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Spatial Variability of Soil Fertility, Wheat Yield and Weed Density in a One-hectare Field in Shahre Kord

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ABSTRACT

Spatial patterns of soil fertility parameters, and other extrinsic factors need to be identified to develop farming practices that match agricultural inputs with local crop needs. Little is known about the spatial structure of yield and weed density across fields. In this study, geostatistics was used to describe and map spatial patterns of soil total nitrogen, available phosphorus, available potassium, grain yield and density of *Sisymbrium irio L.* (tumble mustard), as a common annual weed of wheat fields at Shahre Kord university. The spatial continuity of each variable was examined by variogram function. The variograms showed that the distribution of all variables is not random but spatially-dependent as their estimated variogram values increase with increasing distance. The average range values were 26.5, 23.4, 31.4, 27.7, and 27.2 m for total nitrogen, available phosphorus, available potassium, grain yield and weed density, respectively. Thus, the range beyond which the property is not longer spatially dependent was almost the same for total nitrogen, grain yield and weed density. This implied close spatial interactions among these variables over the field. Applying the variogram models with the kriging algorithm, the values for each variable were estimated on a 5×5 grid. The disrribution of all variables is spatially dependent and continuous over a short distance. Furthermore, the maps illustratc a joint spatial dependence between grain yield and weed density. Spatial patterns of soil properties identified by these geostatistical techniques are of great importance in the fertility management of spatially variable soils. By studying the spatial structure of yield and mapping, it could be used in determining different factors controlling yield over the field. Moreover, a better knowledge of annual or perennial weed density distribution over fields might be helpful in better designing long-term field experiments in weed control programs.

Keywords : Geostatistics, Grain yield, Kriging, Variogram, Weed density.

INTRODUCTION

Soil properties and soil nutrients often vary across a field and influence soil and crop management efficiency as well as the design and effectiveness of field research trials. Variability in soil fertility causes uneven crop growth that confounds treatment effects in field experiments and decrease the effectiveness of uniformly applied fertilizer on a field scale. Soil scientists and agronomists have recognized the variability of soil properties in a field for a long time. Up until now, extension services dealt with field heterogeneity by advising farmers to take composite soil samples consisting of a number of soil cores which were taken from visually uniform areas. The analysis of these soil samples yields a mean nutrient level for the field. In sampling fields in this way, spatial variability was removed and a mean fertilizer advice could be formulated. However, for spatially variable crop production the interest is not only in the variability itselt but in how the quantities of different soil variables are distributed over the whole field. The question is whether some of spatial patterns in the measured values of soil nutrients

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can be detected and described. Moreover, the study of spatial variability in crop yield and mapping it provides important information for developing strategies for site-specific crop management. The recommendation rates for many inputs are influenced by yield goals which, in turn, may be estimated from previous yield maps. Additionally, yield maps are a necessary tool in the agronomic and economic assessment of site-specific crop management.

In agriculture, there are routine and intensive attempts to control most serious weeds. If weeds are left uncontrolled, many of them are capable of reducing yield by over 80 percent [2]. The behavior of a weed population will depend, in part, on many environmental factors including soil chemical properties. Therefore, to control a weed, its population levels (i.e. weed density) need to be managed. Moreover, in order to make weed management programs as effective as possible, a farmer needs to understand the spatial dynamics of weed population at the farm level.

An understanding of the dynamics of weed populations in the field depend on a knowledge of the effects of the various extrinsic factors and their spatial interactions. Weed species vary in their demand for nutrients under similar soil conditions. Some species are argued to be nitrophilus. Of the many studies of interference between weeds and cereals, it has shown that nitrogenous fertilizers increase yield loss owing to a positive response of weed populations to fertilizers [2]. The spatial variability of soil properties has been studied in the past by many soil scientists [1,10]. To a lesser extent, studies have also been conducted on spatial variability in crop yields [5,8] and weed distribution [4].

Conventional statistical methods are generally inadequate to describe data that are spatially correlated. Regionalized variable theory, popularly known as geostatistics, is a methodology for the analysis of spatially correlated data [9]. Regionalized variables are measured variables, such as soil nutrient concentrations or weed density, which are assumed to have spatial dependence. Originally, geostatistics was developed for geology and mining, where ore and mineral quantity estimates were generated for specific locations within a defined area of variation [6]. This method has also been used in entomology [7], agronomy [1.5], and ecology [14].

Keeping the importance of spatial variability, the distribution of soil fertility, wheat yield and weed density in a one-heetare wheat field of Shahre Kord University was studied. The specific goals of the research were twofold: first to study and map the spatial variability of different variables including soil total nitrogen, available phosphorus and potassium, wheat yield and density of *Sisymbriurn irio L.* as a major weed in the wheat field; second, to elucidate the relationships among these variables.

MATERIALS AND METHODS

Field Study

The selected experimental field was a 1-ha subarea of a 7-ha field, situated at Shahre Kord University. A total of 72 sampling points were selected on a 100×100m area using the lay-out shown in figure 1. based on the sampling layout, 36 samples were located on a 20×20 m grid, 16 samples on a 10×10 m grid and 20 samples on a 5×5 m grid. This sampling design fulfilled two conditions, namely (i) it covered the entire field and (ii) it allows one to characterize the close-distance variability. Fifty percent of all sampling points were selected randomly for soil sampling. These points are shown on Figure 1 by a crossed circle. The sampling support was one auger sample down to 30 cm per location. The samples were air dried and analyzed for total nitrogen content by the Kjeldahl method, available phosphorus by the Olsen method and available potassium by the ammonium acetate method [12]. In autumn 1999, the entire field was sown uniformly with winter wheat (Omid culti-

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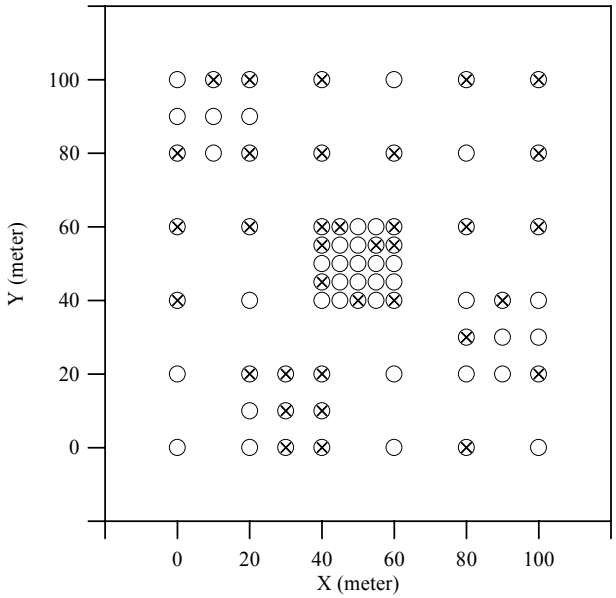

Figure 1. Layout of wheat field with sampling scheme. Selected points for soil analysis were shown by a crossed circle.

var). In spring 2000, the number of the weed *Sisymbrium irio L.* was counted in a 1-m^2 quadrate centered on each of the 72 grid nodes. Grain yield was also measured by harvesting the same 1-m^2 quadrates.

Geostatistical Analysis

Geostatistics consists of variography and kriging. Variography uses variograms to characterize and model the spatial variance of data, whereas kriging uses the modeled variance to estimate values at unsampled locations. In this study isotropic variograms of data were calculated using VARIOWIN software [13]. Variogram function is defined mathematically by:

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

where $\hat{\gamma}(h)$ is the variogram (semivariance) for N data pairs separated by a distance of h, known as a lag, and Z is the value at positions x_i and x_{i+h} [6,9]. An ideal variogram with its parameters is shown in Figure 2. By definition, the variogram value at zero lag should be zero but, in practice, it usually intercepts the ordinate at a positive value known as the nugget variance, C_0. The nugget represents measurement error and unexplained or random spatial variability at distances smaller than the smallest sampling intervals. The variogram value at which the plotted points level off is known as the sill, which is the sum of nugget variance and structural variance, C. The lag distance at which the variogram levels off is known as the range, or the zone of influence. Beyond the range, there is no spatial correlation and, hence, no spatial dependence exists.

Local estimation by kriging requires fitting a continuous function to the computed experimental variogram values. The spherical model for the variogram is the most commonly used to describe data variability and is defined as follows:

$$\hat{\gamma}(h)=C_0+\left[\left(\frac{3}{2}\right)\left(\frac{h}{a}\right)-\left(\frac{1}{2}\right)\left(\frac{h}{a^3}\right)\right] \quad 0<h<a \qquad (2)$$

where C_0, C, and a represent nugget variance, structural variance, and range, respectively. With an appropriate variogram model

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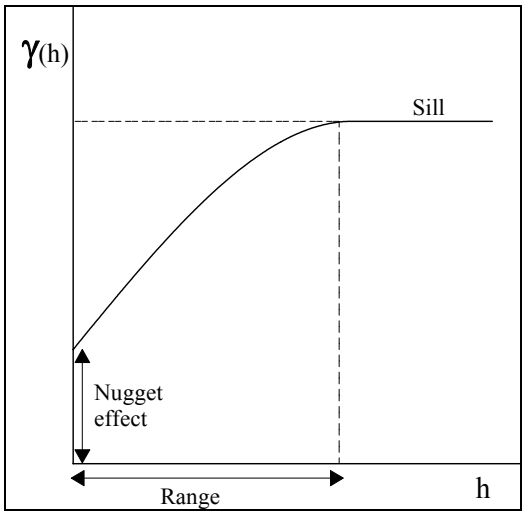

Figure 2. Schematic representaion of a variogram with its parameters.

defined, kriging can be used to interpolate between sample points and to estimate the value for unsampled locations.

Kriging gives weighted moving averages using an estimator:

$$\hat{Z}(x_0) = \sum_{i=1}^{n} \lambda_i Z(x_i) \qquad (3)$$

where n is the number of values $Z(x_i)$ for the sampled locations involved in the estimation of the unsampled location x_0, and λ_i are the weights associated with each sampled location value. Kriging is considered an optimal estimation method as it estimates values for unsampled locations without bias and with minimum variance. There is an error associated with kriging. The magnitude of this error will be a measure of the validity of estimation. For the kriging, a GeoEAS software was used [3].

RESULTS AND DISCUSSION

Variability in Soil Fertility

Descriptive statistics of soil fertility (Table 1) showed coefficients of variation ranging from 14% for total nitrogen to 17% for available phosphorus. These results indicate almost low variability. Normality of data sets was tested using the Kolmogorov-Smirnov test [11]. For all soil fertiltity variables, the mean values are close to the median values and the Kolmogrov-Smirnov test for normality was not failed.

Although univariate measures provided useful summaries, they did not describe the spatial continuity of the data, i.e. the relationship between the value for a property in one location and the values for the same property at another location. The spatial continuity of each soil fertility variable was examined by the variograms computed as an average overall direction using equation 1, assuming isotropic spatial continuity with direction. The results are shown in Figure 3. The parameters for the best fitting models to experimental variograms are given in Table 2. The spherical models were adequate for describing variability in soil fertility variables.

The computed and plotted variograms showed that the distribution of each of the three variables is not random but is spatially-

Table 1. Summary statistics of data.

	Total N (%)	Avail. P (mg/kg)	Avail. K (meq/100gr)	Wheat yield (kg/ha)	Weed (count/m^2)
Number of samples	35	35	35	72	72
Mean	0.12	2.12	0.97	1437.2	9.7
Median	0.12	2.06	0.97	1350	8.0
Variance	0.0003	0.13	0.05	532292	83.9
Minimum	0.09	1.67	0.60	400	0
Maximum	0.16	3.06	1.53	3650	47
Coefficient of Variation (%)	14	17	22	51	94

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Table 2. Parameters of the models fitted to experimental variograms; data on weed density were Ln-transformed).

Property	Model	Nugget effect	Sill	Range (meters)
Total N	Spherical	0.00	0.0003	26.5
Avail. P	Spherical	0.034	0.1411	23.4
Avail. K	Spherical	0.0095	0.047	31.4
Wheat yield	Spherical	0.00	600000	27.7
Weed density	Spherical	0.095	0.5235	27.2

dependent as their estimated variogram values increase with increasing distance. Overall, the variograms were generically similar implying a small-scale spatial pattern of variability for all variables, Despite the overall similarity, the variograms varied with variables suggesting that each variable has a somewhat different spatial pattern imposed by the property itself and other controlling factors.

Of particular importance are the values for the range. The average range values increased from 23.4 m for available phosphorus to 31.4m for available potassium. The range for variogram functions of total nitrogen was 26.5. Thus, the range beyond which the property is not spatially dependent was longer for available potassium than other variables. A larger range indicates that observed values for potassium concentration at each sampling point are influenced by other values of this variable over greater distances. This field has not yet received the potassium fertilizer due to soil enrichment. This explains, in part, the longest range of spatial correlation for potassium.

The nugget parameter of the variogram is a measure of unexplained variability for the given sampling scheme. To compare the nugget effect of different variables, the relative nugget variances-nugget variances out of sills as a percentage-were calculated. There were 0,24.1,20.2 for total nitrogen, available phosphorus and available potassium, respectively. These values elucidate that all soil fertility parameters had less than 25% unexplained variability, reflecting the lesser small-scale randomness of variation.

Variability in Grain Yield

Descriptive statistics of wheat yield (Table 1) indicated relatively high variability. The coefficient of variation is about 50%. The result of the normality test showed that the yield data are almost normally distributed. An omnidirectional variogram for grain yield was developed using a spherical model (Figure 3). The range of influence for grain yield, at 27.7 m is closer in magnitude to the range of soil total nitrogen than other two soil fertility parameters.

Variability in Weed Density

Summary statistics of weed density (Table 1) showed a very high coefficient of variation. The weed density data are positively skewed (mean > median) and failed the Kolmogorov-Smirnov test for normality. Therefore, data were logarithmically transformed resulting in almost normal distribution. Consequently, the transformed data were used in subsequent analyses.

A variogram of weed density data was calculated to determine if the data exhibited spatial variation over the field (Figure 3). The calculated variograin showed that the weed density exhibits spatial dependence. Of particular interest is the value for the range of weed density. The variogram range for weed density is about 27 m which is correlated with soil total nitrogen and grain yield. It illustrated the interaction among different variables. It implies that the spatial structure of weed density might be primarily

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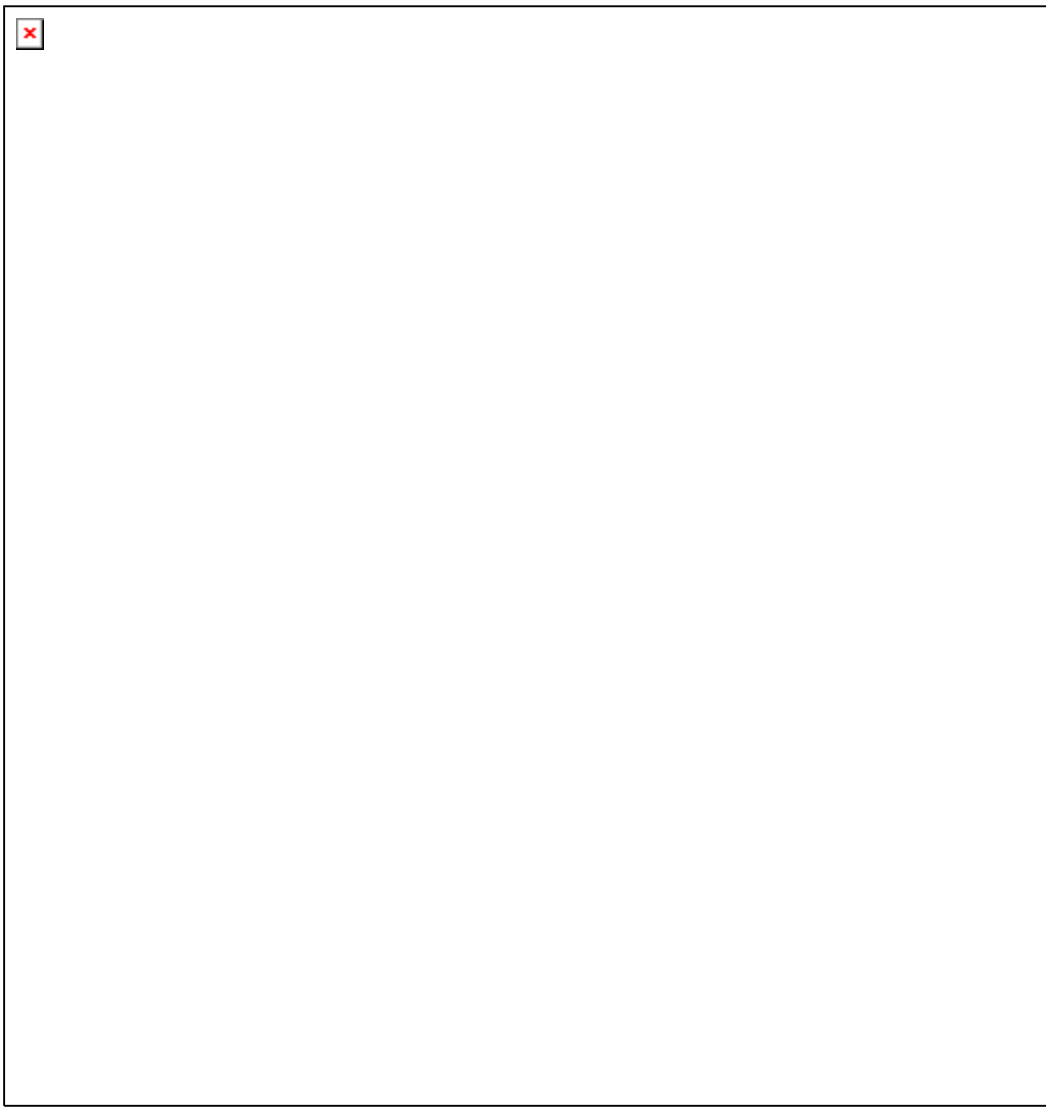

Figure 3. Isotropic variograms with the fitted models for: (a) total nitrogen; (b) available phosphorus; (c) available potassium; (d) wheat yield, and (e) weed density. Number of pairs for each variogram point is also given.

controlled by soil fertility parameters such as the amount of nitrogen. Moreover, one can expect close spatial interactions between weed and crop over the field.

The calculated relative nugget for weed density indicated that its nugget represents about 18 percent of its total variance that can be modeled as spatial dependence from the available sampling scheme. It might be caused by discontinuities in weed distribution in the field. One may suggest that the sampling distance should be decreased and the number of samples increased in the future to characterize better the spatial dependence for this variable.

Geostatistical Mapping of Different Variables

Using the variogram models with the kriging algorithm, the values for each variable were estimated on a 5×5 m grid. Each kriged point was estimated using a maxi-

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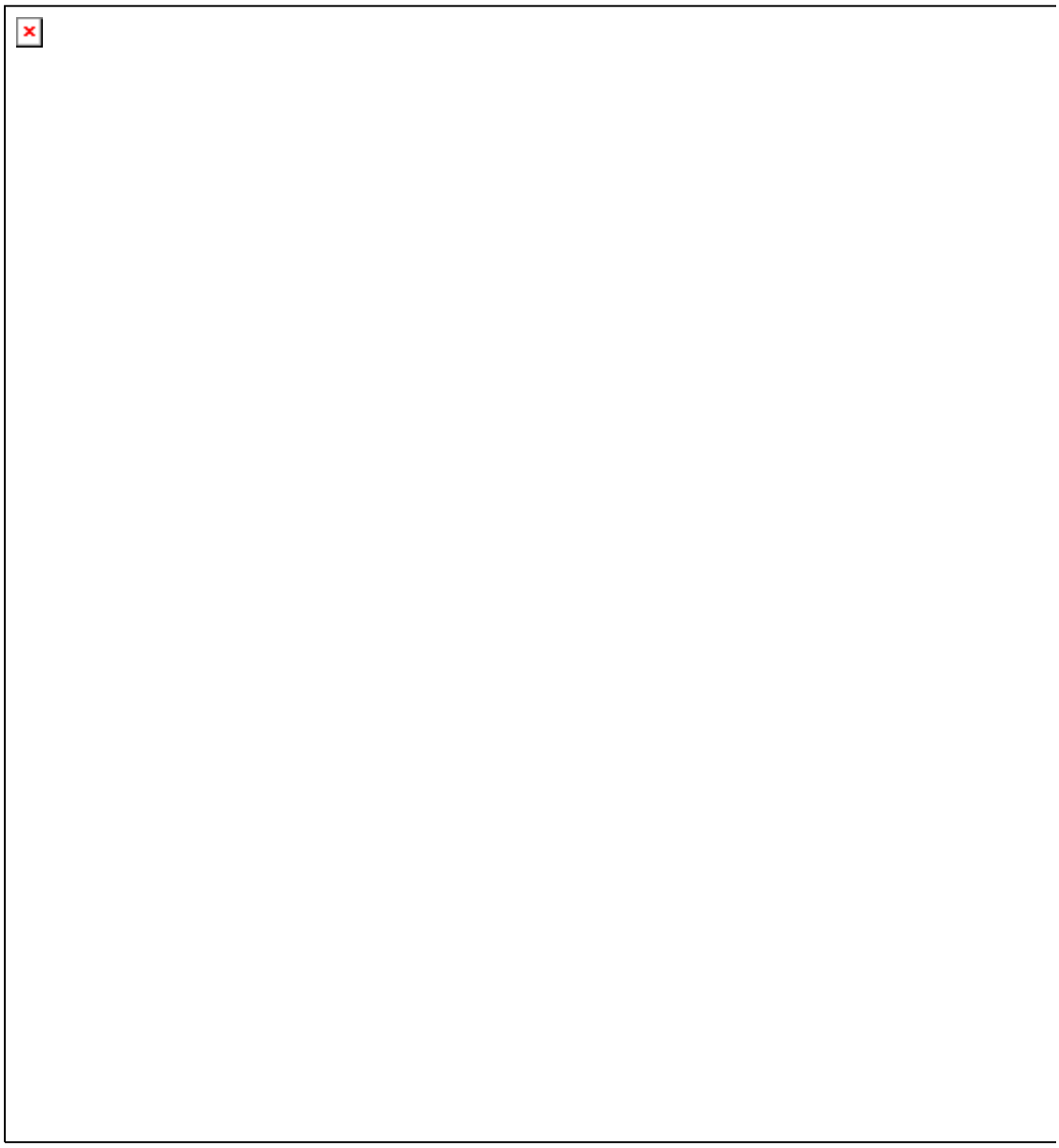

Figure 4. Kriged maps of: (a) total nitrogen; (b) available phosphorous; (c) available potassium; (d) wheat yield; and (e) weed density.

mum of 12 measured points around it. Maps of different variables are given in Figure 4. Such maps provide detailed positional information that is lacking in simple descriptive statistics.

The maps illustrate the interpretations made earlier from variograms. The distribution of all variables is spatially dependent and continuous over a short distance. It seems from these maps that the visual homogeneity of a field may not give a true picture of the variability of different variables over the field. Thus a management decision based on the visual observations or assumption of random distribution may be inadequate.

Furthermore, the maps illustrate an aspect which was not examined in this study: a joint spatial dependence among some variables. For example, the lower right region of

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the field shows a higher weed density. Relative to other regions of the field, the same area is also shown to have a higher total nitrogen content but lower grain yield. While this study was not designed to determine the factors controlling yield patterns, it does illustrate that the spatial pattern of yield over the field could be controlled not only by the soil fertility parameters but also other factors like weed density. A negative correlation coefficient of -0.31 (P=0.001) was found between maps of weed distribution and grain yield. Although positive correlation was obtained between weed density and total nitrogen content of the soil, it was not statistically significant. The negative correlation between maps of grain yield and total nitrogen suggests that yield patterns over the field are in part, controlled by interactions with the weed population. However, a positive correlation coefficient of 0.43 (P=0.001) was obtained between maps of grain yield and available phosphorus.

The results of this study demonstrated that, within the small field, spatial patterns may vary among several soil fertility parameters, grain yield and weed density. The different ranges of spatial correlation among soil fertility parameters could be related to intrinsic factors, such as the chemical properties of ions, and extrinsic ones, such as fertilizer application. However, the results indicated that soil fertility parameters can be used for site-specific soil management. Therefore, spatial patterns of soil properties identified by these geostatistical techniques are of great importance in the fertility management of spatially variable soils.

Moreover, studying the spatial structure of yield and mapping it could be used in determining different factors controlling yield over the field. However, since the yield generally varies both spatially and temporally [5], long-term monitoring of yield is necessary to reveal these spatial properties over a field. So, caution should be used in interpreting yield results from any one growing season, particularly when using yield information to modify chemical inputs.

Finally, a berter knowledge of annual or perennial weed density distribution over fields might be helpful in better designing long-term field experiments in weed control programs [4]. In this frame, geostatistics can be used to provide useful information. Moreover, geostatistical analysis could be used to relate weed distribution to change in the distribution of different soil properties across landscapes. Maps of weed distribution can be used to formulate spatially and temporally weed control treatments. It could result in better effectiveness of weed control strategy in the frame of a new paradigm of site-specific management.

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تغییرات مکانی حاصلخیزی خاک، عملکرد گندم و تراکم علف هرز در مزرعه یک هکتاری واقع در شهرکرد

ج. محمدی

چکیده

بمنظور توسعه عملیات کشت و زرع به گونه ای که نهاده‌های کشاورزی متناسب با نیازهای موضعی محصول اعمال گردد، توصیف الگوی مکانی تغییرات عوامل حاصلخیزی خاک و دیگر عوامل خارجی موثر در تولید مـــورد نیاز می باشد. اطلاعات اندکی در مورد ساختار مکانی تغییرات عملکرد محصول و تراکم علف هرز در سطح مزارع وجود دارد. دراین مطالعه، از مجموعه روشهای آماری مبتنی بر نظریه ژئواستاتیستیک بمنظور توصیف و پهنه‌بندی الگوی تغییرات مکانی ازت کل، فسفر و پتاسیم قابل دسترس، عملکرد گندم و تراکم علف هرز خـــاکشیر تلخ، *Sisymbrium irrio* ، بعنوان علف هرز چندساله رایج در مزرعه گندم دانشگاه شهرکرد، استفاده شد. پیوستگی تغییرات مکانی متغیرهای مختلف با استفاده از تابع واریوگرام بررسی شد. واریوگرام‌ها نشان دادند که تغییرات کلیه متغیرها تصادفی نبوده بلکه بدلیل افزایش مقدار تابع محاسبه شده بموازات افزایش فاصله بین نمونه‌ها، دارای همبستگی مکانی می باشند. دامنه تغییرات برای ازت کل، فسفر و پتاسیم قابل دسترس، عملکرد گندم و تـراکم علف هرز بترتیب برابر با ۲۶/۵، ۲۳/٤، ۳۱/٤، ۲۷/۷ و ۲۷/۲ بود. بدین ترتیب فاصله ای که در ماورای آن هیچگونه وابستگی مکانی بین مشاهدات وجود ندارد، برای ازت کل خاک، عملکرد گندم و تراکم علف هرز تقریباً نزدیک بهم بود. این امر می تواند بیانگر وجود برهمکنش‌های مکانی بین متغیرهای مزبور در سطح مزرعه باشد. با استفاده از مدلهای واریوگرام ها و روش کریجینگ اقدام به تخمین متغیرهای مختلف برای بلوکهای ۵ در ۵ متر در سطح مزرعه شد. نقشه ها حاکی از توزیع و پراکنش مکانی پیوسته متغیرهای مورد مطالعه در

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سطح مزرعه است. علاوه برآن نقشه‌های حاصل وجود وابستگی مکانی دو جانبه بین عملکرد محصول و تراکم علف هرز نشان می‌دهد. الگوهای مکانی عوامل حاصلخیزی خاک که توسط روشهای آماری ژئواستاتیستیک ارائه گردید از نقطه نظر مدیریت حاصلخیزی خاکها حائز اهمیت است. مطالعه ساختار تغییرات مکانی عملکرد محصول و پهنه‌بندی آن می تواند در تعیین عوامل کنترل کننده عملکرد محصول در سطح مزرعه مورد استفاده قرار گیرد. همچنین، اطلاع داشتن از پراکنش تراکم علفهای هرز یکساله یا چند ساله در سطح مزرعه می‌تواند در طراحی هرچه بهتر برنامه های کنترل علف هرز مفید واقع شود.

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