Review article

Geostatistics applied to the study of the spatial distribution of insects and its use in integrated pest management

Geoestadística aplicada al estudio de la distribución espacial de los insectos y su utilización en el manejo integrado de plagas

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Abstract

Integrated Pest Management (IPM) programs based on the temporal variability of insect pests have been successfully implemented worldwide. These programs have been carried out by applying control strategies based on the existing knowledge about pest biology and population dynamics. However, systems based on temporal variability are insufficient to optimize plant protection and especially to reduce the environmental impact of area-wide control measures. This situation drove to the new concept of "site-specific IPM". Currently, there are tools to implement large-scale studies (at a zonal and a regional level), allowing to describe and analyze the spatial distribution of insect populations via the management and analysis of large data sets (GIS, GPS, and geostatistics). Geostatistics measures the spatial fluctuations of the variables under study based on rigorous sampling, afterwards adjusting a semivariogram, interpolating and building maps of iso-lines with different levels of population densities. This has allowed to simplify forecasting and monitoring systems, determining both the location and the optimum number of samples to be taken on sites showed by iso-lines. In order to decide where control measurements should be applied, maps with geographical coordinates showing the spatial location of spots with high population density are used (regardless of the control strategy applied). Furthermore, these methods can be used to identify areas where, considering their special characteristics, selective large-scale control tactics, as mating disruption or the release of natural enemies could be applied.

Keywords: Spatial analysis; Variogram; Interpolation; Maps.

Resumen

A nivel mundial se han implementado programas de Manejo Integrado de Plagas (MIP) exitosos, basados en la variabilidad temporal de insectos plaga. Esto se ha llevado a cabo aplicando estrategias de control basadas en el conocimiento de la biología de la plaga y de su dinámica poblacional. Los sistemas basados en la variabilidad temporal son limitados para optimizar la protección fitosanitaria y sobre todo para disminuir el impacto ambiental de las medidas de control en áreas extensas, lo cual ha dado sustento a un concepto nuevo "el MIP en el Sitio Específico". Actualmente existen herramientas disponibles para implementar estudios a gran escala (zonas o regiones), ya que permiten el manejo y análisis de grandes series de datos para describir y analizar la distribución espacial de las poblaciones de insectos (SIG, GPS y Geoestadística). La Geoestadística mide la variabilidad espacial de las variables en estudio a partir de muestreos rigurosos, para luego ajustar un semivariograma, interpolar y construir mapas de isolíneas con sus diferentes densidades poblacionales. Lo anterior ha permitido la simplificación de los sistemas de pronóstico, determinando tanto la localización como el número óptimo de muestras a tomar en los sitios que indican las isolíneas. Los mapas sirven para tomar decisiones de manejo en los cultivos, señalando la ubicación (según coordenadas geográficas) de focos de altas densidades poblacionales, de amplia utilidad independientemente de la medida de control a seleccionar. Pero además permiten identificar zonas, en las que por sus características particulares se pueden aplicar a gran escala tácticas de control, tan selectivas como la confusión sexual o la liberación de enemigos naturales.

Palabras clave: Análisis espacial; Variograma; Interpolación; Mapas.

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Introduction

The main principle for the sustainable agriculture development involves maintaining crop productivity within minimal negative effects on natural resources (soil, air, water, flora and beneficial insects) and on worker's health (Emmen, 2004). Integrated pest management (IPM) is a process to solve pest problems minimizing risks to people and the environment. However, when IPM is applied only by individual's farmers, it does not have a favorable impact at a regional level if neighbors use their resources irrationally. For example, this is evidenced when a pest from abandoned or uncontrolled farms invade a farm under IPM or when natural enemies are eliminated with repeated applications of broad-spectrum insecticides (Vreysen *et al.*, 2007; Faust, 2008). Moreover, there is still a significant number of farmers that have not yet adopted the IPM as a control strategy and control their pests by relying exclusively on systematic application of insecticides (Kogan and Hilton, 2009). Such conventional strategy that focuses almost exclusively on crops' protection against direct attack of pests tends to be reactive and involves traditional tools and tactics (Klassen, 2005). As a result, integrated production and organic production farms are generally islands in the middle of locations where the most diverse crop management approaches coexist.

The above mentioned situation has not helped to optimize the efficiency of the more selective control measures, modify the environmental impact of these measures, nor promote natural pest control (Vreysen *et al.*, 2007). Therefore, the solution to phytosanitary problems is to "work with the neighbors" to promote the use of an area-wide integrated pest management approach (AW-IPM) and to apply the concept of precision agriculture. Area-wide integrated pest management focuses on the preventive control of pest populations throughout the agroecosystem, trying to include all pest habitats to prevent migration that could restore significant infestations. Planning is required together with an organization dedicated exclusively to its application, tending to use advanced technologies such as precision agriculture (Klassen, 2005). As defined, precision agriculture is the application of technologies and principles to manage the spatial and temporal variabilities associated with all aspects of agricultural production in order to improve crop yields and environmental quality; that is to say, it considers the variabilities existing in the field in order to adjust agronomic practices (Pierce and Nowak, 2002). This is accomplished by generating regional alert systems that not only provide temporal information about the pest but also spatial information about its distribution (Nuñez and Scatoni, 2013).

Populations of insects and mites are distributed heterogeneously in space and generally they present spots with high density alternating with low population areas. The study of the spatial variability of arthropods' populations and their fluctuations over time provides relevant information to optimize plant protection systems, improve their efficiency and reduce the impact of applying unnecessary control measures in the problem areas (Avilla and Ribes-Dasi, 2004). This has lead to a current emphasis in which pest control strategies in wide areas should involve the use of spatially stratified samples to assess the need for treatment in each area (Liebhold *et al.*, 1993). At present there are tools to perform large-scale studies (area-wide or regional studies) which allow the management and analysis of large data sets to describe the spatial distribution of insect populations (Ribes-Dasi *et al.*, 1998, 2001).

Geographic information systems (GIS), global positioning systems (GPS) and geostatistics are tools that have allowed developing strategies tending to a more accurate and efficient management of productive systems and can be of great significance for pest control both at a farm and at a regional level (Tort, 2004). Through relatively simple procedures it is currently possible to obtain maps with pest location and abundance, resulting in an extremely valuable input to decide whether to apply a specific management strategy, depending on whether the pest is present in a specific site or if it is exceeding the control threshold. Furthermore, GIS allows linking pest density with particular characteristics of each area, facilitating the identification of factors associated with abundance, as host density, storage sites, packaging houses, sites where products without commercial value are discarded, abandoned crops, uncontrolled pests and concentration of lights, among others (Calvo *et al.*, 2011). The knowledge of pest distribution in an area and the development of sampling methods and mapping of the species would be extremely useful to streamline and improve the efficiency of control measures (Duarte *et al.*, 2015). In addition, the rational and efficient use of chemical control methods requires knowledge of biological parameters such as pest population dynamics in the farm or in the production area, host phenology and climatic parameters like daily temperatures, rainfall intensity, etc. Considering that spray insecticide is a complex decision-making process, when this information is absent or scarce, decision-making becomes difficult and conservative decisions end in pesticide abuse. For this reason, forecast systems have been developed to foreseen the occurrence, distribution and abundance of pests. The aim of the forecasting system is to rationalize pesticide applications in such a way that they are done at the right time according to the particular epidemiology of each disease or pest (Nuñez and Scatoni, 2013). Hence, forecast systems must provide information about the occurrence of the different pest developmental stages at different periods of time of the crop phenology, for which climate information and that provided by pest monitoring in the field must be analyzed. The fluctuation of several insect populations can be predicted by phenological models using climate parameters, usually ground or air temperature (Scatoni *et al*., 2003). Forecasting systems based only on the temporal variability of pests allow applying control measures when pests are more susceptible. However, these methods have their limitations because they are useful for pests with discrete generations, but are less efficient when generations overlap. Furthermore, these systems cover large areas and are based on count averages without taking into account differences that might exist between different areas, performance of late treatments or treatments in areas where they are not needed (Duarte, 2012). Including the concept of spatial distribution allows adjustments based on the variability of the pest in space, which results in the reduction of treatments and minimizes the environmental impact of control measures on large areas (Koul *et al*., 2008).

The aim of this review is to support the idea that geostatistic is an essential tool to analyze patterns of spatial distribution of ecological and environmental variables sampled in an area of interest. In particular, to discuss its potential used in integrated pest management. Therefore, an update of the main experiences with spatial distribution of insects pests and procedures for population density maps in a given area, are presented.

Spatial analysis

Statistical procedures are usually based on parametric techniques commonly used to summarize information and to perform meaningful inferences about a phenomenon of interest (Rossi *et al*., 1992; Legendre *et al*., 2002). The traditional statistical tools classify insect population distribution in an aggregate, uniform or random manner, based on mean values, variances and frequency distributions (ratio variance/media, Taylor's potential law, *k* parameter, etc.) (Taylor, 1961, 1984; Farias *et al*., 2004). These techniques do not allow correlating the sample data with its location in space, ignoring the distribution of samples (Ellsbeury *et al*., 1998). Ecology is a discipline, which refers to the interactions between organisms and the environment and assumes the existence of temporal and spatial dependence between the different ecosystem´s components (Rossi *et al*., 1992). In insects, the nonrandom distribution in space seems to be the rule rather than the exception (Stewart *et al*., 2000). Although the physical and biological variables generally show strong spatial heterogeneity, this does not mean that they do not have a continuous distribution pattern (Moral, 2004). Events distributed in space, generally have a chaotic or random behavior at a local level but have a structural behavior on a large-scale level (Zhang *et al*., 1992; Cuador, 2004).

Geostatistics and its application

Historically, geostatistical methods have been applied to the study of soil and water variables (Hohn, 1988; Samper and Carrera, 1996). The geo- prefix derives from geological disciplines that firstly provided the main theoretical developments and applications. These methods have been widely used in the search for petroleum or geological minerals and although data was insufficient, they have often provided good predictions about the location of mineral and oil resources. While most geostatistics applications have focused on geological issues, we anticipate that they will also have broader applications on environmental problems. The first studies that supported the idea of using these tools in developing more accurate and efficient strategies to manage production systems were originated in the United States and Europe (Liebhold *et al*., 1993; Schotzko and O'Keefe, 1989, 1990; Ribes-Dasi *et al*., 1998, 2001, 2005;

Avilla and Ribes-Dasi, 2004; Moral, 2004; Tort, 2004). Likewise, in studies of insects spatial distribution, pasture and forest plantations were prioritized, possibly because of their large scales. It is however expected that the development of these tools will incorporate the concept of area-wide pest management for all crops. Regional alert systems have already been successfully incorporated in some parts of the world using GIS and geostatistics as basic tools (Liebhold *et al.*, 1993). Environmental pollution produced by pesticides, toxic residues on agricultural products and the rapid development of resistance to these pesticides have supported a new concept in integrated pest management: "IPM in the Specific Site", accompanying the development of these new tools (Emmen, 2004). These techniques require strong sampling in order to measure the spatial variability of pest densities. Using this information it is possible to create spatial distribution maps. The maps obtained are used to make decisions about pest management in areas with high population density, independently of the control tactic selected (chemical, biological or ethological) (Ribes-Dasi *et al.*, 1998, 2001; Emmen, 2004; Cox and Vreysen, 2005).

It has been shown that the number of insects caught in traps is regionalized and mapping the distribution using iso-lines is likely to be performed if there is enough number of rigorous and systematic records (Tort, 2004). These maps allow to optimize forecasting and monitoring systems, determining the location and the minimum number of traps to be placed on sites that iso-lines suggest (Ribes-Dasi *et al.*, 2001). This information allows to identify areas in which, due to population density or to their particular characteristics, it is possible to apply large-scale selective control tactics, as mating disruption, natural enemies release or the insect sterile technique (Knight, 2008). Based on studies started by Ribes Dasi *et al.* (1988) on spatial distribution of *Cydia pomonella* using geostatistical models, in 2004 in the region of Lleida, Spain, 65,000 hectares of pome fruits were covered with 450 georeferenced pheromone traps. Records of captures from these traps were received and processed at the University of Lleida and returned to technical advisors of the Plant Protection Service as iso-capture maps (Ribes-Dasi *et al.*, 2005). This experience demonstrates the potential application of these tools in pest forecasting systems.

Geostatistics: the method

The development of geostatistics and geographic information systems allows the analysis of pest distribution in space, enabling the management of large data sets. These procedures are used to quantify and to model spatial correlations using semi-variograms, correlograms and covariance functions and interpolating sampling points by kriging (Liebhold *et al.*, 1993). Kriging, thus named in honor to Danie Krige who first formulated this approach in 1951, is a geostatistical procedure that allows to perform the "best interpolations", based on the information provided by the sample points, in those places where the magnitude of attribute investigated is not known (Moral, 2004). Between 1960 and 1970 Matheron (1970) developed the theory of regionalized aleatory variables, which have a spatial correlation structure, promoting the development of what is now known as geostatistics (Maestre, 2006). Geostatistics is the application of the theory of regionalized variables to estimate spatially continuous phenomenons (Chica Olmo *et al.*, 2007; Diggle and Ribeiro, 2007). The regionalized variables are characterized by presenting a position in space. Geostatistics considers a set of spatial data as a realization of a random process, associating a random variable to each spatial point xi (Webster and Oliver, 2007). Observations from different locations (x and x+h) are not independent, and the correlation level will reflect the continuity of the phenomenon under study (Cuador, 2004). Sample points at near locations are more similar than sample points at farther apart locations (Rossi *et al.*, 1992).

There are certain necessary assumptions to validate the analysis. At each point x_i, there is a random variable $Z(x_i)$ with a mean μ, a variance σ^2, and a cumulative distribution function, so the observed value at this point is drawn from this probable distribution. The set of random variables at each spatial point $(Z(x_1), Z(x_2), \ldots, Z(x_n))$ have the same probable distribution. If this distribution is known, we can estimate values at unrecorded locations (Webster and Oliver, 2007). As there is only one realization for each $Z(x_i)$ stationary assumptions have to be made in order to consider the observed values at different locations as different realizations of the same random process. In these stationary assumptions the mean and the variance are constant for all x_i and the covariance depends on their separation and not on their absolute position (Goovaerts, 1997).

In this sense, Moral (2004) argues that there are three key stages to carry out a geostatistical work: exploratory data analysis, structural analysis and predictions.

Exploratory data analysis

Exploratory data analysis is a prerequisite for the application of any statistical technique. This procedure allows to evaluate the quality and consistency of information, to investigate the variables distribution and the compliance with statistical assumptions necessary in later stages of the analysis; it also summarizes information using various statistics and graphics, evaluates the need to change the variables and detects outliers values, among other things (Rossi *et al*., 1992; Liebhold *et al*., 1993). It may include central tendency measures: mean, median, percentile limits, maximum and minimum values, dispersion measures, standard deviation, variance, symmetry indicators as kurtosis, skewness, etc. It can also be useful to include frequency graphs and scatter plots (Cuador, 2004; Gallardo, 2006). These elements allow deciding on stationary conditions needed to go on with the process. The proximity of mean and median values is one of most commonly used statistical reference, if the data distribution is close to the normal curve and if there are no outliers affecting the development of structural analysis. Normality tests, such as Shapiro-Wilk and Anderson-Darling, can also be applied to define the need to transform the original data (Figure 1). If necessary, data can be normalised using logarithmic or square root transformations.

Structural analysis: empirical variogram and theoretical model adjustment

Structural analysis studies the spatial continuity of the variable, process in which an empirical model is constructed and subsequently it is adjusted to a theoretical model (Hevesi *et al*., 1992; Rossi *et al*., 1992; Moral, 2004; Gallardo, 2006). There is a wide range of geostatistical tools that facilitate the structural analysis of distributions, among which scatter-h plots or h-scattergrams, variograms, correlograms and covariance measures are included (Rossi *et al*., 1992; Cuador, 2004; Moral, 2004).

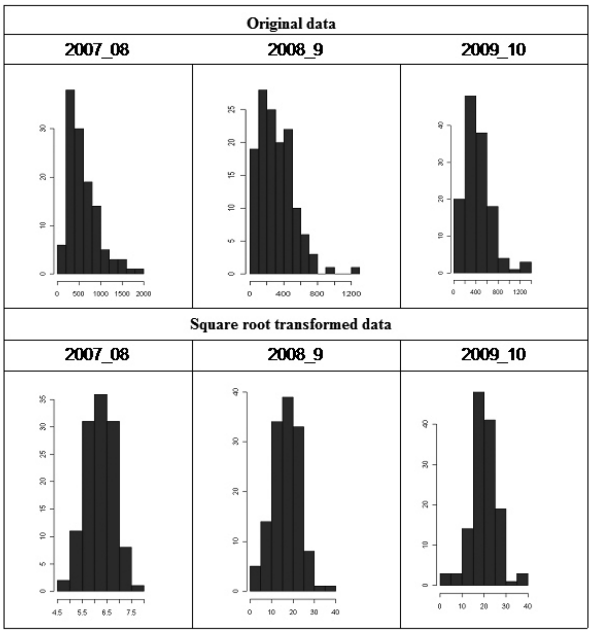

Figure 1. Frequency distribution of *Grapholita molesta* captures at pheromone traps during three seasons; up: original data, down: transformed data (from Duarte, 2012).

h-scattergrams. In geostatistics, the bold letter **h** is generally used to represent a separation in space vector, which has a direction and a magnitude of distance. Very frequently, however, the distance between intervals refers to a scalar magnitude, this being an average of all directions, in which case the letter "h" is used instead of **"h"** (Rossi *et al*., 1992). The h-scattergram shows the joint distribution of pairs of points, z (x) versus z (x + h), separated by a distance h. If the values are similar, the cloud of points on the graph will be close to the bisector of the first quadrant, which will indicate the existence of autocorrelation in the variable. If the distance h is small, points are expected to be closer to the bisector, increasing its dispersion as the h value increases. One of the advantages of the scatter plots is that its asymmetry with respect to the line of 45º can show trends or differences in mean and local variances. Although this tool gives a good idea of the degree of autocorrelation of the variable under study, its use is impractical. It requires making as many graphics as distances h are considered for the study area and even more graphics if different directions are analyzed. Hence, the variogram or semivariogram, the covariance and correlograms appear as more simple tools to summarize this information (Rossi *et al*., 1992; Moral, 2004).

Variogram o semi-variogram functions. Most of the recent research on insect population distribution used the variogram function to analyze the spatial structure of the variable of interest. Examples of research on the spatial distribution of insects are *Diabrotica virgifera* (Midgarden *et al*., 1993), *Cydia pomonella* (Ribes-Dasi *et al*., 1998; Tort, 2004; Trematerra *et al*., 2004), *Alabama argillacea* (Tannure and Mazza, 2004), *Xylella fastidiosa* (Farias *et al*., 2004), *Jacobiasca iybica* (Ramirez-Davila *et al*., 2005), *Leptinotarsa decemlineata* (Boiteau, 2005), *Phymastichus coffea* (Castillo *et al*., 2006), *Grapholita molesta* and *Anarsia lineatella* (Sciarretta and Trematerra, 2006), *Helicoverpa armigera* (Moral *et al*., 2006), *Ceratitis capitata* (Sciarretta and Trematerra, 2010), *Grapholita molesta* (*Duarte et al*., 2015), among others.

The variogram function is defined as "the arithmetic average of all the squares of the differences between experimental pairs values separated by a distance h" (Journel and Huijbregts, 1978). This function summarizes the scatter plots for all possible pairs of data and distances h. Then:

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

being $\hat{\gamma}(h)$ the estimator semi-variance for the interval h, and N(h) the number of pairs of points separated by distance h. (Rossi *et al*., 1992; Cuador, 2004).

Traditionally, two types of spatial dependence, structural and stochastic were defined. The difference between these two types is scale-dependent. The variogram is a statistical model for large-scale or structural spatial dependence analysis (Rossi *et al*., 1992).

For the structural analysis, an empirical variogram should be first developed. This involves applying the function γ (h) for all predefined distances h to obtain a set of semivariances, which is plotted as a function of the distance h. If the variogram is constructed as an average of all possible pairs of data regardless of orientation or direction relative to each other, it is called omnidirectional variogram. Variograms may also be calculated for specific directions in order to perform what is known as anisotropy analysis, in situations where it is believed that there may be different behaviors of the variable according to the direction (Rossi *et al*., 1992; Cuador, 2004; Moral, 2004; Comas *et al*., 2012). In any case, this variogram summarizes the spatial relations in the data set. From the empirical variogram, a theoretical model is fitted to represent the continuous regional variation which describes the overall trend. In anisotropic analysis, one variogram is obtained for each direction to be analyzed. The number of samples required to fit an isotropic variogram is at least 100 and it is higher in anisotropy conditions. Also, to calculate each semivariance value at least 30 pairs of data are needed (Isaaks and Srivastava, 1989).

Fitting a theoretical model. The following key point in the process is selecting the model and its parameters. The adjustment of the theoretical model can be done through a visual and interactive process, modifying the parameter values until the right model is found or by performing an automatic adjustment selected by the method of least squares (Cuador, 2004). However, the automatic adjustment may not necessarily produce better results in the estimation process. It is worthwhile to mention that the aim is to adjust a set of models with statistical significance, and among them selecting those that best explain the pattern of spatial variability of the variable under study; however, this is not always the best statistical method to use (Moral, 2004). The automatic adjustment models using least squares or R^2 of the equation do not necessarily produce models with greater biologic significance (Cuador, 2004).

The most used semivariogram models are the spheric, exponential, gaussian, potential, linear and pure nugget effect (Kiyono and Suzuki, 1996; Armstrong and Carignan, 1997; Pinheiro and Bates, 2000, Gamma design software, 2004) (Figure 2). These models can be described based on three parameters. Although by definition, at the origin the variogram is zero, in practice the functions obtained show discontinuity at the origin given by the spatial variability in distances, smaller than the minimum distance sampling. This is known as nugget effect (Co), and it is represented by intercept points with the ordinate axis (Y). Usually the variogram appears as a monotone increasing function which reaches a point where it stabilizes, the sill (Co + C), represented by the asymptote of the model, equivalent to the sample variance. The value of h that determines the sill is called range. The range (A) represents the average distance around a point, to which there is some degree of spatial correlation (Figure 3). The ratio Co / (Co + C) is an indicator of the variable autocorrelation. Values close to one (>0.75) indicate low correlation and values close to zero (<0.25) indicate high correlation (Cambardella *et al*., 1994).

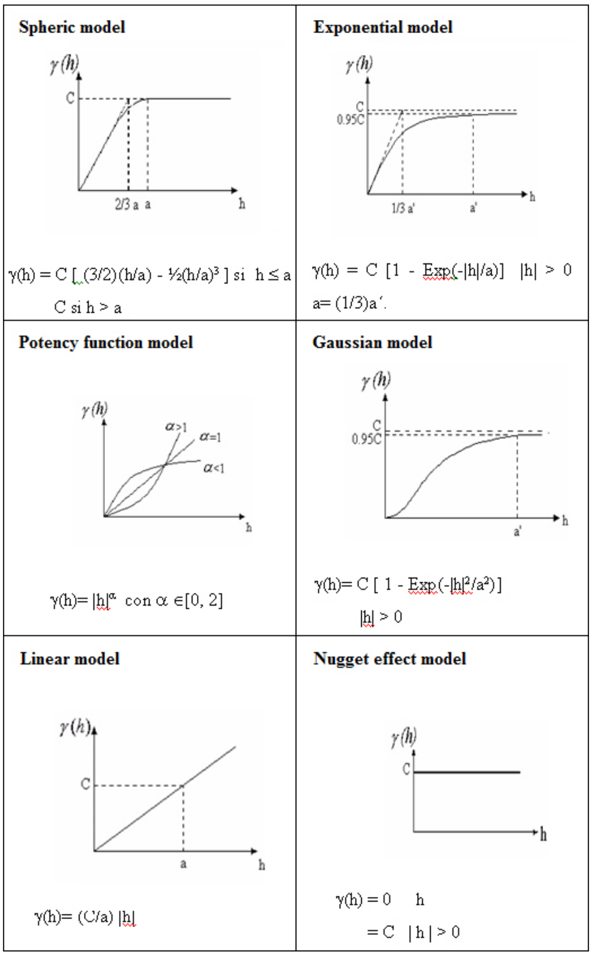

Figure 2. Most used theoretical models in adjusting semivariograms (Adapted from Cuador, 2004).

The model called pure nugget effect corresponds to a purely random phenomenon, with no correlation between samples, regardless of the distance that separates h. In this case, the variogram tends to horizontality with values next to the sample variance. It may also be possible that the variogram does not tend asymptotically to the variance, but tends to infinity when so does h, implying that there is spatial dependence beyond the maximum distance of samples (Rossi *et al.*, 1992; Moral, 2004; Webster and Oliver, 2007).

If work objectives arise when comparing the model parameters obtained in different situations, it is desirable to maintain a single model, if possible. The ranges of the exponential and Gaussian models should be considered in order to reach the sill asymptotically while the spherical model is the one that reaches a true sill; hence the sill and the range are not directly equivalent between models. The spherical model is generally the most used due to its true sill (Gallardo, 2006).

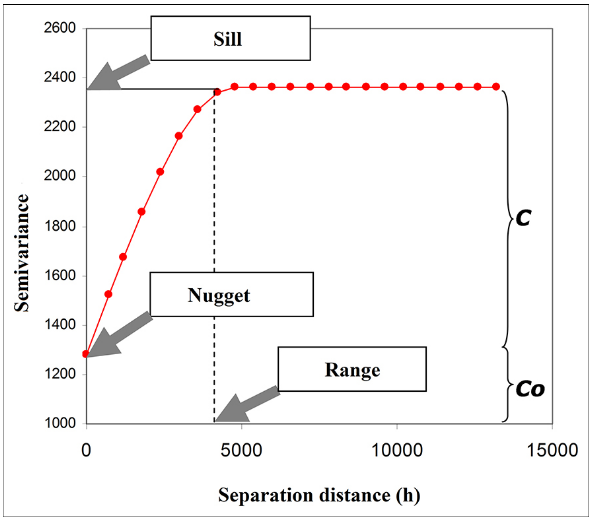

Figure 3. Graphical representation of a generalized variogram model (Adapted from Gamma design software, 2004).

The aforementioned procedure can be carried out by various software, such as Geostatistics for the Environmental Sciences (GS+, Gamma design software). With this software, structural analysis and mapping by kriging can be performed. The R software is very flexible and has implemented various packages for working with spatial data that provides a wide range of univariable and mulitvariable geostatistical modelling, prediction and simulation functions. Alternatively, the Mixed procedure of SAS (Littell *et al.*, 1996) can be used to adjust semivariogram models. These software are among the most well known in the area.

Cross-validation analysis. As a way of selecting the true model, the cross-validation method is recommended. This method consists on removing each of the sampled values (one at a time) and on estimating them from neighbors values by the kriging procedure mentioned in the following point. Validation errors are the difference between the observed and the estimated values, using the kriging method. Some criteria for the selection of the model are: the average error E(xi)=(1/n)Σni=1 [z*(xi) - z(xi)]) which must tend to zero, the mean square error (MSE=(1/n) Σni=1 [z*(x) - z(xi)]2) which must be small, and the measure (1/n) Σni=1 {[z*(x) - z(xi)]/σ}2 which must be equal to or be less than one, or what is the same as MSE is to ≤σ2 (Legrá *et al.*, 2004; Vieira *et al.*, 2010).

Prediction: Kriging Method

The geostatistical method for estimating values in unrecorded locations is called kriging (Figure 4).

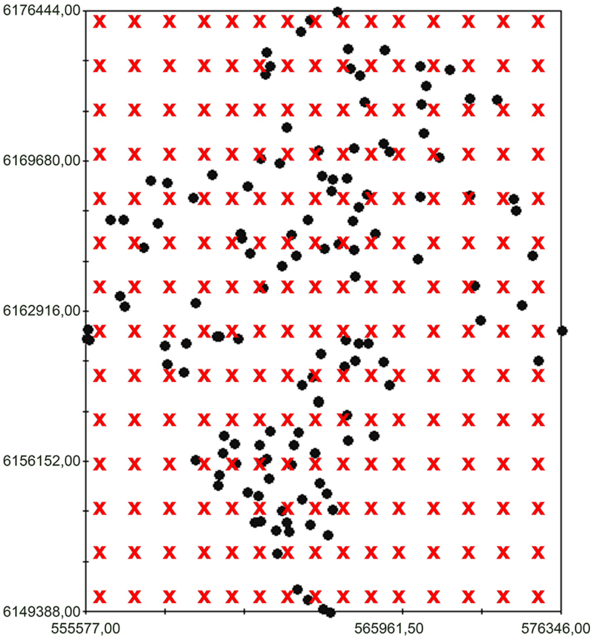

Figure 4. Location of pheromone traps (circles) and representation of the grid built for data interpolation (crosses).

This method uses the results of the structural analysis, considering both the distance and the geometry of the sampled location (Diaz-Viera, 2002).

The kriging estimators are defined as:

$$\hat{Z}(x_0) = \sum_{i=1}^{N} \lambda_i z(x_i)$$

where $\hat{Z}(x_0)$ is the kriging estimator of Z at a point, x_0, λ_i are the weights and $z(x_i)$ are the observed values of Z at points x_i. To ensure unbiasedness of the estimators the sum of the weights must be 1 (Webster and Oliver, 2007).

Kriging method allows to calculate the kriging variance, providing an estimation error depending on the variogram model selected and the location of sampled data, giving an indicator of the goodness of estimates (Journel and Huijbregts, 1978; Armstrong and Carignan, 1997; Cuador, 2004). The last step of this process is to obtain maps, which can present lines or areas in two or three dimensions (Figure 5) (Avilla and Ribes-Dasi, 2004).

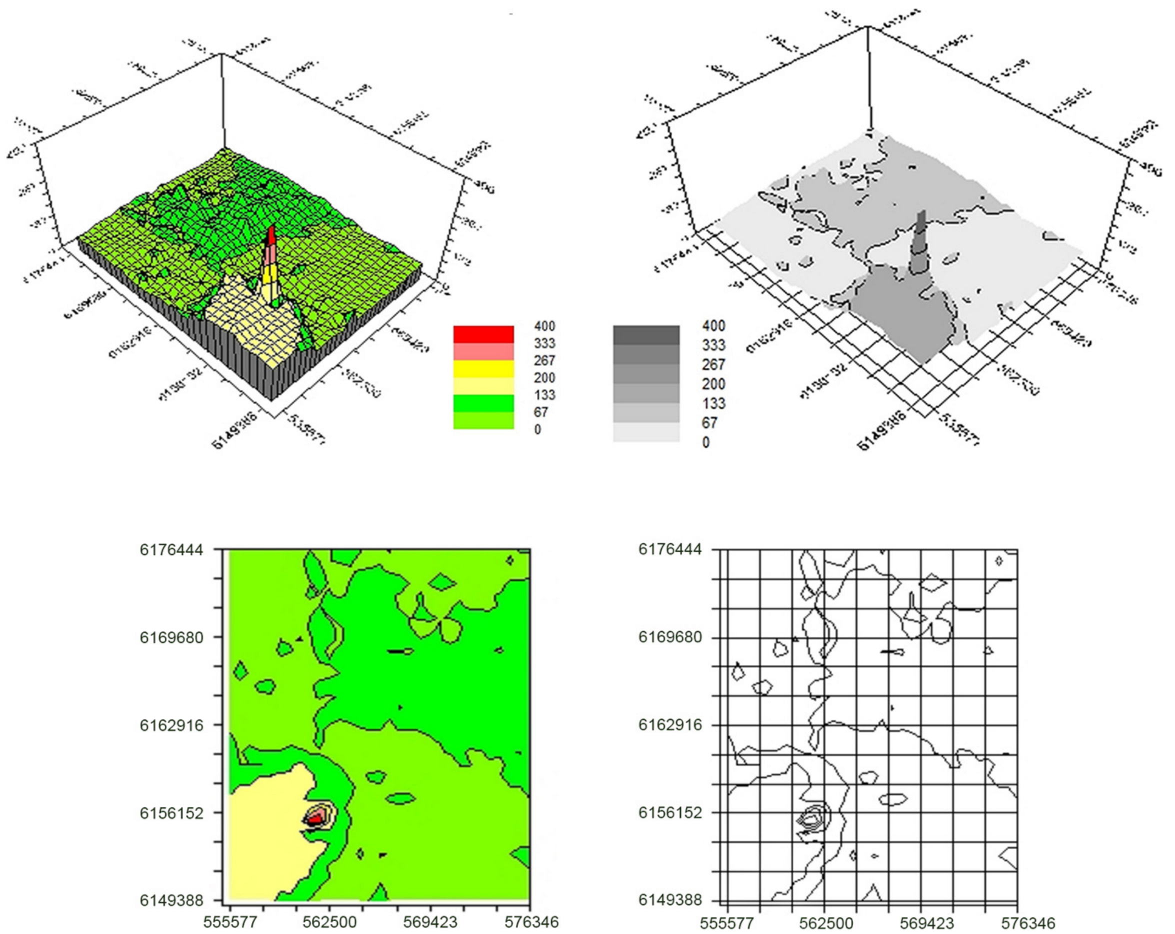

Figure 5. Graphical representation of maps in three and two dimensions (up and down respectively), and by areas or lines (left and right respectively) (Adapted from Gamma design software, 2004).

Other tools for spatial analysis

Although geostatistics appears as a useful and accurate tool for estimating the spatial distribution of a variable, other tools are available and can be used to find out how a variable is distributed in space. Geographic information systems (GIS) are technologies that facilitate pest management due to their capability to store, retrieve process and display spatially referenced data (Liebhold *et al*., 1993). GIS is a set of computer programs that allows to create maps which can incorporate all kind of information regardless of its origin and through different formats: points, lines or polygons (vectors) and to overlap layers, including maps obtained by kriging (Figure 6). Geo-referenced data, such as insect density or crop and soil type, can be incorporated into a GIS to produce layers on a map. A map layer is generally composed of a single kind of data or theme. In addition, themes representing similar areas can be combined to form a complete database. GIS works as a tool for the analysis of interactions between and within different themes from spatially referenced data. Management and analysis of large spatial databases would not be possible without such programs.

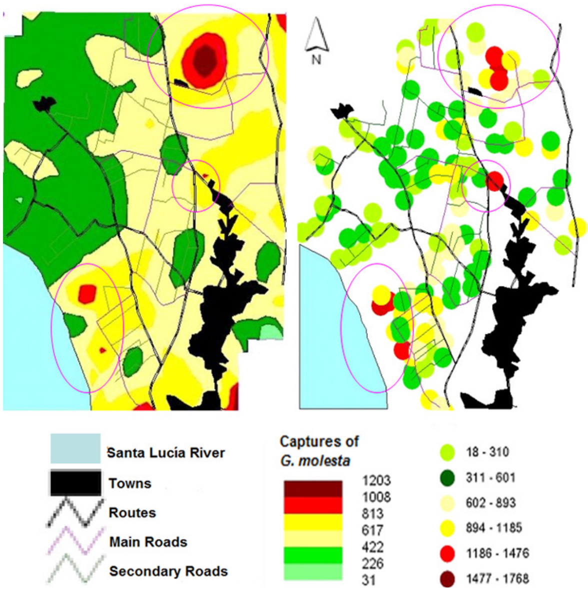

Figure 6. Maps of cumulative captures of *Grapholita molesta* in pheromone traps overlaid on a basic GIS obtained by kriging (left) and actual capture data without interpolation process (right) (Adapted from Duarte, 2012).

GIS technology in pest management has been mostly used to relate the demographic explosion of insect populations with biological and physiographic landscape features, including the availability and host abundance, weather conditions, etc. (Liebhold *et al*., 1993).

Moreover, maps obtained in geostatistic software can be added as layers on basic cartography software such as ArcGIS (ESRI Geoinformatik GMBH), Quantum GIS (Quantum GIS Development Team) and Google Earth (Google Inc.). Moreover, some GIS software have incorporated extensions to perform geoestatistical analysis that can be incorporated directly as a layer of the system.

In all, tools such as GIS and geostatistics, have allowed to incorporate space in ecology theory and models, and are generating substantial and very positive changes in pest management practices. To complement pest forecasting systems with maps of spatial distribution to identifying risk areas, requires a large number of sample points (at least 120). Studies are easier when the species of interest can be monitored with specific tools, as pheromone traps. Carrying out such systems requires the collaboration of different actors, for example, farmers who send on a weekly basis the number of catches to a public institution that centralizes the information, makes the estimates to draw maps, and return them to the users. These maps allow each farmer to identify if they are within an area of high pest population or not, and thus to take more effective and accurate management decisions. Also, it allows to identify areas with the high density of pest that persists over time, to minimize the injuries and decrease the pest population level in these areas in which area-wide pest management strategies should be incorporated.

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