

Spatial and Probability Distribution of Mexican Bean Beetle (Coleoptera: Coccinellidae) Egg Mass Populations in Dry Bean

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ABSTRACT The spatial pattern and probability distribution of Mexican bean beetle, *Epilachna varivestis* Mulsant, egg masses were studied in four dry bean, *Phaseolus vulgaris* L., fields near Scottsbluff, NE, during the 1994 and 1995 growing seasons. Sampling was conducted in a regular and uniform grid to guarantee coverage of the field. The experimental unit in all fields was 0.30 row-m, and five measurements were made at 0.76-m intervals. A total of 12,290 locations was sampled. Geostatistics and discrete statistics were used to describe the egg mass distribution. Regression was used to detect and separate macroscale trends from the microscale variation. The presence of macroscale variation indicated a significant edge effect with ovipositing females moving into dry bean fields from their overwintering sites. The microscale variation estimated from the estimated residuals from regressions to estimate trends was studied using semivariograms for all fields. Semivariograms strongly indicate that Mexican bean beetle eggs are randomly distributed across the field and that this random distribution holds across 10-fold differences in population densities. As a result of the significant macroscale trends observed, we conclude that egg mass densities may be greater in areas of the field near edges adjacent to beetle overwintering sites. The probability distribution that best fit the data was the negative binomial. Our results illustrate the importance of scale in discussing and characterizing distribution. Although there is evidence of edge effect at the field level, there is no evidence of spatial dependence between egg samples at the sampling region level. At an even lower level, the egg mass itself, eggs are aggregated.

KEY WORDS *Epilachna varivestis*, geostatistics, probability distribution, sampling

THE MEXICAN BEAN beetle, *Epilachna varivestis* Mulsant, is an important pest of dry bean, *Phaseolus vulgaris* L. In western Nebraska, larval populations reach their peak damage potential in late July to early August. This period coincides with bean flowering and the beginning of the pod filling stages, which are the most susceptible stages to defoliation injury.

Information on adult Mexican bean beetle distribution at an agronomic field scale is not available. Mexican bean beetle females lay clusters of eggs with $\approx 40-60$ eggs per cluster (Howard 1924). Because eggs are laid in masses and larvae do not greatly disperse (Barrigossi 1997), larvae and young adults may have an aggregated distribution. Adult Mexican bean beetles have an aggregated distribution that varies with host patch size in *Phaseolus vulgaris* patches of $\approx 1-10$ m (Turchin 1987, 1988). However, the distribution pattern of older adults and egg masses themselves in commercial-scale dry bean is not known. Egg mass distribution is important for developing an integrated

pest management program for Mexican bean beetle, because sampling for egg masses may be a valuable method for assessing populations in dry bean fields. First generation egg masses are laid before the canopy is large and plants have begun to vine across rows, whereas larvae and adults occur later when beans are larger and vining makes sampling much more difficult. Also, the possibility of inadvertently spreading pathogens is greater during sampling when the canopy is large than earlier in the season.

Determining the probability distribution of a population (the proportions of 0, 1, 2, and so on in sampling from a field population) is necessary for establishing a sampling procedure (Southwood 1978). Combined with knowledge of the spatial distribution of the population (the spatial arrangement of individuals in a habitat), the probability distribution allows a more accurate estimate of the total injury produced and, therefore, a better prediction of yield loss (Hughes and McKinlay 1988). Patterns can be used to decide which field should be sampled first and to indicate in which part of the field sampling should start. It may be possible to restrict sampling to those times and locations that provide the most information, increasing sampling efficiency. However, to reduce sampling, it is important to understand how the spatial relationship of the pest population changes with time

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(Schotzko and O'Keefe 1989, Schotzko and Knudsen 1992). Spatial distribution is affected by factors such as uniformity of the habitat, age of the insect population, host plant density (Bach 1980, Turchin 1987), and sites available for occupation (Schotzko and O'Keefe 1989). Also, distribution patterns may change over time (Schotzko and Knudsen 1992). Traditionally, aggregation was measured as a function of mean and variance. However, mean and variance alone are not enough to describe variation across a spectrum of spatial scale, because the spatial location of the samples is not taken into account (Taylor 1984). Moreover, the results are greatly dependent on the size of sample units (Liebhold et al. 1993). An alternative is to use geostatistics for describing spatial patterns. Geostatistics uses information about both the value and the location of samples to summarize the correlation among points. These methods have the advantage of characterizing spatial contagion across a spectrum of scales and directions. Therefore, geostatistical methods provide better estimates of spatial dependence than dispersion indices (Liebhold et al. 1991).

Geostatistical analysis tests whether the observed value of a variable at one locality is independent of values of the variable at neighboring localities. If dependence exists, the variable is said to exhibit spatial autocorrelation. If a value of the variable at one location tends to be associated with a similar value at neighboring localities, the spatial autocorrelation is positive. If, instead, a value is dissimilar to neighboring values, spatial autocorrelation is negative (Sokal and Oden 1978). In entomology, spatial autocorrelation is generally positive implying that sites with high population densities tend to be surrounded by high populations and sites with low population densities tend to be surrounded by low population densities.

Recently, two geostatistical tools have been implemented in ecological studies: the semivariogram, for modeling spatial dependence and kriging for making estimates at unrecorded locations (Rossi et al. 1992). Kriging generated maps have been used in area-wide management programs for gypsy moth (Liebhold et al. 1991) and grasshopper (Johnson 1989). In this article, we use semivariograms to describe spatial relationships of Mexican bean beetle egg masses in dry bean.

Young and Young (1998) provide a review and discussion of the calculation and use of semivariograms. Briefly, a semivariogram $\gamma(h)$ is a plot of $1/2$ the average squared difference of all points separated by distance (h) versus those distances; that is

$$\gamma(h) = \frac{1}{2N(h)} \sum_{(ij)|h_{ij}=h} (c_i - c_j)^2, \quad [1]$$

where $N(h)$ is the number of pairs separated by distance h , c_i is the value (number of egg masses) for the first member of the pair and, c_j is the value for the second member of the pair. The h indicates not only the distance between points but also the direction. If there is spatial variability and the variances are plotted against their respective h values, the semivariogram values will be small for low values of h , and will in-

crease with larger values of h (greater distances). The values will eventually become constant after some distance, indicating no further spatial influences (Liebhold et al. 1993). Consequently, the shape of the semivariogram provides a picture of the spatial dependence between samples at different distances.

Spatial correlation between samples can occur at different scales. For example, insect eggs might be clumped on the leaf of a plant but the clumps of eggs themselves may be randomly distributed over a field. It is important to distinguish between the trends at the field level versus correlation at some smaller level of interest. Statistically, this is a question of homogeneity in the sampling universe, or what is called intrinsic stationarity (Young and Young 1998). To calculate semivariograms, intrinsic stationarity is assumed. In data sets where this is not the case, such as when insect numbers are greater on one side of a field than another, the data set must be modified by removing these trends. Identifying these trends is important both for allowing the calculation of semivariograms and for describing the biology of the spatial distribution of an insect.

Semivariogram values can be computed either as averages over all directions or specific to a particular direction. Usually, the analysis of spatial continuity starts with an omnidirectional semivariogram in which all possible directions are combined. Because the omnidirectional semivariogram is not affected by direction it is useful to reveal the best distance to produce the clearest structure. If the omnidirectional semivariogram does not produce a clear structure, better results from directional semivariograms usually are not expected (Isaaks and Srivastava 1989). In entomology, semivariograms have been used to demonstrate spatial dependence in *Lygus hesperus* Knight in lentil fields (Schotzko and O'Keefe 1989), *Diabrotica virgifera* LeConte in corn (Midgarden et al. 1993), and *Lymantria dispar* (L.) in forests (Liebhold et al. 1991, Sharov et al. 1996).

In this study, we use geostatistics to describe the spatial variability of Mexican bean beetle egg masses in dry bean fields. This description is based on >12,290 total samples from four fields over 2 yr. The data set includes high and low beetle population densities. Once the spatial structure was described, it was possible to examine if the spatial structure for egg mass densities was aggregated and varied from one sampling area to another.

Materials and Methods

A field study was designed to collect sufficient information to generate semivariograms for describing the spatial structure of Mexican bean beetle egg mass distribution. The study was conducted in Scottsbluff during the 1994 and 1995 growing seasons in four dry bean fields, referred to throughout this paper as field 1-1994, field 2-1994, field 1-1995, and field 2-1995. Field 1-1994 (3.93 ha) was sampled from 29 June to 3 July 1994, and counts were made in 3,840 locations. Field 2-1994 (4.21 ha) was sampled from 5 to 13 July

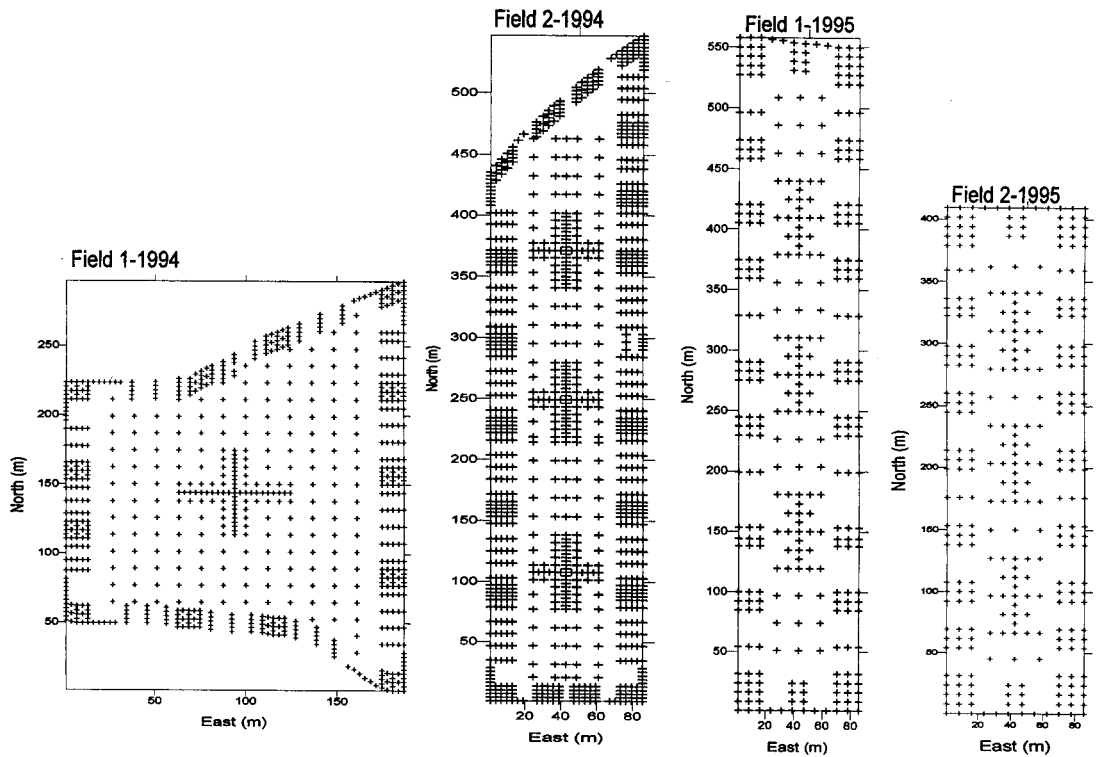


Fig. 1. Locations of the sites where egg mass data were collected. Each "+" represents cluster of five 0.3 row-m sampling units equally spaced at 0.76 m from the central unit.

1994, and counts were made in 5,210 locations. Field 1-1995 (4.78 ha) was sampled on 17 July 1995, and counts were made in 1,695 locations. Field 2-1995 (3.77 ha) was sampled on 18 July 1995, and counts were made in 1,545 locations. In total, 12,290 locations were sampled, which provides a detailed data set for examining spatial variability.

The sampling plan was designed on a regular grid to guarantee coverage of the field and to ensure any directional trends in the data would be discovered. Distances between neighboring sampling locations ranged from 0.76 to 15 m in 1994, and from 0.76 to 30 m in 1995 (Fig. 1). At each sampling location, a cluster of five, 0.3-m sampling units were sampled. Four of these sampling units were equally spaced at 0.76 m in each cardinal direction from the central unit. This sampling scheme ensured that spatial structure could be modeled for reasonably short distances with a good estimate of the nugget effect (the distance between the origin and first point on the semivariogram). Also, five measurements taken together at each location can be combined in different ways to allow estimates of statistics for different sample unit sizes. By comparing these statistics, inferences can be made with respect to the best sample unit size.

To facilitate sampling, flags were used to mark the center of the sampling cluster and to establish a grid where samples would be taken. The experimental unit was the same for all fields sampled and consisted of

0.3 m of row, centered about the flag. All plants in that 0.3-m row space were checked for egg masses. The contrast between the orange color of the eggs with the green of the bean leaf facilitated the egg search. The number of egg masses and the sampling location point were registered for each sampling unit. At the conclusion of sampling, and before the flags were removed from the fields, data were organized according to locations using X and Y co-ordinates. Maps containing all sampling locations were drawn on graph paper to ensure that no mistakes were made when writing the distances in the field. If a mistake was found, the distances in the field were immediately measured.

As recommended for analyzing spatial patterns, an exhaustive exploratory data analysis was undertaken (Young and Young 1998). The first step in spatial description was to post all data locations to certify that no mistakes were made when entering the data. Any blank area indicating missing value was checked with the field map and with the original data set. The computer software used for data posting was SURFER for windows (Golden Software 1994). Postplots were useful to investigate any trends in values from one part of the field to another. In addition to the postplots, h-plots and bivariate scatter plots of the egg mass counts against their east and north directions were constructed to investigate any highly influential observa-

tion and directional trends, which might affect estimates of semivariances (SAS Institute 1985).

The question of directional trends in the data are important, because spatial models generally assume the response variable in question (here egg counts) is intrinsically stationary (the mean does not vary over the sampling region). For the data set to meet the requirement of being intrinsically stationary, two types of variation are recognized: large and small-scale variation. Once large scale variation is removed, small scale variation is described by semivariograms (see Young and Young 1998 for additional details and discussion). Given the biology of Mexican bean beetle, we expected, a priori, that large scale variation might be associated with edge effects as beetles moved into the field to oviposite. Consequently, least square regressions, involving polynomial functions of spatial indices, were used to investigate and to remove large scale variation so that small scale variation could be used to account for the spatial dependence. Four models (linear, quadratic, cubic, and quartic) were tried using PROC GLM (SAS Institute 1985). Cubic trend surface performed best to remove large scale variation (field 1-1994: $F = 13.35$; $df = 9, 3,825$; $P > F = 0.0001$, $r^2 = 0.03$; field 2-1994: $F = 13.33$; $df = 9, 3,825$; $P > F = 0.0001$; $r^2 = 0.03$; field 1-1995: $F = 34.42$; $df = 9, 5,195$; $P > F = 0.0001$, $r^2 = 0.06$; and field 2-1995: $F = 34.42$; $df = 9, 5,195$; $P > F = 0.0001$, $r^2 = 0.06$). The equation used was as follows:

$$\begin{aligned} Count_i &= \beta_0 + \beta_1(east_i) + \beta_2(north_i) \\ &+ \beta_3(east_i * east_i) + \beta_4(east_i * north_i) \\ &+ \beta_5(north_i * north_i) \\ &= \beta_6(east_i * east_i * east_i) \\ &+ \beta_7(east_i * east_i * north_i) \\ &+ \beta_8(east_i * north_i * north_i) \\ &+ \beta_9(north_i * north_i * north_i), \quad [2] \end{aligned}$$

where *i* references individual grid points. The complexity of this model is necessary because of the edge effect associated with Mexican bean beetle oviposition.

After large scale trends were removed, the residuals from the regression were then used to examine the spatial dependence in the egg mass counts. Semivariograms for all sampled fields were generated from the cubic residuals of the trend using PROC VARIOGRAM (SAS Institute 1996). PROC VARIOGRAM computes sample semivariograms, grouping the pairwise distances with LAGDISTANCE = and MAXLAG = options. Because few points will be exactly *h* units apart, distances close to *h* are included in the estimation of $\gamma(h)$. LAGDISTANCE refers to the width of a distance interval at with the pairwise distance interval will be grouped and MAXLAG is the number of intervals. Semivariograms were computed using LAGDISTANCE = 0.77 m and MAXLAG = 100 m. The values established for LAGDISTANCE and MAXLAG are reasonable because there were sufficient pairs of observations available for each lag spacing. Moreover, similar re-

sults were produced with smaller values for MAXLAG. These calculations of the semivariograms provide a robust estimation and are not subject to influence by a high proportion of zeros in the data set (Cressie 1991).

In addition to the geostatistical analysis, we tested seven conventional probability distributions including Poisson, Poisson with zeros, binomial, negative binomial, double Poisson, Neyman type A, Poisson binomial, and logarithmic with zeros. Data analysis started with traditional descriptive statistics to compare the distribution of egg mass counts, using the following SAS procedures: PROC UNIVARIATE, PROC MEANS, and PROC FREQ (SAS Institute 1985). The analysis included descriptions of the spread of values such as the minimum, maximum and interquartile range, measures of central tendency, such as, mean and median, and measures of variability, such as the standard deviation, and coefficient of variation. In addition, skewness and kurtosis were recorded to describe the overall shape of the distributions. To test if the hypothesis that the mean and variance in each sampling field were equal, a chi-square test ($\chi_p^2 = [n - 1] s^2/x^2$) was performed at a 5% level of significance. Because the number of observations was high, the egg mass counts were transformed using the formula

$$[2\chi_p^2]^{-1/2} - [2(n - 1) - 1]^{-1/2}, \quad [3]$$

(Young and Young 1998). This transformed variable *n* as an approximate standard normal distribution under the null hypothesis.

A Fortran program (Gates et al. 1987) for fitting the discrete frequency distributions was used to determine the probability distribution of egg mass populations. The eight possible distributions were tested and the goodness-of-fit was indicated by chi-square test. Observations with an expected frequency value lower than five were pooled until the sum exceeded five. The expected frequencies generated from the probability distribution that best fit the data were plotted in a histogram together with their respective observed values to visually compare observed and expected probabilities.

Results and Discussion

Egg Mass Distribution and Geostatistics. The numbers of egg masses on all sampled dry bean fields are represented in Fig. 2. Field 1-1994 was sampled early in the season and the egg mass population was very low (0.047 egg mass/row-m). The egg population at the north side of the field probably occurred because dry bean was grown in the adjacent field the year before. Field 2-1994 was sampled 1 wk later and had a higher population mean (0.483 egg mass/row-m), and it also showed a trend of higher populations in the northeast of the field. Fields sampled in 1995 exhibited similar patterns as in 1994. Field 1-1995 had a lower mean (0.247 egg masses/row-m) than field 2-1995 (0.647 egg masses/row-m), even though they were sampled 1 d apart.

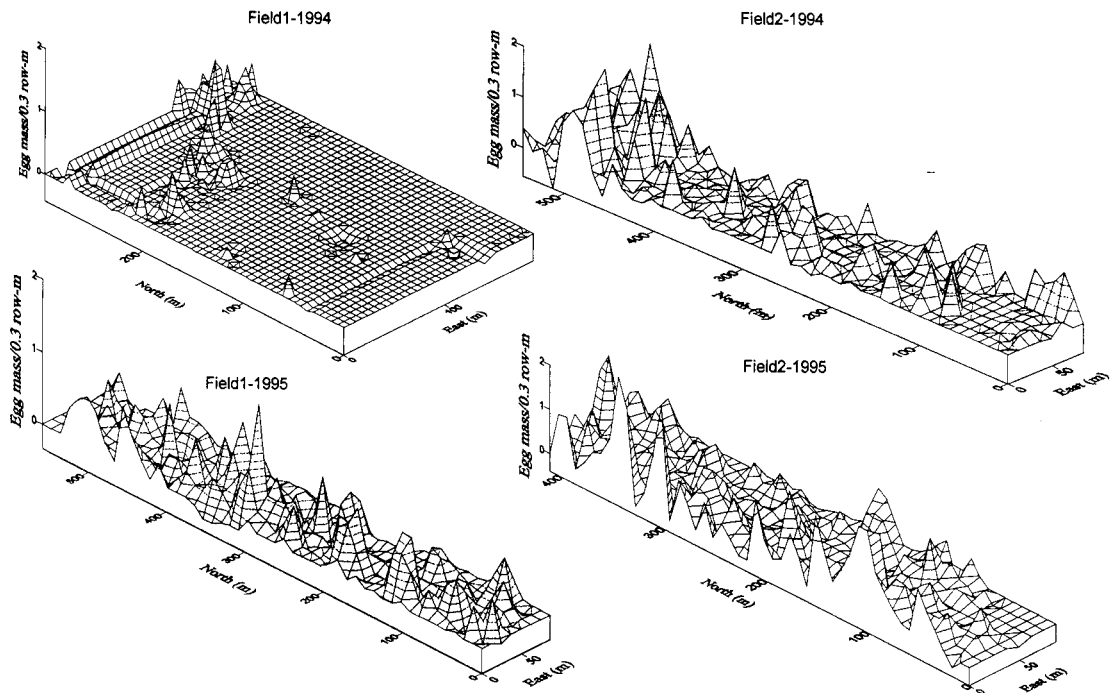


Fig. 2. Three-dimensional plots of Mexican bean beetle egg mass counts in four dry bean fields.

Before estimation of the semivariograms, the assumption of intrinsic stationarity of the error had to be verified (Cressie 1991). Intrinsic stationarity implies that the mean value does not change over the sampling region (Young and Young 1998). Regression analysis revealed the presence of trends in three data sets, violating the assumption of stationarity for semivariogram estimation. Macroscale variation was removed, and semivariograms for all fields were estimated using the residuals from fitting the cubic trend surface. Trend removal had a strong effect on the shape of the semivariograms. The cubic trends were significant for all fields, except for field 1–1995. Therefore, spatial representation changed significantly after trends were removed.

The biological meaning of significant macroscale trends in three of four fields is that egg masses in the fields were not randomly distributed at the field level. Fig. 2 indicates the raw values for egg mass distribution across fields, and Fig. 3 shows the distribution of these egg masses as predicted by the cubic regression (significant at the 0.05 level for all fields except field 1–1995). The field immediately north of field 1–1994 was planted to dry bean in 1993 and was a likely overwintering site and source of ovipositing Mexican bean beetles in 1994. Similarly, dry bean fields were located to the east of field 2–1994 and field 2–1995 in the previous year. The greater numbers of beetles on the east sides of these fields undoubtedly reflects movement from overwintering sites. A dry bean field had been located immediately east of field 1–1995 in the previous year, therefore we might anticipate the

same pattern of egg mass distribution in this field as in field 2–1994 and field 2–1995. Substantially smaller beetle populations in field 1–1995 and the narrow width (only 80 m) may have obscured movement of beetles from the east. In total, the results of the macroscale variation demonstrate a significant edge effect with ovipositing females moving into dry bean fields from their overwintering sites.

Standard omnidirectional semivariograms generated from each field data set are presented in Fig. 4. For all data sets, the general shape of the semivariogram is similar. All semivariograms are entirely flat and exhibit only a pure nugget effect. The only variation is that associated with the difference between the first measurement and the origin. These patterns indicate that no detectable spatial dependence occurred at the scales sampled. Interpretation of these semivariograms indicates that egg masses are laid at random; therefore, density at any sampled point has no predictive value for egg mass density nearby. No attempt was made to determine spatial continuity with directional semivariograms because no spatial correlation was found in omnidirectional semivariogram (Isaaks and Srisvastava 1989).

The semivariograms in Fig. 4 strongly indicate that Mexican bean beetle eggs are distributed randomly and that this random distribution holds across 10-fold differences in population densities (between means of 0.014 and 0.194 egg masses/0.3 row-m). In combination with the significant macroscale trends observed, we can conclude that egg mass densities of Mexican bean beetle may be greater in areas of the field near

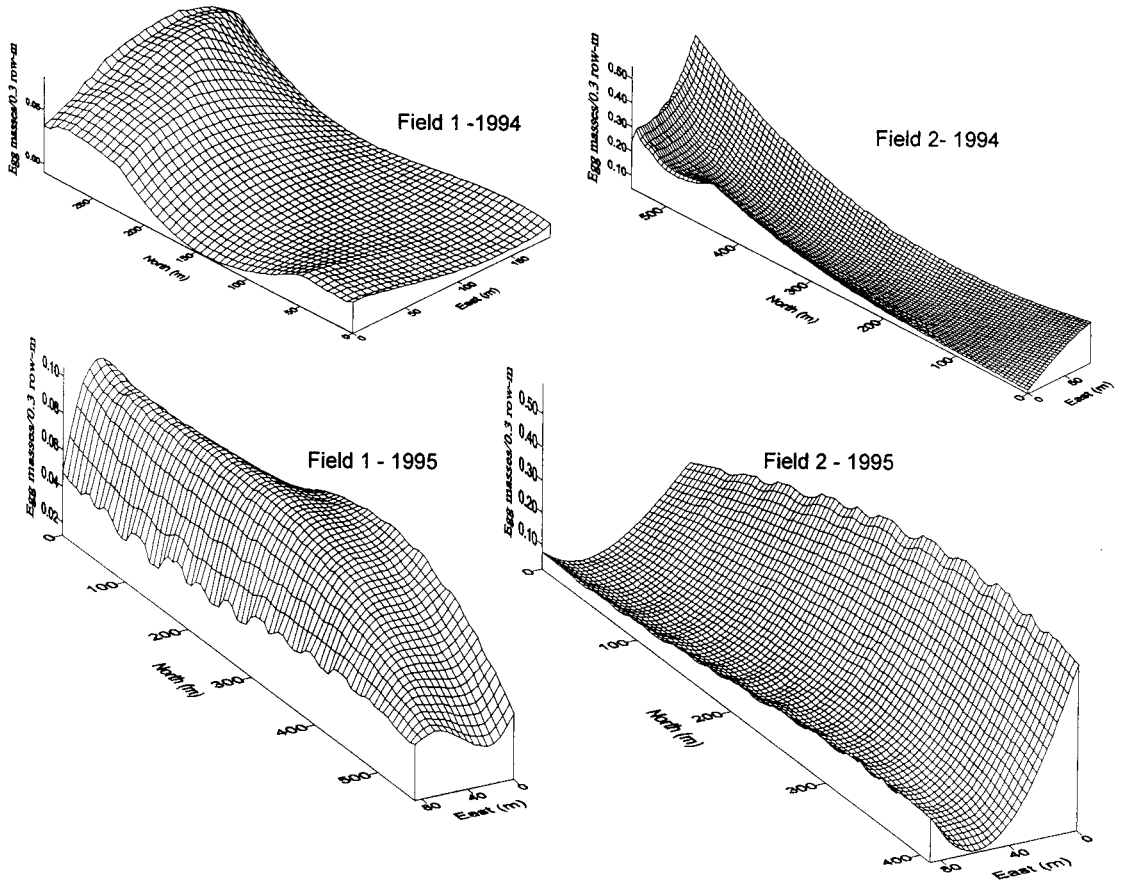


Fig. 3. Three-dimensional plots of the estimated trends, by cubic regression, of Mexican bean beetle egg masses in four dry bean fields.

edges adjacent to beetle overwintering sites (typically where dry beans were grown the previous year). At smaller scales (below field level), there is no evidence of spatial correlation among egg masses. Practically, these results indicate that it may be more efficient to sample field edges near overwintering sites because densities are likely to be greater. But egg mass distribution within these areas will be random.

Egg mass distribution is not clumped, although eggs themselves obviously are clumped in masses. Larvae do not disperse far from the egg mass, typically no more than 1.8 m from the egg mass and often within 0.6 m (Barrigossi 1997), so larval aggregation is a reflection of oviposition via egg masses. Presumably, pupal distribution and that of general adults would be similar to that of larval Mexican bean beetles. Aggregative behavior by Mexican bean beetle adults, reported by Turchin (1987) is not reflected by patterns of egg mass distribution in this study. Indeed, if egg mass distribution is representative of female Mexican bean beetle distribution, then this data set indicate that females are not aggregated, at least during oviposition in commercial-scale dry bean fields. Because

previous work on adult Mexican bean beetle distribution focused on relatively small habitat patches, it may be that adult distribution at least as evidenced by ovipositional patterns is more random where the resource (i.e., host plants) is less limiting.

Probability Distributions. The frequency distribution of the Mexican bean beetle egg masses was positively skewed in all fields sampled. In 1994, no egg mass was found in 98.6 and 87.4% of the sampling units in field 1-1994 and field 2-1994, respectively. In 1995, the percentages of sampling units free of egg masses were 93.5 and 84.9%, respectively, in field 1-1995 and field 2-1995. Most of the infested sampling units had only one egg mass, even though the range was higher in 1995 (Fig. 5).

A chi-square test of the variance to mean ratio was highly significant for all fields, indicating the null hypothesis that the mean and variance are equal should be rejected (field 1-1994: $\chi^2(3,839) = 4,058, P < 0.001$; field 2-1994: $\chi^2(5,209) = 6,063, P < 0.001$; field 1-1995: $\chi^2(1,694) = 2,191, P < 0.001$; field 2-1995: $\chi^2(1,545) = 2,254, P < 0.001$. Table 1 shows the chi-square values for goodness-of-fit to standard probability distribu-

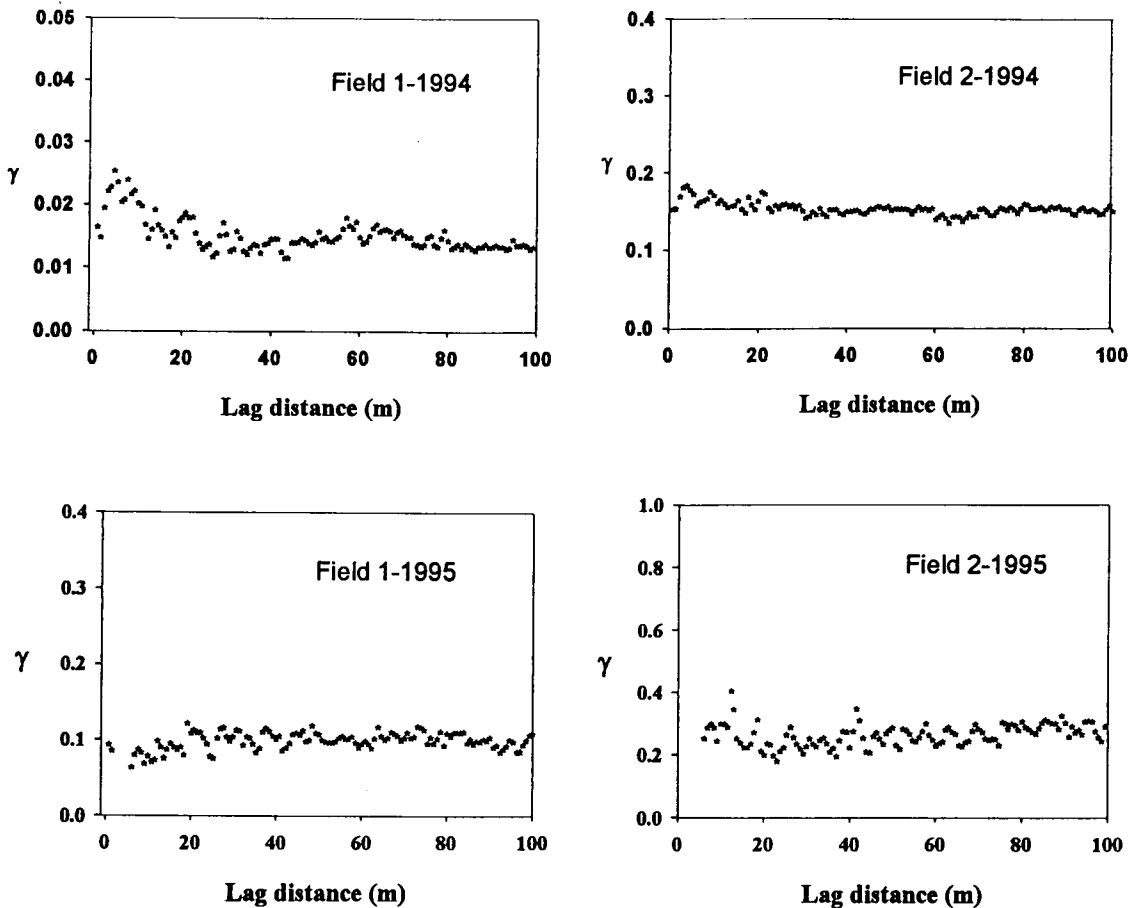


Fig. 4. Standard semivariogram plots of the Mexican bean beetle egg masses in four dry bean fields. γ is the semivariance for each lag distance.

tions for all fields sampled. No distributions could be tested for field 1-1994, because too few classes were available in the data set (i.e., all points were zero or one). The null hypothesis tested was that the distribution in question represents a good model for fitting the data (the observed equal the expected value). Therefore, a significant chi-square indicates the distribution failed to fit the observed data. As indicated in Table 1, the null hypothesis could be accepted (chi-square not significant) only for the negative binomial distribution in all fields in all years, although the Newman type A distribution fit the data for two of three fields tested. Estimated K values from the negative binomial of three fields were 0.93, 0.28, and 0.49, respectively, for field 2-1994, field 1-1995, and field 2-1995. Given the very large number of samples used to fit distributions (5,210 for field 2-1994, 1,695 for field 1-1995, and 1,545 for field 2-1995), it is somewhat surprising that an adequate fit was obtained for any distribution.

It is important to distinguish between probability distribution and spatial pattern. Often a significant fit

to a probability distribution is used incorrectly as evidence of spatial distribution, such as an aggregated spatial distribution with a significant fit to the negative binomial (Young and Young 1998). Properly, however, spatial distribution cannot be assumed from probability distributions alone. Results from this study clearly demonstrate this point. Although data fit a negative binomial probability distribution, the geostatistical analysis demonstrates field-level trends in spatial distribution of egg masses and a random, or spatially independent, distribution of egg masses at the sampling-region level.

Interpretation and Implications. Patterns of herbivore dispersal are associated with the availability of food (Crawley 1983), as well as other factors. Where food distribution is patchy, beetle distribution is likely to be patchy. In a large host site like a commercial dry bean field, we would not expect beetle distribution to vary because of limited host differences. However, even in large bean fields some heterogeneity is possible. For example, differences in plant densities across a field have been reported to result in greater

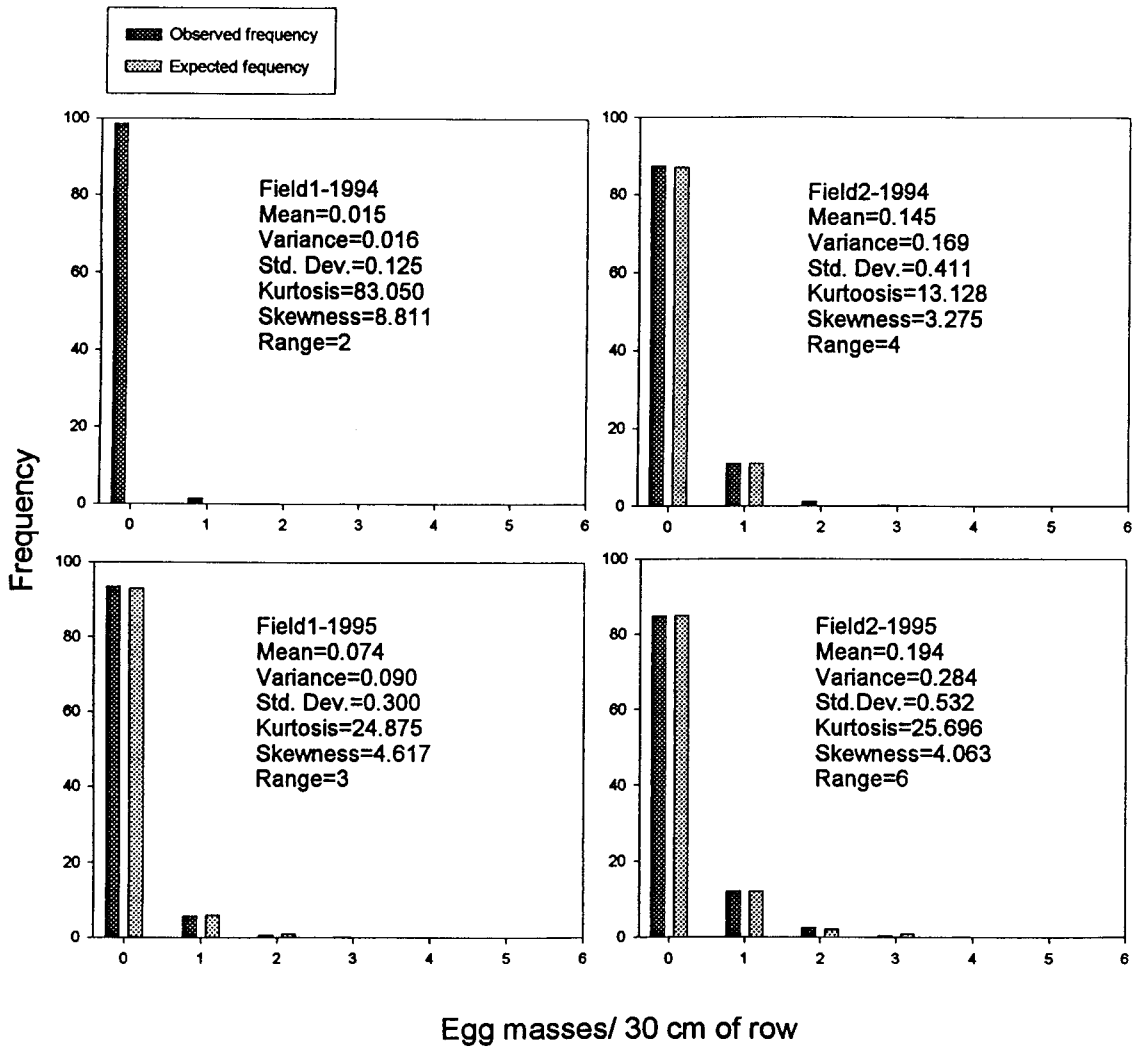


Fig. 5. Frequency distribution and summary statistics of Mexican bean beetle egg mass in dry bean fields.

infestations of Mexican bean beetles with high plant densities (Turner and Friend 1933). Similarly, differences in plant phenology within a field might produce variation in host use by adult Mexican bean beetles.

One effect of irrigating dry beans is to remove some of the variation among plants associated with different availability of water across a field. Consequently, in irrigated dry bean production, plant conditions should

Table 1. Chi-square and P-values testing the null hypothesis that the observed egg mass distribution fits a given distribution (therefore, a significant chi-square shows lack of fit)

Distribution	1994				1995			
	Field 1		Field 2		Field 1		Field 2	
	χ^2	P-value	χ^2	P-value	χ^2	P-value	χ^2	P-value
Poisson	-	-	83.1	<0.01	27.3	<0.01	67.4	<0.01
Poisson with zeros	-	-	6.6	<0.01	1.5	0.10	9.3	<0.01
Binomial	-	-	237.9	<0.01	41.3	<0.01	116.8	<0.01
Negative binomial	-	-	2.1	0.16	0.2	0.28	1.4	0.40
Double Poisson	-	-	5.2	0.01	2.0	0.08	10.7	<0.01
Neyman type A	-	-	3.8	0.03	1.1	0.15	4.4	0.11
Poisson binomial	-	-	5.2	<0.01	2.1	0.07	12.9	<0.01
Logarithmic with zeros	-	-	0.5	0.24	0.5	0.42	11.4	<0.01

be sufficiently uniform that substantial plant discrimination by feeding or ovipositing Mexican bean beetles seems unlikely. Data in this study regarding oviposition supports this point.

Results of this spatial analysis will be useful in developing sampling plans for Mexican bean beetles. Although populations across the entire field should be sampled, particular attention should be given to field edges near Mexican bean beetle overwintering sites, where egg mass densities may be larger. Greater injury to dry bean in these areas seems likely. Because the semivariograms showed that spatial dependence did not occur at scales below the field level, sampling locations within sections of the field can be chosen at random. Also, the random distribution of egg masses and limited dispersal by larvae indicate that injury from Mexican bean beetle should be randomly distributed within a given section of field, although sections near edges by overwintering sites may experience more total injury. Despite the overall random distribution of egg masses, some patchiness of injury may be noted in association with individual egg masses. The lack of spatial correlation between egg mass samples at any distance indicates that in a sampling program designed to estimate mean density, individual samples need not be separated by large distances.

The data set obtained in this study is the largest we are aware of for characterizing an insect distribution. Consequently, interpretations of data are not limited by the size of the data set as often occurs. These findings illustrate the importance of scale in discussing and characterizing distribution. At the field level we see evidence of edge effects, with higher egg mass densities near field edges associated with Mexican bean beetle overwintering sites. At the sampling region level, we see no evidence of any spatial dependence between egg mass samples. At an even lower level, the egg mass itself, eggs are aggregated. Because larvae do not greatly disperse, larval distribution and corresponding larval injury to dry bean will be aggregated in plants around the oviposition site of the egg mass. These results highlight the great importance of scale when discussing distribution patterns.

A final point from these data and our analysis is the illustration of the value of geostatistics in describing distribution. Although our data set is perhaps exceptional, given the very large number of samples we collected, geostatistical techniques do not require such large sample sizes and can be used with much smaller data sets. With the geostatistical analysis we were able to describe macro and sampling region distribution of Mexican bean beetle egg masses with considerable detail. Additionally, our results demonstrate the fallacy of associating probability distribution with spatial distribution. Our data do fit a negative binomial distribution, but this does not mean the egg mass samples have an aggregated spatial distribution. Indeed, semivariogram indicate just the opposite—spatial independence between egg mass samples.

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