Forum

The Impact of Spatial Structure on the Accuracy of Contour Maps of Small Data Sets

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J. Econ. Entomol. 96(6): 1617–1625 (2003)

ABSTRACT Spatial analysis of insect counts provides important information about how insect species respond to the heterogeneity of a given sampling space. Contour mapping is widely used to visualize spatial pest distribution patterns in anthropogenic environments, and in this study we outlined recommendations regarding semivariogram analysis of small data sets ($N < 50$). Second, we examined how contour maps based upon linear kriging were affected by the spatial structure of the given data set, as error estimation of contour maps appears to have received little attention in the entomological domain. We used weekly trap catches of the warehouse beetle, *Trogoderma variabile*, and the accuracy assessment was based upon data sets that had either a random spatial structure or were characterized by asymptotic spatial dependence. Asymptotic spatial dependence (typically described with a semivariogram analysis) means that trap catches at locations close to each other are more similar than trap catches at locations further apart. Trap catches were poorly predicted for data sets with a random spatial structure, while there was a significant correlation between observed and predicted trap catches for the spatially rearranged data sets. Therefore, for data sets with a random spatial structure we recommend visualization of the insect counts as scale-sized dots rather than as contour maps.

KEY WORDS IPM, contour mapping, semivariogram, spatial analysis, *Trogoderma variabile*

The spatial distribution of an insect species may be considered a "fingerprint" of how it responds to the environmental heterogeneity and patchiness of a given sampling space. For ecological studies and/or implementation of control strategies of an insect, it is often desirable to characterize whether the insect species is equally abundant throughout the entire sampling space and whether its abundance at sampled locations seems positively associated with the occurrence of certain spatially aggregated environmental conditions. Contour maps are used to visualize the spatial distribution pattern of insect trap catches and environmental conditions (e.g., temperature) and are popular in both extension and pest control services and research on spatial insect ecology. These maps have been used to visualize spatial distribution patterns of moth pests (Arbogast et al. 1998, 2000a; Campbell et al. 2002) and beetle pests (Arbogast et al. 1998, 2000a, b; Campbell et al. 2002) in stored-product habitats, and such mapping techniques are relevant for spatial studies of insects in other anthropogenic environments as well. Contour maps of insect counts represent a conversion of point observations, typically spatially referenced insect trap catches, into a continuous surface, so that insect abundance is estimated over unsampled locations within the given sampling space. The conversion of point observations into a surface is based upon a user-defined interpolation technique, such as inverse distance weighting (Weisz et al. 1995), linear kriging (Arbogast et al. 1998, Campbell et al. 2002), or radial basis function (Arbogast et al. 2000a, b). Thus, using such standard interpolation techniques, the estimated insect abundance at an unsampled location is based upon the assumption that the observed insect abundance at a fixed number of locations can be modeled mathematically.

For some data sets, such as temperature patterns along a gradually increasing altitudinal gradient, it seems intuitively logical that the temperature at a point mid-wise between two weather stations will be close to the mean temperature readings of the weather stations, because such data have fairly unidirectional spatial trends. However, simple unidirectional spatial trends are rarely to be expected in data sets involving insect counts, so a basic question to pose is how effectively can insect counts be predicted at points between locations in which samples are obtained? The short answer is that it depends on the spatial structure of the data, and in this study we intend to demonstrate how this is important for the development of accurate contour maps.

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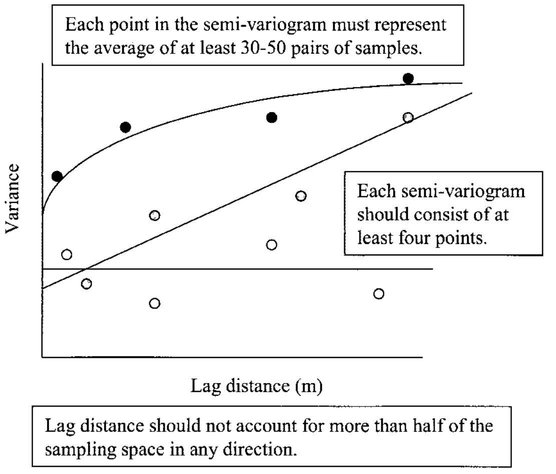

Fig. 1. Three theoretical semivariograms illustrating the general relationships between lag distance of paired observations and variance of counts: white dots represent a data set with lack of spatial dependence (random spatial structure), gray dots represent a data set with positively linear spatial dependence, and black dots represent a data set with an asymptotic spatial dependence. The three main requirements for development of a meaningful semivariogram analysis are presented in boxes.

The spatial structure of a data set describes the variance of counts at different distances and directions and is typically characterized through semivariogram analyses (Isaaks and Srivastava 1989, Schotzko and O'Keeffe 1989, Rossi et al. 1992, Liebhold et al. 1993, Armstrong 1998, Brenner et al. 1998). A data set normally has one of four spatial structures (Schotzko and O'Keeffe 1989), and three of these are outlined in Fig. 1: random or lack of spatial dependence (white points in Fig. 1), which means that the variance of trap catches is independent of the geographical distance between paired trap locations. A data set with a random spatial structure (denoted "pure nugget variogram" [Liebhold et al. 1993]) has no spatial component, so the sample mean with corresponding confidence levels is an adequate estimate of trap catches at unsampled locations. Consequently, the accuracy of any predictions at unsampled locations depends on the variance associated with the mean trap capture at sampled locations. Spatial dependence (Rossi et al. 1992, Liebhold et al. 1993) or spatial continuity (Isaaks and Srivastava 1989) means that trap catches that are close to each other are generally more similar than catches at locations further apart, and that this spatial relationship among trap catches can be modeled mathematically. Spatial dependence is linear (gray points in Fig. 1) when the variance in counts increases proportionally with lag distance, or asymptotic when the variance of counts levels off after a certain lag distance (black points in Fig. 1). Asymptotic spatial dependence is a required assumption for most interpolation techniques, including kriging methods (Roberts et al. 1993, Perry 1997). However, some software packages for developing contour maps, such as Surfer 7.02 for Windows (Golden Software, Golden, CO), can be used without a priori characterization of the spatial structure.

In this study, we outline recommendations regarding semivariogram analysis of small data sets ($N < 50$), and we determine the accuracy of contour maps when data sets have either a random spatial structure or asymptotic spatial dependence. This study is based upon pheromone trap catches of the warehouse beetle, *Trogoderma variabile* Ballion (Coleoptera: Dermestidae), in a food warehouse, but the analytical approach is relevant to contour mapping of most small data sets of insect counts. We focused on the use of linear kriging as interpolation technique, as this technique is considered "BLUE" (best linear unbiased estimator) (Isaaks and Srivastava 1989). We discuss the importance of characterizing the spatial structure of a data set before using contour mapping as a decision support tool in integrated pest management (IPM). We also propose an alternative mapping technique when contour mapping is not appropriate.

Materials and Methods

The Sampling Space and Traps. This study was conducted in a 106 × 61-m (6,466 m^2) portion of a food warehouse, which is described in more detail by Campbell et al. (2002). Pheromone trapping was conducted over consecutive 9 wk (10 May to 12 July 2000), which are referred to in this study as wk 1–9. All pheromone-baited traps were serviced the same day at weekly intervals, and two types of traps were placed at each of the 37 locations; a FLITe-TRAK beetle trap (Mullen 1992) was placed on the floor below a Pherocon II trap (Trécé, Salinas, CA), which either hung on walls or from pillars from 1.5–2.1 m above the warehouse floor. The FLITe-TRAK trap has a ramp-and-pitfall design and is mainly used for capture of walking insects, while the Pherocon II trap is a simple diamond-shaped sticky trap intended to capture flying insects. Both trap types were baited with three rubber septa, each impregnated with synthetic pheromone of *T. variabile, Tribolium* spp. (Coleoptera: Tenebrionidae), and *Lasioderma serricorne* (Fabricius) (Coleoptera: Anobiidae). FLITe-TRAK traps also contained a commercial blend of food oils as attractant (Trécé). Pheromone lures and food attractants were produced by Trécé, and they were replaced after 8 wk. As the purpose of this study was to describe the accuracy of contour maps and importance of analyzing the spatial structure of data sets before developing contour maps, we only examined trap catches of *T. variabile.* We analyzed the correlation between trap catches of *T. variabile* with the two trap types before proceeding with the spatial analysis. Trap locations were georeferenced according to the distance in meters from a reference point in the southwestern corner of the food warehouse.

Theoretical Background to Semivariogram Analysis of Small Data Sets. The spatial structure of a data set is determined by fitting regression lines to the points in the semivariogram (Fig. 1) (e.g., Young and Young

1998). Several authors have outlined minimum requirements regarding the size of data sets to obtain a meaningful semivariogram analysis (Journel and Huijbregts 1978, Liebhold et al. 1993), and with the increasing use of contour mapping in spatial ecology studies of stored-product pests and other small-scale systems, it becomes highly relevant to outline standards for spatial structure analysis for small data sets to be visualized as contour maps. The total number of paired trap catches (P) for a given data set is:

$$P = \frac{n \times (n-1)}{2} \qquad [1]$$

where "n" is the number of trap catches. As in any other type of regression analysis, the reliability of the curve fit increases proportionally with the number of points in the semivariogram. Thus, the semivariogram must contain enough points to characterize the spatial structure, and each point must be calculated on the basis of a minimum number of paired observations. To determine whether the spatial dependence in a data set is random, linear, or asymptotic (see Fig. 1), it seems reasonable to suggest that minimum of four points is required in the semivariogram. The number of points in the semivariogram is user defined and determined by the width of the lag-distance intervals. Narrowing the lag-distance intervals increases the number of points, but reduces the number of paired observations used to calculate each point in the semivariogram. According to Liebhold et al. (1993), there are at least two requirements to be able to characterize the spatial structure of a data set using semivariogram analysis: 1) each point must represent the average of at least 30–50 pairs of observations to minimize the influence of extreme variance values, and 2) a semivariogram analysis should not account for more than about half of the sampling space in any direction (that is why it is called a "semi"-variogram), otherwise the semivariogram may become directionally biased when data sets are obtained from sampling spaces with highly unequal dimensions. For example, if a food warehouse is 50 m long and 20 m wide, and the semivariogram is based upon 5-m lag-distance intervals up to 30 m, then the longest lag-distance intervals will only include paired observations in one direction. Thus for the theoretical warehouse, the second requirement by Liebhold et al. (1993) suggests that the semivariogram should not account for observations that are >10 m apart. The number of paired observations included in the semivariogram analysis therefore is influenced by a combination of trap catch density, the physical shape of the sampling space, and the pattern of trap placement.

A semivariogram analysis also can be used to detect directionality or anisotropy in data sets. Isotropy means that the level of spatial dependence is described purely by the distance between the paired observations and is similar in all directions, while in anisotropic data sets spatial dependence is determined by a combination of angle and distance between observations (Armstrong 1998, Krajewski and Gibbs 2001). Although including directionality into the semivariogram analysis may improve the characterization of the spatial structure, it imposes a considerable restriction on the number of paired observations included in the semivariogram, because it means that only paired observations within a given angle are included. Therefore, it is not recommended to include directionality into the semivariogram analysis when the data set is small.

Semivariogram Analysis. In this study, the food warehouse was 106 × 61 m, which means that ideally the semivariogram should not account for >30.5 m. With the current placement of traps and when no traps were lost, an initial analysis of the number of paired observations showed that using a maximum lag distance of 30.5 m would include 134 paired observations in the semivariogram analysis, while extending the maximum lag distance to 34.15 m meant that 205 paired observations were included. Although a maximum lag distance of 34.15 m is slightly longer than half the shortest dimension, we found this modification acceptable as it allowed us to generate semivariograms with, on average, five points of ≈40 pairs compared with only four points of ≈35 pairs. According to the recommendation by Krajewski and Gibbs (2001) and similar to Sharov et al. (1996), absolute pheromone trap catches of *T. variabile* were $\log_{10}(x + 1)$ transformed before conducting the semivariogram analysis. We used the **OUTPAIR** option in the **PROC VARIOGRAM** procedure in PC-SAS 8.0 (SAS Institute 2000) to calculate lag-distance interval and variance of all paired observations within a 34.15-m range. To obtain similar numbers of paired observations in each lag-distance interval (35–45 paired observations), we calculated the mean variance of trap catches for the paired observations when divided into the following lag-distance intervals: <15.40 m, ≥15.40 and <21.59 m, ≥21.59 and <30.14 m, ≥30.14 and <31.00 m, ≥31.00 and <34.15 m. The **PROC NLIN** procedure in SAS 8.00 (SAS Institute 2000) was used to fit a spherical curve (Schotzko and O'Keeffe 1989) to the mean variance ($\gamma[h]$) of the five lag-distance intervals:

$$\gamma(h) = b + c \times \left[\frac{1.5(h)}{a} - \frac{0.5(h)^3}{a}\right] \qquad [2]$$

where "b" is the intercept with the y-axis (the "nugget"), "c" is the "sill," "h" is the mean lag distance, and "a" is the "range," which is the lag distance at which the variance reaches the sill (Liebhold et al. 1993, Brenner et al. 1998). Paired observations further apart than the distance indicated by the range are not spatially autocorrelated.

Spatial Rearrangement of Weekly Trap Catches. Based upon semivariogram analyses, we determined that all nine weekly data sets of actual Pherocon II trap catches of *T. variabile* had random spatial structures. Subsequently, we manipulated the weekly trap catch data sets selected from wk 1, 4, and 7 by spatially rearranging the trap catches to create significant asymptotic spatial dependences. The trap catches were

Table 1. Weekly pheromone trap catches of *T. variabile* with FLITe-TRAK traps and Pherocon II traps in a food warehouse during 9 wk from 10 May to 12 July 2000

	Wk 1	Wk 2	Wk 3	Wk 4	Wk 5	Wk 6	Wk 7	Wk 8	Wk 9	Mean (SE)
					FLITe-TRAK					
Zero catches[a]	10	4	0	3	2	5	3	1	2	
Maximum[b]	15	32	16	32	17	16	20	18	42	
Mean[b]	2.32 (0.58)	5.08 (1.32)	5.65 (0.87)	6.36 (1.20)	4.86 (0.84)	4.24 (0.87)	5.00 (0.97)	4.23 (0.98)	8.13 (1.97)	5.1 (0.5)
Sites[c]	31	26	26	28	29	25	24	22	22	26.11 (1.0)
					Pherocon II					
Zero catches[a]	19	11	7	9	11	8	13	13	5	
Maximum[b]	5	16	12	11	10	8	13	5	13	
Mean[b]	0.86 (0.20)	2.51 (0.52)	3.06 (0.54)	1.95 (0.42)	2.14 (0.42)	1.86 (0.30)	2.49 (0.50)	1.46 (0.25)	3.85 (0.60)	2.24 (0.3)
Sites[c]	37	37	34	37	37	36	37	36	35	36.22 (0.4)

[a] Number of traps per week with zero catches of *T. variabile*.
[b] Weekly maximum and mean (with corresponding standard error) of *T. variabile* trap catches with FLITe-TRAK traps and Pherocon II traps.
[c] Number of trap catches obtained (37 traps were installed each week).

spatially rearranged by moving trap catch counts among the same trap locations without changing the weekly trap catch totals or frequency distribution of trap catches. The Pherocon II trap catches from wk 1, 4, and 7 were used for the validation because: 1) no traps were lost during those weeks, 2) the weeks were all separated in time, and 3) these trapping periods represented three different relative magnitudes of weekly mean trap catches.

Mapping and Accuracy Assessment of Contour Maps of *T. variabile* Trap Catches. The software package PC-Surfer 7.02 (Golden Software) was used to develop contour maps of the *T. variabile* trap catches. Similar to Arbogast et al. (1998) and Campbell et al. (2002), we used the software default settings for "linear kriging" with assumptions of "zero nugget" and "isotropy." We wanted to use a technique for accuracy assessment that requires little time and is easy to perform, so we used the "jackknife" procedure described by Krajewski and Gibbs (2001) in which one trap catch was removed from the data set before the contour mapping, and the estimated catch from the contour map at that location was compared with the observed trap catch. This procedure was repeated 20 times by individually removing 10 of the lowest trap catches and 10 of the highest trap catches for each data set to determine how well the contour maps predicted both high and low trap catches. We only examined the predictions of the 10 highest and the 10 lowest trap catches as the type of spatial structure of the data set that was believed to have the highest influence on the predictions of extreme trap catches. For all data sets, the relationship between observed and predicted trap catches was analyzed with a linear regression analysis.

Results and Discussion

Trap Catches. Of the 333 possible weekly trap catches (9 wk × 37 trap locations), 7 Pherocon II trap catches and 98 FLITe-TRAK trap catches were lost (Table 1). Despite the considerable loss of FLITe-TRAK traps, a paired *t*-test showed that FLITe-TRAK trap catches of *T. variabile* were significantly higher than those with Pherocon II traps (Table 1, $t_8 = 10.297$, $P < 0.001$). A similar difference in magnitude of trap catches was reported by Campbell et al. (2002). We have no clear explanation for the significantly higher catches of *T. variabile* on the floor compared with the air, but it emphasizes the need for analyzing the spatial distribution pattern of such insect trap catches in a three-dimensional context rather than only analyzing trap catches in a two-dimensional plane. Despite the significant difference in magnitude of catches, a regression analysis showed that trap catches with the two traps were significantly correlated (adjusted $R^2 = 0.22$, $F_{232} = 67.13$, $P < 0.001$). As concluded from other studies involving simultaneous trapping with several trap types (e.g., Nansen et al. 2003), a trap catch is relative to the type of trap that was used, so catches with different trap types are not easily comparable and may therefore indicate different spatial distribution patterns.

Loss of pheromone traps represents a frequently occurring problem in monitoring programs, and it has profound implications for the development of meaningful semivariograms. For instance, in the present case with a maximum lag distance of 34.15 m, 37 trap catches equaled 205 paired observations, while 34 trap catches (loss of three Pherocon II traps) in wk 3 equaled 169 paired observations. Hence, with each point in the semivariogram representing ≈40 paired observations, the semivariogram analysis of Pherocon II trap catches from wk 3 was only based upon four points compared with five for the other weekly data sets. Journel and Huijbregts (1978) recommended that at least 30 observations be included in a data set to obtain a meaningful semivariogram analysis. Because of the considerable loss of FLITe-TRAK traps, the spatial structure of weekly *T. variabile* catches with these traps was not analyzed.

Spatial Randomness. Table 2 summarizes the results from the semivariogram analyses of the nine weekly data sets of *T. variabile* catches with Pherocon II traps. The fit of equation 2 to the relationship between lag distance and trap catch variance was found to be nonsignificant for the 9 wk of actual trap catches ($P > 0.05$), and this relationship suggests that the weekly

Table 2. Mean variance among Pherocon II trap catches of *T. variabile* at given lag-distance intervals

Mean lag distance (m)[a]	Wk 1	Wk 2	Wk 3	Wk 4	Wk 5	Wk 6	Wk 7	Wk 8	Wk 9
Observed Pherocon II trap catches									
15.0	0.560	0.720	0.775	0.654	0.934	0.689	1.039	0.700	0.966
18.6	0.567	0.670	0.578	0.539	0.644	0.689	0.906	0.636	0.941
23.2	0.488	0.789	0.751	0.476	0.716	0.578	0.900	0.555	0.793
30.5	0.587	0.858	0.849	0.660	0.749	0.675	0.892	0.654	0.870
33.5	0.708	0.800	0.822	0.635	0.913	0.666	0.904	0.652	0.965
Regression (*F* value)	8.85	2.08	−0.18	1.76	2.86	0.98	5.11	2.80	4.36
Regression (*P* value)	0.10	0.32		0.36	0.26	0.51	0.16	0.26	0.19
Spatially rearranged Pherocon II trap catches									
15.0	0.373			0.531			0.561		
18.6	0.450			0.620			0.737		
23.2	0.551			0.737			0.855		
30.5	0.581			0.848			0.942		
33.5	0.599			0.797			0.970		
Regression (*F* value)	68.80			55.27			87.59		
Regression (*P* value)	0.01			0.03			<0.01		
Range ("*a*")	31.05			30.91			31.53		
Nugget ("*b*")	−0.082			−0.10			−0.19		
Sill ("*c*")	0.68			0.92			1.15		

[a] Mean lag distance of paired observations divided into five intervals: <15.40 m, ≥15.40 and <21.59 m, ≥21.59 and <30.14 m, ≥30.14 and <31.00 m, ≥31.00 and <34.15 m. Values in weekly columns represent the mean variance of *T. variabile* trap catches for the five lag-distance intervals. Trap catches were $\log_{10}(x + 1)$ transformed prior to the semivariogram analysis. A nonlinear curve (equation 1) was fitted to the relationship between lag distance and mean variance. A regression analysis was used to evaluate the significance of the curve fit, and the *F* value and *P* value from this analysis are presented. Three of the weekly trap catch data sets were spatially rearranged without changing the weekly trap catch mean or frequency distribution. Range ("*a*"), Nugget ("*b*"), and Sill ("*c*") are coefficients in the nonlinear curve fit (equation 2).

trap catch data sets had a random spatial structure. It is possible that an asymptotic spatial dependence would have been detected if we had been able to take directionality (anisotropy) into account in the semivariogram analysis. Alternatively, stratified sampling approaches could be suggested to eliminate the directionality. However, because of the small size of these data sets, the development of separate semivariograms for different directions or any grouping of trap locations (as part of a stratified sampling approach) would have reduced the number of paired observations substantially and therefore not allowed us to develop meaningful semivariogram analyses. The trap density had to be at least twice as high to incorporate directionality into the semivariogram analyses. Table 2 also shows the results from the semivariogram analyses of the three spatially rearranged data sets, and there we obtained a highly significant fit of equation

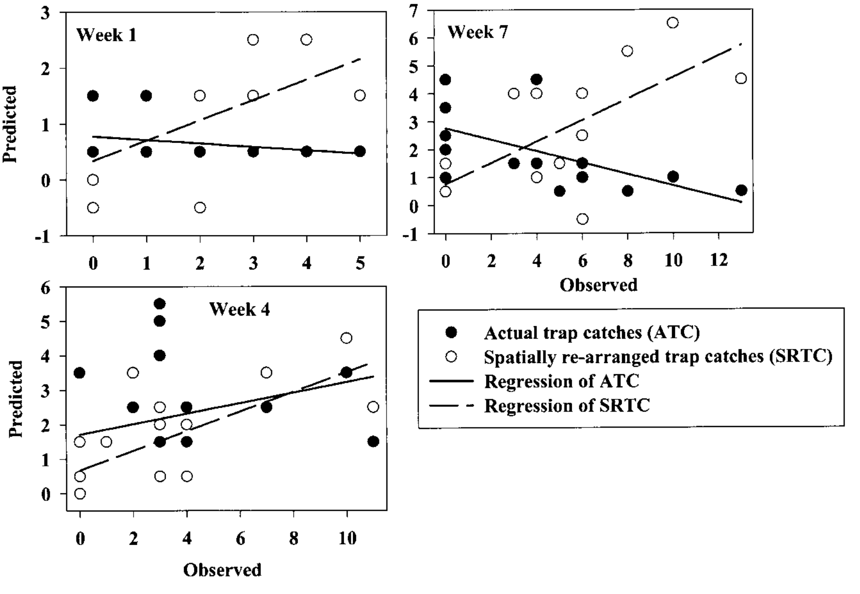

Fig. 2. Regression analyses of the relationship between observed and predicted *T. variabile* trap catches from wk 1, 4, and 7 for actual trap catches and spatially rearranged trap catches.

Table 3. Results from the regression analyses of observed and predicted *T. variabile* trap catches for actual trap catch data that had a random spatial structure and spatially rearranged trap catches with asymptotic spatial dependence

Data set	Type	df	adj. R^2	F	P	a	Y_0
Wk 1	Actual	19	0.002	1.03	0.323	−0.062	0.77
Wk 1	Rearranged	19	0.438	15.78	<0.001	0.363	0.34
Wk 4	Actual	19	0.065	2.31	0.146	0.152	1.71
Wk 4	Rearranged	19	0.499	19.96	<0.001	0.285	0.674
Wk 7	Actual	19	0.287	8.64	0.009	−0.206	2.77
Wk 7	Rearranged	19	0.536	22.98	<0.001	0.382	0.758

As validation of actual and spatially rearranged trap catches, 10 of the lowest and 10 of the highest trap catches were removed individually from each data set, and linear kriging was used to generate contour maps. The predicted trap catch on the contour maps for each of the 20 individually removed trap catches was compared with the observed trap catch and analyzed with a regression analysis (Fig. 2).

2 to the relationship between lag distance and trap catch variance, which indicated spatial dependence of trap catches.

Spatial Structure of Pheromone-Baited Trap Catches. Perry (1997) cautions about applying geostatistical techniques to certain ecological data sets, because these methods were developed for spatial research on physical (essentially immobile) variables and not for data sets of mobile organisms. There are at least five possible explanations for the lack of spatial asymptotic dependence in the *T. variabile* trap catches: 1) the movement pattern of the *T. variabile* population may have been biased by directionality because of, for instance, predominant directional flight relative to air currents or light regimes, which were not accounted for; 2) the pheromone-baited traps may have been unequally affected by the environmental heterogeneity of the warehouse, so adjacent pheromone trap sites may have caught the beetles with different efficiency; 3) the number of pheromone-baited traps may not have been sufficiently high to fully characterize the spatial distribution pattern of the *T. variabile* trap catches; 4) the trap catch range (mainly determined by the pheromone concentration in the lure) may have been too high, so that flying *T. variabile* males were confused, as it occurs under augmentative releases of pheromone in mating disruption, and therefore *T. variabile* males were caught in a random pattern within the sampling space; or 5) the human activity in the food warehouse caused so much persistent disturbance that the *T. variabile* population was flying in a spatially random pattern. It was beyond the scope of this study to investigate reasons for the observed spatial randomness of *T. variabile* trap catches, but it raises some concern about the practical use of pheromone-baited traps, especially for precision targeting and monitoring of *T. variabile* populations in food facilities.

Validation of Contour Maps. In wk 1, 4, and 7, there were 9–19 trap catches of zero *T. variabile* individuals (Table 1), and validating the accuracy of contour map predictions on these locations is important to estimate the level of type 2 (e.g., Green 1979) associated with each contour map. For the three data sets of actual trap catches, the predictions of low trap catches were generally higher than the predictions of high trap catches (Fig. 2), and in wk 7 as much as seven *T. variabile* individuals were predicted for a location where no beetles were caught. Hence, the regression analyses of the relationship between observed and predicted for the 10 low and 10 high trap catches for the 3 wk were found to be nonsignificant ($P > 0.05$). In wk 7, there was even a significantly negative correlation between observed and predicted trap catches (Table 3). However, for the spatially rearranged trap catches, the predictions of low trap catches were very close to observed for all 3 wk. A type 1 error, false negative, is generally the most concerning type of error in model hypothesis testing (Green 1979). In wk 1, 4, and 7, the highest trap catches were 5, 11, and 13 *T. variabile* individuals, respectively. For the three weekly data sets of actual trap catches, there were several predictions of high trap catches that were very close to zero, while the predictions of high trap catches for the spatially rearranged data sets were all significantly correlated with the observed (Table 3).

Similar to Campbell et al. (2002) and Arbogast et al. (1998), we used linear kriging for the interpolation procedure in the contour mapping, but "radial basis function" has also been used for contour mapping of stored-product insects (Arbogast et al. 2000a, b). For comparison, we therefore used actual trap catches from wk 7 to validate contour maps based on radial basis function and found that the relationship between observed and predicted trap catches was almost identical to the results from the linear kriging ($a = -0.200$, $Y_0 = 2.801$, adjusted $R^2 = 0.283$, $F_{19} = 8.8485$, $P = 0.009$). The fairly inaccurate trap catch predictions from contour maps of the actual trap catches are caused directly by the random spatial structure of these data sets, and thus the spatial structure of the data set is more important than the choice of interpolation procedure.

Visualization of Insect Counts. The actual and spatially rearranged Pherocon II trap catches used for the validation are presented as contour maps based upon linear kriging in Fig. 3. The three maps of actual *T. variabile* trap catches showed a fairly patchy scattering of high and low catches, which explains why the semivariogram analyses indicated a random spatial structure for these data sets. Because of the random spatial structure of the actual *T. variabile* trap catches, the sizes and shapes of the polygons have no meaning, and a more appropriate visualization would be to present the trap catches as scale-sized dots (Fig. 4). The visualization of insect counts as scale-sized or

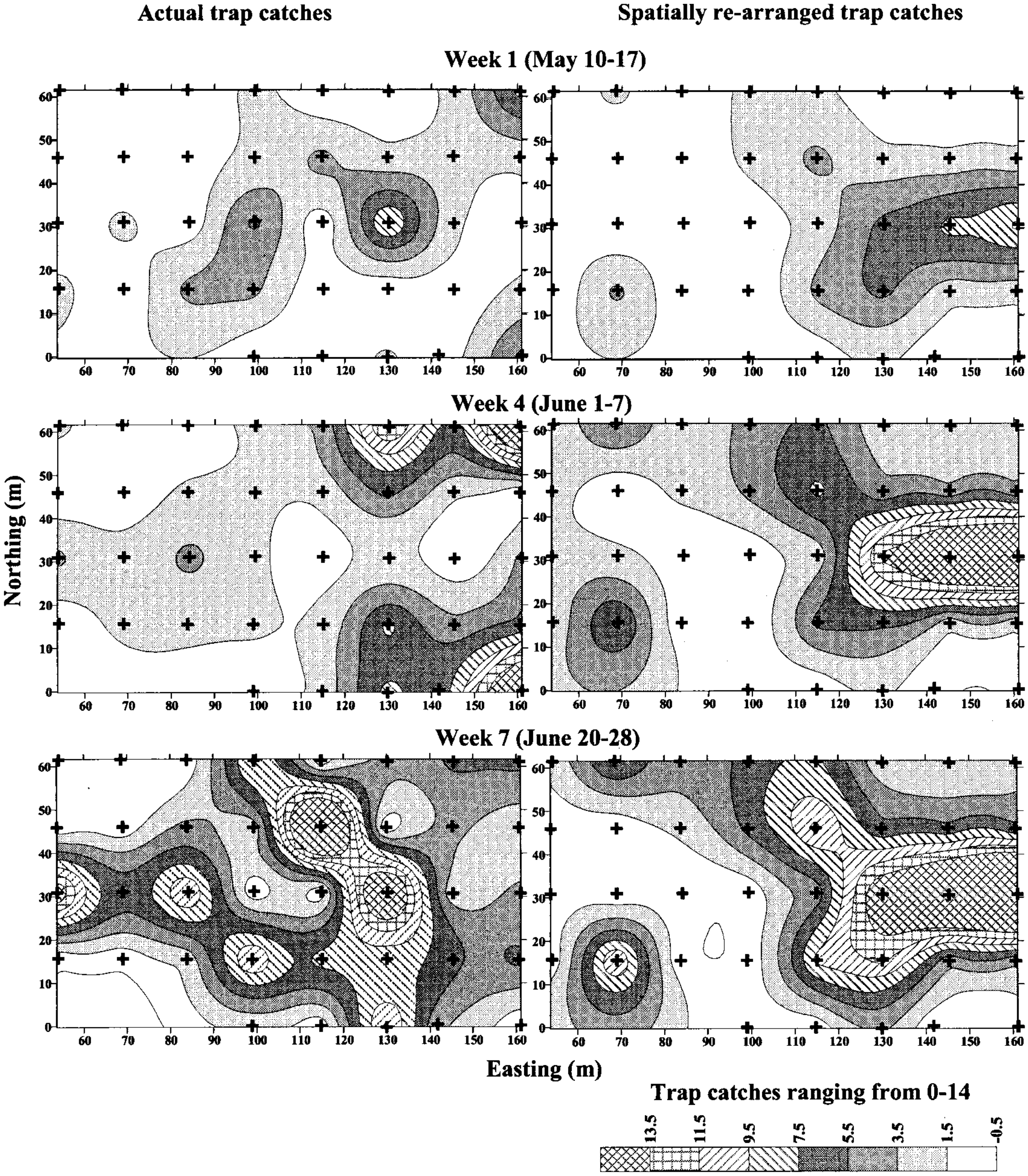

Fig. 3. Contour maps of pheromone-baited trap catches of *T. variabile* with Pherocon II traps at the 37 trap locations for wk 1, 4, and 7. Trap locations are presented as crosshairs. The actual trap catches are presented to the left, and the spatially rearranged trap catches are presented to the right. Actual trap catches had a random spatial structure, while the spatially rearranged trap catches were manipulated so that the trap catches showed asymptotic spatial dependence (Table 2).

color-coded dots involves no mathematical procedures, is totally unbiased, and provides about the same information as contour maps without making predictions of insect numbers at unsampled locations.

The contour maps of the spatially rearranged data sets indicated more consistent spatial distribution patterns with either high or low *T. variabile* trap catches in different parts of the food warehouse. The semivariogram analyses of the spatially rearranged *T. variabile* trap catches indicated asymptotic spatial dependence within a 30- to 32-m range, which was close to the maximum range of the semivariogram analysis (34.15 m). With spatial dependence of ≈30 m, the overall distance of ≈15 m

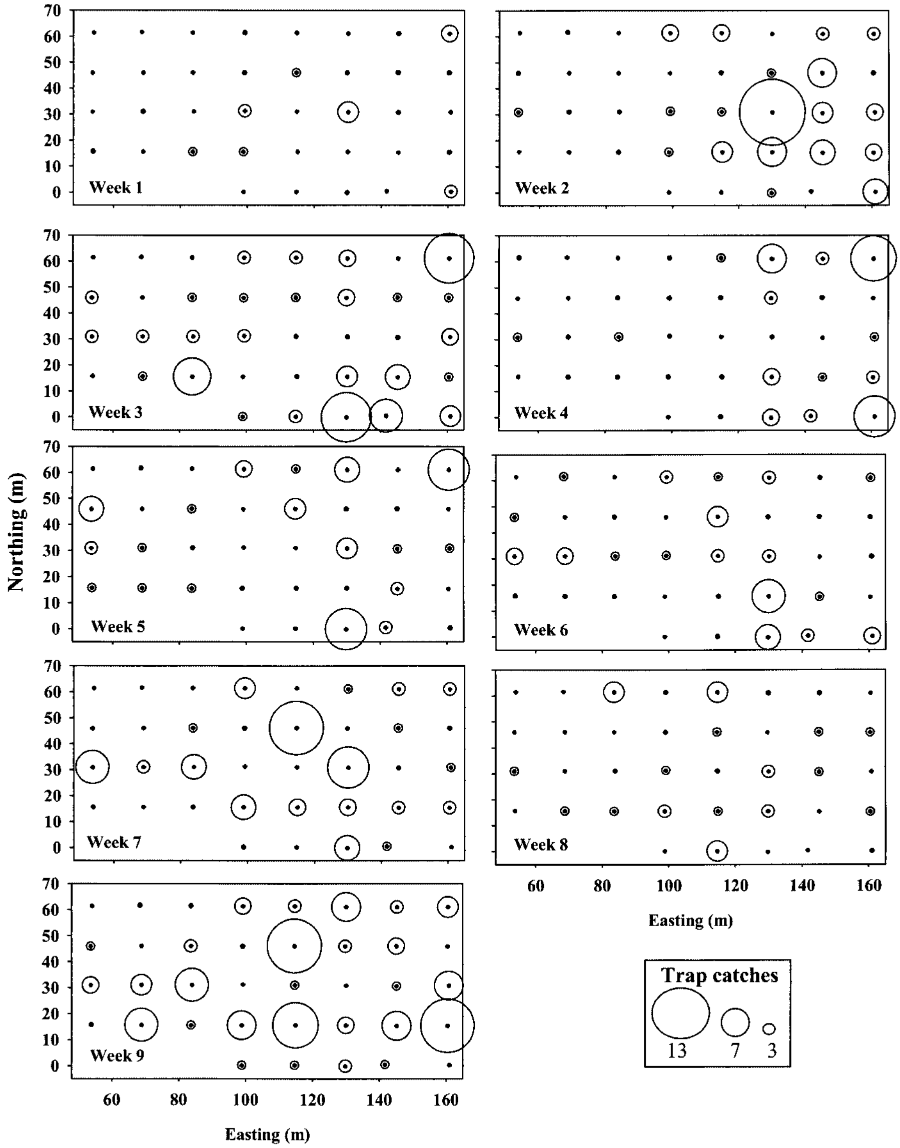

Fig. 4. Pheromone-baited trap catches of *T. variabile* with Pherocon II traps at the 37 trap locations for consecutive 9 wk (10 May to 12 July 2000). The size of the circles represents the magnitude of trap catches.

between trap locations may not be a high enough density of traps, and this may at least partially explain the random spatial structure of the actual trap catches.

Conclusion

We outlined the basic requirements for semivariogram analysis of small data sets. Our analysis demonstrated that it is necessary to consider the spatial structure of a data set before developing contour maps, because trap catches at unsampled locations were not predicted accurately when the data set has a random spatial structure. Arbogast et al. (1998) considered the development of contour maps a three-step process: 1) posting of data points on a map, 2) interpolation, and 3) establishment of contour lines. We recommend two additional analytical steps. First, analysis of the data sets' spatial structure should be characterized before developing contour maps. If the analysis of the spatial structure of the data sets indicates other structures than an asymptotic relationship between lag distance and variance of insect counts, then interpolation and subsequent contour mapping should not be used to visualize the data. To develop a meaningful semivariogram analysis, we suggest that each point in the semivariogram represents the mean of at least 30 paired observations, and that the paired observations are divided into at least five lag-distance intervals within half of the shortest dimensions of the sampling space. Second, before generating the final contour map, we recommend an accuracy assessment in which some high and low trap catches are removed individually from the data set before the contour mapping, and the predicted catch from the contour map at that location is compared with the observed. The relationship between observed and predicted trap catches can subsequently be analyzed in a regression analysis.

Acknowledgments

We thank Drs. Carlyle C. Brewster, Mark E. Payton, Norman C. Elliott, Kristopher L. Giles, and three anonymous reviewers for their reviews of earlier drafts of this manuscript. We thank the sanitarian and the management at the food processing plant for allowing us access to their facility, and A. St. Cyr for facilitating this research. This research was supported in part by a grant from the United States Department of Agriculture, Cooperative and State Research, Education and Extension Service in the Risk Avoidance and Mitigation Program, Agreement 00-51101–9674. This manuscript was approved for publication by the Oklahoma Agricultural Experiment Station and supported by Agricultural Experiment Station Project OKL 02320. Mention of trade names or commercial products in this publication is solely for the purpose of providing specific information and does not imply recommendation or endorsement by Oklahoma State University or the United States Department of Agriculture.

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Received for publication 5 March 2003; accepted 3 July 2003.