Geostatistical Tools for the Study of Insect Spatial Distribution: Practical Implications in the Integrated Management of Orchard and Vineyard Pests

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Abstract

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Spatial heterogeneity in agricultural systems is recognised as an important source of variability to be investigated. In the evolution of Integrated Pest Management (IPM), patterns and processes that influence spatio-temporal dynamics in insect populations tend to assume more importance compared to the classical theory. Geostatistics represent a valuable tool to investigate the spatial pattern of insect populations and to support pest control. After an explanation of the geostatistical analysis, in the present paper we provided an overview of practical applications in managing pests, focusing on fruit orchards and vineyards. The utility of geostatistical tools is illustrated with examples taken from field studies, with attention to the analysis of spatial patterns, monitoring schemes, use of traps, scale issues, precision targeting, and risk assessment maps. Potential approaches in the context of IPM are discussed in relation to future perspectives.

Keywords: kriging; insect pests; monitoring; precision agriculture; IPM; spatial analysis

Agricultural systems are intrinsically heterogeneous. In fact, they contain variable arrangements of soils, habitats, microclimatic features, plant communities, and consequently they show an extensive variability in soil fertility, water retention, crop productivity, and so on. Basically, this is true also when we consider single fields that are typically composed of a central part and a border with many biotic and abiotic parameters showing gradients and edge effects (van Helden 2010).

The same principles apply to insect populations. In this case, spatial variation is caused by the interaction between population dynamics on the one hand and biotic or abiotic factors on the other. Processes that influence the spatial heterogeneity include population growth (reproduction, mortality) and dispersal (immigration, colonisation, emigration). For example, aggregations can be determined by the position of initial immigrants influencing the behaviour of other individuals/species through the emission of pheromones or inducing the formation of new plant volatiles. Similarly, the colonisation process is strongly influenced by birth/death rates that differ locally, so that the total population density in the whole field will increase, while in limited areas population will become extinct, leading to a clumped spatial pattern (Fleischer *et al.* 1997).

At the landscape level, the fragmentation of farmland has resulted in a scattered resource distribution that strongly enhances the importance of landscape structure in determining the final spatial pattern of a pest inside and outside a crop field. In fact, the distribution of host plants, including alternative hosts, will influence the short-distance foraging flights of herbivores, and often also the dispersal of predators and parasitoids (Mazzi & Dorn 2012). In the same way, the location of overwintering sites will determine the reinvasion pattern in the following season.

In the past, many efforts have been dedicated to improving the efficiency in the design of agricultural experiments minimizing the residual variability that in field trials is due mainly to the spatial heterogeneity. The strong advance of the space issue in biological sciences has arisen from the recognition that spatial variability, or patchiness, is widespread in natural populations and this characteristic is an interesting quantity rather than a statistical nuisance to be overcome (Schneider 1994).

In the new evolution of Integrated Pest Management (IPM) concepts, the spatial variation in pest populations tends to assume more and more importance compared to the classical theory. In site-specific IPM, the heterogeneity at the single field level is analyzed with the aim of optimizing chemical treatments (Park *et al*. 2007). In area-wide IPM, the importance of managing the whole pest population at landscape or regional level is emphasised, for example by identifying pest shelters inside and outside crops (Hendrichs *et al*. 2007). As a matter of fact, however, incorporation of the spatial component in management plans is still isolated in practice.

In these contexts, geostatistics represent a valuable set of statistical tools to investigate the spatial pattern of pests and to support the facilitation of practical pest control applications.

In the present paper we provide an overview of geostatistical applications in the study of insect spatial distribution, focusing on fruit orchards and vineyards, and their utility in managing pests is illustrated with examples taken from field studies. Potential approaches in the context of IPM are also discussed in relation to possible future perspectives.

GEOSTATISTICS

After the advent of calculators for the capture and elaboration of experimental data, largely accessible today thanks to new technologies such as personal computers, GPS, remote sensing, and GIS tools, statistical approaches that incorporate space in the elaboration have found new applications in many science subjects. In this context, a major role is played by geostatistics, first developed for mining explorations and then adopted by many environmental disciplines such as agriculture, hydrology, meteorology, soil sciences, fisheries, forestry, epidemiology, landscape ecology, environmental pollution, and risk assessment.

Geostatistics are a collection of statistical methods analyzing spatial dependence among samples (autocorrelation) and obtaining estimates of the variable under study at unsampled locations. For a detailed description of the general theory and principles, refer, among others, to Cressie (1993), Webster and Oliver (2001), and Chilès and Delfiner (2012). Various internet sources are available for both beginners and experts to this subject; for an overview of geostatistical methods implemented in real applications, it is possible to consult the active list service of AI_GEOSTAT (1995) or the website of GeoENVia Association (2011), that organize every two years the International Conference on Geostatistics for Environmental Applications.

In brief, the main steps in the geostatistical analysis are:

(1) Exploratory data analysis. Some elementary statistical analysis is useful to highlight general characteristics of data. Normality of data distribution can be evaluated using histograms and box-plots or by calculating some coefficient of asymmetry. Skewed variables often show a proportional effect, i.e., a higher variability in high valued areas and a lower variability in low valued areas that distort variogram results (Manchuk *et al*. 2009). Although formally not required, a normal distribution of data improves the autocorrelation analysis and can be achieved with a logarithm transformation.

(2) Estimation and modelling of spatial autocorrelation. To evaluate the spatial variation, different tools can be used, analyzing correlation coefficient (in correlograms), covariance (in covariance functions) or variance (in semivariograms). On choosing between these methods in ecological applications, see Rossi *et al*. (1992). Next, we will refer mainly to semivariograms, the most commonly used method in geostatistics.

The experimental variogram is a graph of discrete points at particular lag intervals, showing the semivariance of sample pairs against the distance between sampling points. The semivariance γ for lag distance h is given by:

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

where:
$z(x_i)$ – measured sample point at x_i,
$z(x_i + h)$ – measured sample at point $x_i + h$
$N(h)$ – number of pairs separated by the lag h

Because these estimates can strongly fluctuate from point to point due to sampling errors, a model describing the spatial variation must be fitted. Among the approaches available for use there are exponential, spherical, linear, polynomial, and Gaussian functions that can also be combined to obtain nested models (Pannatier 1996). Figure 1 illustrates key features of a semivariogram: the nugget is the y-axis intercept; the sill is the point at which variance no longer increases; the range corresponds to the distance where the sill is reached. Differences in spatial variation with geographical direction are known as anisotropy: a diverse semivariogram model can be produced for each considered direction. A geostatistical rule of thumb is that each lag interval must be represented by at least 30 pairs of points (Journel & Huijbregts 1978). This means that a minimum number of 25–30 sample units is required to obtain variograms with 4–5 lag classes, but often more points are necessary to accurately estimate sample pair variances (Nansen *et al.* 2003). Webster and Oliver (1992) pointed out that a minimum number of 100 sampling points is needed to give reliable results, but in a practical context it is often necessary to work with many fewer points. Semivariogram modelling is not an easy exercise and much practice should be devoted to this analysis. For more information on these techniques and interpretation of results, consult Isaaks and Srivastava (1989) and Cressie (1993) for a general overview, and Oliver (2010) for their use in an agricultural context.

(3) Estimation of a surface area using interpolation procedures. In geostatistics we can define the interpolation as a method of value estimation and/or prediction at unsampled locations in the geographical space. The objective of interpolation is to create continuous surfaces based on point samples. Many different methods are available, both deterministic and probabilistic, based on the mathematical algorithms used to compute the weights to be assigned during the interpolation; examples are triangulation, inverse distance weighted, natural neighbour, kriging, radial basis function, and also more sophisticated Bayesian techniques, such as the stochastic conditional simulation (Rossi *et al.* 1993).

The ordinary kriging is considered the best linear unbiased predictor and is by far the most utilised. The estimated Z at unsampled location x_0 is:

$$Z(x_0) = \sum_{i=1}^{n} w_i(x_0)\, Z(x_i)$$

where:

w_i – weight calculated for the sampled location x_i

$Z(x_i)$ – observed value at x_i

n – number of locations

The kriging weights depend on both the spatial autocorrelation measured in variograms and the spatial configuration of the sample points around the prediction location. Various forms of kriging have been developed to accommodate different types of data (i.e. block kriging for mean values from local areas, universal kriging when a spatial trend is detected, indicator kriging for binary data, cokriging for two or more variables spatially autocorrelated, etc.).

When insect populations are sampled, it is very common to obtain count data with many zeros. In these cases, indicator kriging represents an alternative choice. More detailed information on this method is reported in the paragraph "Risk assessment maps".

It is possible to assess the quality of interpolation by computing the errors (interpolated value minus observed value) and applying the cross-validation procedure; various statistics can be used as a quantitative measure of quality. For more information on geostatistical interpolation techniques, refer to Isaaks and Srivastava (1989) and Cressie (1993).

Different kinds of maps can be generated to visualise the results of the interpolation process, such as contour maps, surface maps, image maps or wireframes, where the variable densities are represented as different lines, colours, shadows or in 3 dimensions. A base map can be overlaid to show landscape features.

SAMPLING

Geostatistics represent a significant change in the methodology of sampling. In fact, traditionally we need to have independent data and sampling plans are designed to avoid correlations. On the contrary, geostatistics look for autocorrelations, and so sampling plans became less restrictive (Sharov 1997). Moreover, the final objective of a geostatistical survey is not to obtain the estimation of a mean, as in classic plans, but to map the spatial variability of samples. For example, areas that are avoided because they might be a source of bias, such as field edges, become primary areas to be explored. Similarly, areas usually discarded because they are considered to be without or with a low pest presence, should be included: in a geostatistical survey, areas at zero levels are as important as high density areas (Brenner *et al.* 1998).

Nonetheless, new aspects arise that must be considered in spatially explicit surveys. It is known that precision, which indicates how well the mean is estimated, increases with sampling size (Fleischer *et al.* 1997). Classically, sampling plans are designed to balance such precision with the costs of sampling; in this case many sampling units are evaluated in the field and they are used to obtain a unique mean. In geostatistical applications, a large number of sample units are needed to perform a variogram analysis, but sampling units are evaluated individually at each location and this results in a poor local estimate. This effect is more accentuated when the distribution is aggregated – a very common condition in pest populations. In such a situation, clusters of sampling units and interpolation data with block kriging can be a solution, but the costs of large sample sizes are often prohibitive (Fleischer *et al.* 1997).

In general, irregularly spaced sampling points are not a problem, especially for kriging interpolation and this characteristic gives some freedom in setting up a sampling design, but the orientation, scale, and arrangement of sampling units can still influence the result of geostatistical analysis. Moreover, an optimal sampling scheme for variography can be different from that designed for kriging interpolation, so the final purpose of our survey should be clear when the sampling plan is arranged (Marchant & Lark 2012).

Various classical sampling schemes can be adopted, such as simple random, stratified random, cluster, nested or systematic sampling (Wollenhaupt *et al.* 1997). Among them, systematic design is generally considered more precise than simple or stratified random (Webster & Oliver 1990), but it must be remembered that in fruit orchards and vineyards there is usually a regular pattern composed of plants positioned at fixed distances within and between rows, and this can strongly influence geostatistical elaborations. Schotzko and O'Keefe (1990), evaluating the effect of sample placement on the geostatistical analysis of *Lygus hesperus* Knight in lentils, considered a staggered grid to give a better map precision than a uniform grid.

In the case of insects, very often no prior information is available, the variation is complex and the scale of the phenomenon is unknown. An exploratory survey of spatial variation can help to select the appropriate size, number, and location of observations (Baldacchino *et al.* 2012; Marchant & Lark 2012), but in practical situations it can rarely be done. In similar situations, it is possible to use e.g. a cluster sampling, where clusters of individual units are selected at random and each unit in the cluster is measured; this approach fits particularly well when populations tend to be clustered (Gilbert 1987). Another possibility is the nested survey, where, following a classification, clusters are subdivided, then the subdivisions are randomly selected and further subdivided until the smallest units are identified (Wollenhaupt *et al.* 1997). This approach allows the exploration of several orders of magnitude of spatial scale in a single analysis (Kerry *et al.* 2012). Bacca *et al.* (2008) used a cluster sampling plan to interpolate and simulate the male leaf miner *Leucoptera coffeella* (Guérin-Méneville & Perrottet) distribution at different trap densities in a coffee plantation.

Another approach can be the adaptive survey, consisting of changing sampling efforts in the space, according to the data collected earlier (Thomson 1990). An example of insect adaptive surveys, related to tsetse fly population, is provided by Sciarretta *et al.* (2005).

PRACTICAL APPLICATIONS

After the first studies carried out in North America to investigate the distribution of *Pectinophora gossypiella* (Saunders) in cotton, *L. hesperus* in lentil fields, and grasshoppers in uncultivated areas (Borth & Huber 1987; Kemp *et al.* 1989; Schotzko & O'Keefee 1989), geostatistics have seen many applications in various fields of crop protection against worms or arthropods pests (for more details see Liebhold *et al.* 1993; Brenner *et al.* 1998; Arbogast *et al.* 2000; Brandhorst-Hubbard *et al.* 2001; Park *et al.* 2007; Sciarretta & Trematerra 2009; Webster 2010) and, in a few cases, to highlight predator and parasitoid distribution (Karimzadeh *et al.* 2011; Perović & Gurr 2012).

One of the most significant examples of applications in this field was carried out over the last two decades in the eastern United States against the gypsy moth *Lymatria dispar* (L.), which was introduced in North America from Europe in 1869 (Liebhold *et al.* 1989). Pheromone trap catches and egg mass data were analysed using geostatistical tools at regional scale to model the gypsy moth spatial dynamics, with the aim of: delimiting the boundary of pest dispersion, estimating the spread rate at the expanding population front, forecasting the spatial dynamics of moth outbreaks, predicting the larval defoliation levels, and evaluating the treatment effects (Liebhold *et al.* 1991, 1998; Hohn *et al.* 1993; Sharov *et al.* 1995; Tobin *et al.* 2004, 2007).

Examples of practical applications focusing on fruit orchard and vineyard insect pests are reported in Table 1.

Analysis of spatial patterns

Because spatial variation is due to so many factors, generalisation about the causes of patchiness

Table 1. Geostatistical tools for the study of insect spatial distribution: list of papers, arranged in chronological order, on orchard and vineyard pests

Species	Order	Fruit orchard and vineyard	Scale	Country	Sampling methods	References
Asymmetrasca decens, *Edwardsiana rosae*	Rhynchota	apple, peach	field	Israel	sticky traps for adults	Nestel and Klein (1995)
Cydia pomonella, *Pandemis heparana*	Lepidoptera	apple, pear	regional	Spain	pheromone traps	Ribes *et al.* (1998)
Grapholita funebrana	Lepidoptera	plum	landscape	Italy	pheromone traps	Sciarretta *et al.* (2001)
Jacobiasca lybica	Rhynchota	vineyard	field	Spain	visual counts for eggs and nymphs	Ramírez-Dávila *et al.* (2002, 2005), Ramírez-Dávila and Porcayo-Camargo (2008 a,b)
Ceratitis capitata	Diptera	mixed orchards	field	Greece	McPhail traps	Papadopoulos *et al.* (2003)
Cicadellidae various species	Rhynchota	sweet orange, lime	field	Brazil	sticky traps	Farias *et al.* (2004)
Cydia pomonella	Lepidoptera	apple	landscape	Italy	pheromone traps	Trematerra *et al.* (2004)
Cydia pomonella	Lepidoptera	apple	field	Italy	kairomone traps	Trematerra and Sciarretta (2005)
Ceratitis capitata	Diptera	citrus	field	Spain	multilure traps	Alemany *et al.* (2006)
Leucoptera coffeella	Lepidoptera	coffee	field	Brazil	pheromone traps	Bacca *et al.* (2006, 2008)
Lobesia botrana	Lepidoptera	vineyard	field	Greece	visual counts of larvae	Ifoulis and Savopoulou-Soultani (2006)
Lobesia botrana	Lepidoptera	vineyard	field	Spain	pheromone traps	Peláez *et al.* (2006)
Grapholita molesta, *Anarsia lineatella*	Lepidoptera	mixed orchards	landscape	Italy	pheromone traps	Sciarretta and Trematerra (2006)
Capnodis tenebrionis	Coleoptera	apricot	field	Italy	visual counts of adults	Bonsignore *et al.* (2007)
Empoasca vitis	Rhynchota	vineyard	field	France	sticky traps for adults, visual counts for nymphs	Decante and van Helden (2008)
Lobesia botrana	Lepidoptera	vineyard	landscape	Italy	pheromone traps	Sciarretta *et al.* (2008)
Cydia pomonella	Lepidoptera	apple	landscape	Chile	pheromone traps	Basoalto *et al.* (2010)
Ceratitis capitata	Diptera	coffee, mango, orthanique	field	Honduras	multilure traps	Epsky *et al.* (2010)
Ceratitis capitata	Diptera	mixed orchards	landscape	Italy	trimedlure traps	Sciarretta and Trematerra (2011)
Frankliniella spp.	Thysanoptera	blueberry	field	USA	sticky traps	Rhodes *et al.* (2011)
Cydia pomonella	Lepidoptera	apple	regional	Spain	pheromone traps	Comas *et al.* (2012)

in insect populations is very problematic; often it is not possible to understand the main factors determining the spatial pattern in a specific context or to predict *a priori* any form of distribution (van Helden 2010). Often, each orchard is unique and the features of experimental variograms are not the same also for neighbouring fields. Further, the distribution can change according to the insects' developmental stage, the season, the phenological status of the crop, and the weather conditions. For example, alternating periods of clumped and random patterns were observed to be recurrent in fruit orchards and vineyards for leafhoppers, thrips, and fruit flies (Nestel & Klein 1995; Papadopoulos *et al.* 2003; Farias *et al.* 2004; Decante & van Helden 2008; Rhodes *et al.* 2011). Consequently, *in situ* observations are necessary to depict the spatio-temporal dynamics of a pest and descriptive maps must be developed to have a visual representation of pest presence in the agro-ecosystem.

The study of spatial variation patterns is crucial from this point of view and the features of semivariograms give us much information about the spatial structure of our data.

An asymptotic function indicates an aggregated insect distribution and the range represents approximately the extension of hot spots (areas of aggregation); on the contrary, linear functions indicate a uniform/random distribution, with the random component increasing with the increase of the variance variability; when the slope is near to zero we obtain a pure nugget effect, indicating a complete lack of any autocorrelation and a pure random distribution (Schotzko & O'Keefe 1989).

A zero nugget indicates a strong confidence in sample data, while the presence of a nugget represents two sources of variability: the micro variance occurring at a scale smaller than the minimum lag distance and the measurement error.

Figure 1 shows common types of variograms underlying different insect distributions. An index that can summarize the level of randomness is the k parameter, defined as the ratio between the nugget and the sill, and this indicates the degree of spatial dependence measured in the variogram (Journel & Huijbregts 1978). Values below 0.8 indicate that the distribution is aggregated; as the k parameter approaches zero, the level of spatial dependence will become greater.

Monitoring schemes

Monitoring pest population is a key issue in IPM schemes. The objectives of monitoring are to detect

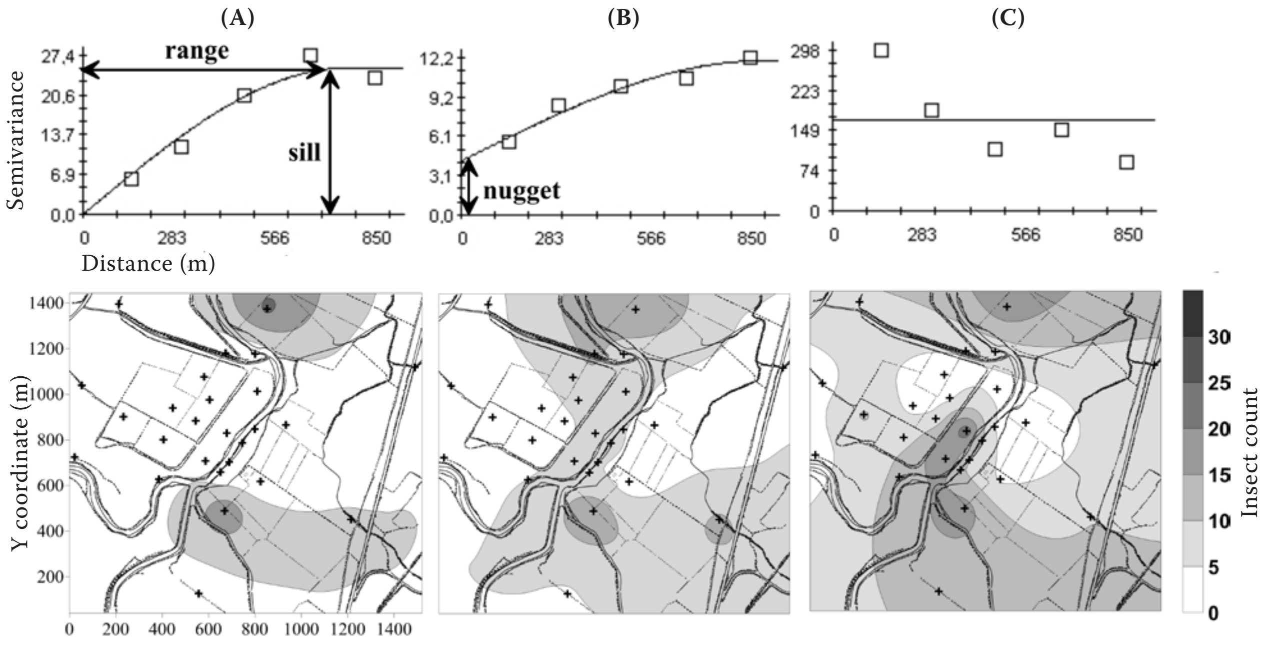

Figure 1. Variogram shapes of different *Anarsia lineatella* weekly pheromone trap catches and maps of the corresponding spatial distribution in the investigated agro-ecosystem: A – clumped distribution without nugget, B – clumped distribution with nugget, C – random distribution

the presence or absence of pests and quantify their abundance (and/or their natural enemies) through time and space. Follow the spatio-temporal dynamics of the population by regular, periodic sampling, monitoring allows us to reach a decision as to whether, when and where a pest population requires a control action.

In this context, geostatistics applied to a grid of monitoring points allows us to obtain a map providing useful information on the pest spatial distribution, in particular:

– origin of infestations in the investigated agro-ecosystem, both inside and outside the considered crops;
– position and temporal dynamics of hot spots;
– role played by cultivated and wild host plants as potential sources of infestation;
– effect of landscape structure on the dispersal of the pest population.

As an example, we report the studies conducted on the distribution of *Grapholita funebrana* Treitschke and *Cydia pomonella* L. in two heterogeneous agro-ecosystems of central Italy (Sciarretta *et al.* 2001; Trematerra *et al*. 2004).

In the case of *G. funebrana*, pheromone trapping was carried out inside a 12-ha plum orchard and to the surrounding area, covering a surface of about 250 ha. The results revealed a distribution strongly influenced by the fragmented structure of the landscape and the presence and dissemination of host plants in the area investigated, where adults showed a strong capacity for dispersal and movement between elements of the landscape (Sciarretta *et al.* 2001). In particular, irrigation canals and the hedgerows around the plum orchard served as corridors along which the adults passed from one zone to another of the territory. The highest catches in the orchard were just at the point of contact with these corridors, highlighting the movements that occur between the plum orchard and a ravine, where there was an abundance of blackthorn, another host plant of the insect.

For *C. pomonella*, the monitoring by means of pheromone traps, carried out in two agro-ecosystems with productive apple orchards and scattered trees of apple, pear, service, and walnut, highlighted a limited dispersion of adults in the territory; catches of male moths were clumped and the hot spots were confined to the productive apple orchards or in small groups of wild apple, pear, service, and walnut trees. The colonised areas were isolated from each other and this suggests that strips free of host plants around orchards may be an effective barrier against immigration from infested zones. In this case, a strip of 200–300 m was found to be an obstacle to the movement of the moth (Trematerra *et al.* 2004).

Use of traps

When attractive devices are used for a spatial monitoring scheme, some geostatistical properties must be taken into account (Perry *et al.* 2002): the extent, describing the dimension of the study area; the support, i.e. the sampling unit size corresponding to the attractive range of the trap; the lag, i.e. the distance between the sampling units (Figure 2).

The grid of the traps will give different sampling results according to the following conditions:

– when lag > support, the experimental design allows a large individual movement (Figure 2A);
– when lag = support, the movement of individuals is more limited (Figure 2B);
– when lag < support, there may be an alteration in the spatial distribution because of the phenomena of mutual interference between traps (Figure 2C).

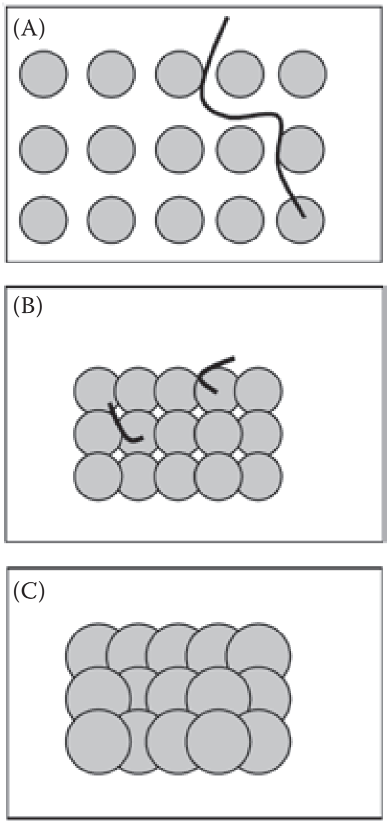

Figure 2. Possible situations that can occur during sampling with attractive traps: A – lag > support, B – lag = support, C – lag < support. The circles represent the range of a trap, the black lines represent the trajectories of a moving individual

Geostatistical techniques can help to establish the correct distance between monitoring devices.

For example, Bacca *et al.* (2006) determined the optimal spacing of pheromone traps for monitoring the coffee leaf miner *L. coffeella* in a coffee plantation, thus allowing an efficient trap distribution in the field, finding also a significant difference between the orthogonal directions of the plant rows.

Using experimental variograms, Epsky *et al.* (2010) determined the sampling range of a female-targeted protein-based attractant for the Mediterranean fruit fly *Ceratitis capitata* (Wiedemann) in various fruit crops; geostatistical results were confirmed by combining a release-recapture experiment with the use of contour maps illustrating the spatial distribution of recaptured flies.

Scale issues

Spatial patterns are usually strongly scale-dependent and this is true also when the object of our investigations is a pest species. This means that the change in some measures of the pattern, i.e. extent, support and lag, will change in both the resolution and range of measurement (Schneider 1994).

After changing the scale, prevailing processes defining that particular pattern will be different and will consequently lead to different results. For example, if we study the spatial structure of a pest population at the within-field level, forces such as local population dynamics will dominate in our analysis. If we move to a landscape level, patch composition and metapopulation processes will prevail. At a regional level, other variables will act over the others, i.e. climatic features, altitudinal trend, genetic drift, etc.

The choice of the appropriate scale depends on the objective of our study. If we intend to understand the distribution of a pest inside an orchard for optimising control or monitoring actions, a sampling point grid will be deployed to cover every part of the field, including peripheral sectors to verify the presence of peculiar spatial patterns such as the border effect (van Helden 2010).

At this scale, fruit species and cultivars, in relation to their spatial location and phenological phase, can have an important role in determining the spatio-temporal dynamics of pests, particularly the polyphagous ones. Studies on the spatio-temporal dynamics of *C. capitata* carried out to evaluate the effect of the host plants on the pest spatial distribution, in an agricultural landscape of 500 ha located in central Italy, showed that fruit flies were caught sequentially in orchards with host plants (i.e. peach, apple, pear, oriental persimmon, and prickly pear) at varying times of maturation, especially when the fruits remained on the trees (Sciarretta & Trematerra 2011). Distributional maps provided evidence that made it possible to identify fruit species in which the fly developed early in the season (mixed peach orchards) and afterwards during the periodic flights.

The experimental design will be different if we want to identify sink and sources in an agricultural landscape. In this case, because spatial distribution can easily be affected by landscape composition, sampling strategies should be extended to cover the whole area and designed to adequately differentiate variable properties at each important landscape unit, including those in which we assume the pest is not present. In these cases, useful information will be obtained about the role played by host plants as potential sources of infestation outside the considered crops. In the case of the European grapevine moth *Lobesia botrana* (Den. & Shiff.), contour maps highlighted that adult spatial distribution was not limited to vineyards, but its presence was high inside olive groves, particularly during the first seasonal flight (Sciarretta *et al.* 2008).

The landscape structure, through the presence of elements such as hedgerows, uncultivated fields, streams, and woodlots, which act as barriers or ecological corridors, can have a strong effect on the dispersion of the pest population. Examples on this topic were reported for *G. funebrana*, *Grapholitha molesta* (Busck), *Anarsia lineatella* (Z.), and *C. pomonella* (Sciarretta *et al.* 2001; Sciarretta & Trematerra 2006; Basoalto *et al.* 2010). The presence of overwintering sites outside deciduous orchards was reported to influence the colonisation and spread of leafhoppers into the orchards from the surrounding vegetation (Nestel & Klein 1995).

At regional level, sampling points are often located at great distances (kilometres or more), and this hides the population dynamics occurring at lower scales. Studies at this level can have the objective of obtaining a general frame of the pest presence in a large area, but investigations can also be directed to verify spatial relationships of the pest with specific variables (Ayalew *et al.* 2008). For example, a study carried out on 160 000 ha in Catalonia, Spain, aimed at analysing the current codling moth pheromone trap spatial distribution and verifying the presence of anisotropic effects due to predominant wind directions (Comas *et al.* 2012).

Precision targeting programs

The incorporation of spatial variability into an Integrated Pest Management program is called site-specific IPM or precision targeting for IPM and relies on the use of maps showing a pest distribution, to be used to minimize direct control tactics (Weisz *et al*. 1995; Brenner *et al*. 1998). Such an approach follows the principles of precision agriculture, but in spite of the progress made by the latter in recent years (Oliver 2010), the practical development of site-specific IPM programs is still limited today (Park *et al*. 2007; Sciarretta *et al*. 2011).

Among the difficulties in incorporating precision targeting into IPM are the identification of external infestation foci, the necessity to have aggregated populations with limited dispersal ability, and the high sampling costs, which are often not economically sustainable. Also, an evaluation of insecticide application costs, related to the site-specific *versus* whole field IPM, needs to be addressed.

The development of a site-specific IPM was carried out against *L. botrana* in vineyards located in a hilly landscape in Italy (Sciarretta *et al.* 2011). In this case, two tactics were used: the first was directed at reducing the source of infestation from outside the vineyards, and specifically from the olive groves, which were found to host an important part of the pest population (Sciarretta *et al.* 2008), by establishing a pheromone trap barrier to prevent male movements into the vineyards. The second was to reduce the quantity of insecticides used and the treated area, focusing curative efforts towards the sectors of vineyard with the highest level of *L. botrana* oviposition, while excluding areas with low egg density. The results highlighted that male hot spots in olive groves disappeared, and that the number of larval nests on vine inflorescences was significantly decreased when additional traps were deployed, compared to the period before. The site-specific control, i.e. treating only egg hot spots with *Bacillus thuringensis* var. *kurstaki*, allowed for a decrease in the surface of the vineyard treated and, consequently, the quantity of insecticide utilised; no significant damage differences between whole field and site-specific IPM in vineyards were observed when treatments were carried out against both second and third *L. botrana* generations. An analysis of costs related to insecticide application in the field highlighted that the site-specific approach was economically advantageous, if compared to the whole field IPM, with greater damage to up to 1% of infested berries per bunch, covered by the saving of reduced treatments (Sciarretta *et al*. 2011).

Risk assessment maps

One of the possible outcomes of geostatistical analysis is the creation of risk assessment maps for pest management. Such an instrument has seen strong development especially in epidemiological studies, and maps can be obtained merging data from many different kinds of sources (Eisen & Eisen 2011). For example, a risk map for *L. botrana* was obtained by utilising three-year data on larval damage, with both the number of attacked berries per bunch and the percentage of infested bunches (Figure 3).

The utility of similar instruments in IPM programs was shown by Brenner *et al.* (1998), who gave details on using the indicator kriging to define and quantify areas that exceed predetermined action thresholds. In short, an indicator is a variable with values only of 1 or 0, obtained by dividing our scale of counts into one or more thresholds. The interpolation of the indicator variable will give the distribution of the estimated probability that a sampling point placed in a specific location will exceed the established threshold.

Figure 4 illustrates the case of *C. pomonella* distribution in an apple orchard, where the indicator kriging was

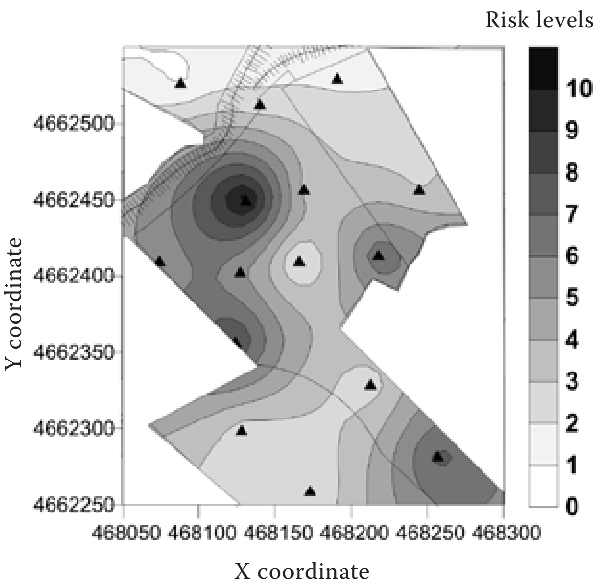

Figure 3. Risk map of the *Lobesia botrana* larval damage sampled in a 4.5 ha vineyard. An index, obtained multipling the mean number of attacked berries per bunch and the percentage of infested bunches from 3-year data, was transformed in a scale with levels ranging from 0 (no risk) to 10 (maximum risk) and interpolated using ordinary kriging; *x* and *y* axes are expressed as UTM coordinates

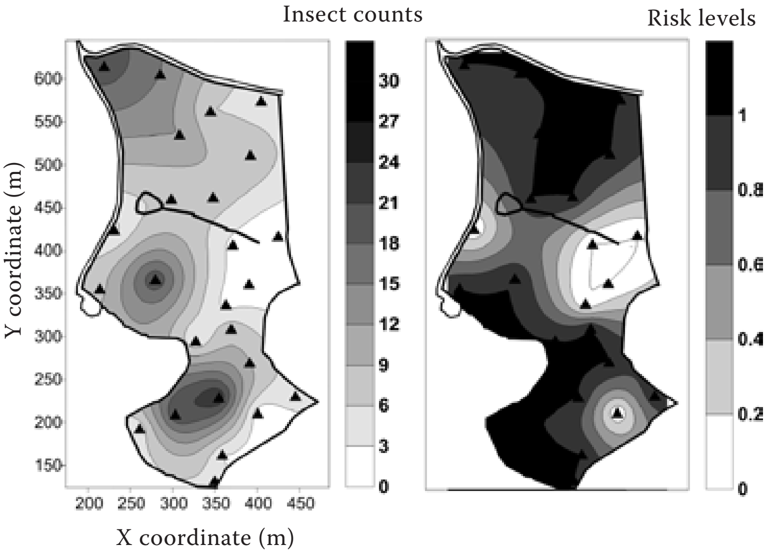

Figure 4. Distributional map of *Cydia pomonella* weekly pheromone trap catches (on the left) and corresponding risk map obtained calculating the indicator kriging for an action threshold of 2 males per trap per week (on the right). Risk levels correspond to the estimated probability that a sampling point placed in a specific location will exceed the established threshold. Black areas are the best places where to put a monitoring trap

elaborated considering an action threshold of 2 males collected in a pheromone trap per week. In this case, the map provides support for selecting sectors of the orchard where correct positioning of a trap will give a reliable indication of the achievement of the threshold.

FUTURE PERSPECTIVES

Currently, many GIS softwares incorporate spatial analysis tools, including geostatistics, for producing distributional maps. The widespread use of GIS-based studies suggests that the utilisation of geostatistical methods will become more widespread in applied contexts and at different scales, making it easier to develop efficient local or regional pest management plans.

The use of GIS technology today appears very promising in area-wide IPM programs, where activities are conducted over large geographical areas, involving the use of decision support systems, taking into account the pest and beneficial species colonisation and dispersal and evaluating the presence of environmental factors that, changing across the managed area, could affect the success of an IPM program (Faust 2008). Although there are some examples of the use of geostatistics in area-wide IPM programs (Tobin *et al.* 2004; Carrière *et al.* 2006; Smith *et al.* 2006; De Luigi *et al.* 2011), their use in fruit orchard and vineyard protection is still very limited. At this regard, in a sterile insect release program initiated in British Columbia, Canada, in 1992 and still active nowadays, to obtain an area-wide suppression of *C. pomonella* from its fruit-growing valleys (Okanagan-Kootenay SIR Program 2012), a GIS software combined with geostatistical analysis was developed for managing moth population and fruit damage data and to determine how key activities in the program could be streamlined (Vernon *et al.* 2001, 2006).

A further improvement may arise from models that better define spatio-temporal dynamics of a pest. In this regard, a promising approach is space-time geostatistics, designed for variables that vary in both time and space. They involve the use of the variogram to characterize the variation along the time dimension as well as the spatial one (Heuvelink & van Egmond 2010). The difference with respect to the classical approach is that both these sources of variation are elaborated and their effects are taken into account, for example, to predict the target variable at an unmeasured time by kriging. They are not intended as temporal forecasting models, but can provide predictions and be used to move from a series of freeze-frames to a continuous recording of the phenomenon under study.

The problem of the high cost of pest management in a spatial context, especially for sampling, is currently the most serious constraint to the diffusion of geostatistical techniques in practice. This limitation may in part be overcome if efforts are directed to the development of intelligent Location-Aware Systems that allow automation of trapping devices and treatment operations (Wen *et al.* 2009; Pontikakos *et al.* 2012).

Ultimately, an important shift may be achieved gradually as practices such as sustainable agriculture, organic farming, zero-residue production, etc. gain more importance in the growing of high value crops, and as the environmental advantages of using a reduced or zero input of chemicals are incorporated as the added value in determining the final product price.

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