distributions (e.g. [23]). Such *results suggest that nutrient cycling properties in natural and recently disturbed systems are spatially complex, and moreover that this complexity may significantly affect plant community structure. Hypotheses that plant communities are structured largely in response to the availability of limiting nutrients [40] take these suggestions one step further.*

Such hypotheses argue that spatial patterns of nutrient availability constitute a critical component of the structure of plant communities, though this variability has yet to be comprehensively quantified [40]. To evaluate potential relationships between patterns of nutrient cycling and community structure in natural plant communities first requires the demonstration that nutrient availability can vary significantly across the community (Figure 6).

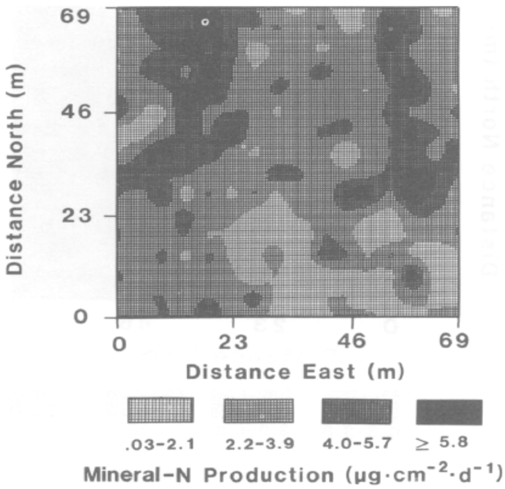

Figure 6. Isopleths for N mineralization potentials across the study site. Estimation standard deviations for interpolated point (Example from [40])

Soil testing has been the method most used to determine the spatial distribution of plant nutrient element availability within fields [13]. Soil testing is a more commonly used tool for determining plant nutrient element needs than plant analysis based on the numbers of samples analyzed annually by the nation's laboratories [26]. The timing of plant sampling is critical in establishing critical nutrient element levels for the crop [13], while the timing of soil sampling is not as critical, giving samplers a longer period of time to work and gather samples [37, 39].

Plant sample preparation in the laboratory may require strong acids to dissolve plant tissue and free elements for analysis, while most soil testing procedures require less caustic extractants, making soil testing somewhat safer for technicians and less expensive to conduct. Critical levels of nutrient elements within plants in relation to plant nutrient element availability are similar regardless of where the plants are grown, making plant analysis more universal than soil testing [12]. A soil analysis may be misleading because of interactions not explained by the test procedure, soil moisture levels, nutrient interactions, and soil physical characteristics [1] which may affect the response of crops to fertilizer applications beyond responses predicted by the soil test correlation model. Plant analysis results reflect the actual uptake of a nutrient element by the crop, and therefore not as clouded by soil uncertainties [13, 33].

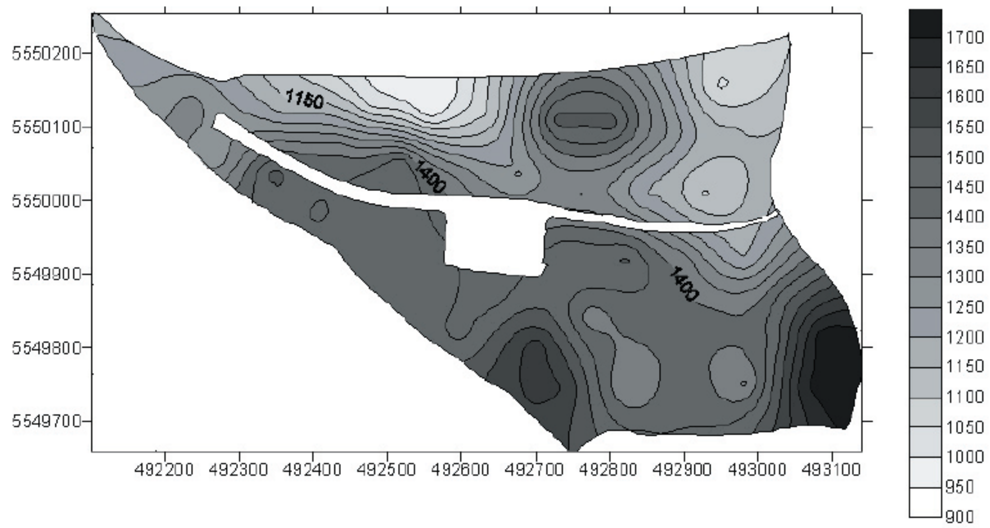

Figure 7. Total soil N content (Example from [45])

Much attention has been paid to studying the nutrient properties in different areas and plots, dealing with total nutrient content, their forms and variability in the soil profile, with respect to their availability to plants [45]. In recent years the attention has been focused on spatial variability of nutrients in soils, comparing different ground covers and locations [16, 49]. Differences in this characteristic were compared between individual plots, as well as within a plot; they were related to the possibility of exact identification of the plot and its parts and further usage of these data for specific measures, locally applied [4]. Apart from the spatial variability of the nutrient content of soil it is important to study its changes with time (Figure 7); these changes are clearly more distinct at labile forms, whose conclusiveness is time-limited. Knowledge of these facts might be useful as a basis for fertilization management practices [45].

CONCLUSIONS

The aim of this study is to review the spatial variation of plant diversity with respect to soil and environmental impacts. Some of conclusions can be summarized as follows:

- *Geostatistical techniques have been useful for characterizing the spatial structure of vegetation communities.*
- *Geostatistics does obviously not offer a statistical model which is advantageous in every situation. Careful analysis of the measurement data using common sense can some times result in the same conclusions as those resulting from lengthily and computationally heavy calculations. In general, as spacing between samples is large compared to the dimensions of the investigated field, the potential advantageous of a geostatistical analysis becomes less.*
- *Logistic regression is a suitable method in prediction of different plant species occurrence. Based on the prediction models, it is possible to estimate the probability of presence/absence of plant species in response to environmental factors.*
- *The identification of vegetation classes on the field and their mapping using satellite image classification were found to discriminate and separate significantly different specie compositions, in such a way that they can provide a useful mechanism for interpolating, and up-scaling values of diversity indices over the entire landscape at unvisited locations within a given class.*
- *Variation of soil resources at the individual scale is likely to affect the local distribution and abundance of plant species.*

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