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Research Article

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Abstract
Infestations of corn rootworms (Coleoptera: Chrysomelidae) create economic and environmental concerns in the Corn Belt region of the United States. To supplement the population control tactics of areawide pest management programs, we believe that a better understanding of the spatial relationships between biotic and abiotic or physical factors at the landscape scale is needed. Our research used several geographical information systems (GIS) and spatial analytical techniques to examine relationships between corn rootworm metapopulation dynamics, soil texture, and elevation. Within GIS, several spatially explicit procedures were used that include an interpolation technique, spatial autocorrelation analysis, and contingency analysis. Corn rootworm metapopulation distributions were found to be aggregated and related to soil texture and elevation. We review techniques and discuss our preferences for using particular spatially explicit procedures. The information derived from the spatial analyses demonstrates how GIS can be used in areawide pest management to provide inputs for spatially explicit models to predict future pest populations and formulate more well-informed pest management decisions. The techniques described in this paper could easily be extended to study the spatial dynamics between other pest populations in agricultural landscapes.

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1 Introduction

Corn rootworms (Coleoptera: Chrysomelidae) are among the most serious insect pests in the United States. Corn rootworm adults feed on various vegetative parts of the maize (*Zea mays* L) plant, while larvae, causing the most severe damage, feed on maize roots. Structural damage to the roots is caused by larval feeding, which inhibits nutrient and water uptake, and weakens the root system leading to stalk lodging (Chiang 1973). Severe stalk lodging causes the maize plant to fall completely over, but usually the lodged plant continues to grow toward the sunlight leading to a curved plant or what is commonly called goosenecking. Because these lodged plants are shorter than undamaged plants they usually are not harvested. Therefore, corn rootworm infestations cause yield reductions, costly chemical applications, and increases in environmental contaminants due to surface water runoff and groundwater alterations. In order to explore new, more environmentally-friendly corn rootworm control options, the United States Department of Agriculture (USDA), Agricultural Research Service (ARS) implemented an areawide pest management initiative in 1995 (Chandler and Faust 1998, Chandler et al. 2000). This initiative maintains several locations in the United States Corn Belt and relies on management of adult corn rootworm populations over large geographical areas (landscape scale). In 1996, the ARS initiated the corn rootworm areawide management program that uses action thresholds to determine appropriate timing for applications of toxic bait formulations that will reduce corn rootworm populations, enhance environmental compatibility, and increase economic gains by producers (Chandler and Faust 1998).

From a landscape perspective, the shape, size, and arrangement of habitat patches can affect species distribution in space (Forman and Godron 1981, Turner 1989, Pickett and Cadenasso 1995, Collinge and Forman 1998). Members of species that interact among habitat patches via dispersal form a metapopulation (Opdam 1988). A metapopulation is spatially subdivided into a series of local populations or subpopulations, and these subpopulations occur in habitat patches that are immersed in a complex mosaic of other habitat patches, corridors, and boundaries (Wiens 1997). A metapopulation can be composed of either a single species or multiple species, depending on ecological relationships such as competition, predation, and mutualism (Nee et al. 1997). A corn rootworm metapopulation consists of multiple subpopulations each inhabiting maize fields (i.e. patches) that are separated by other spatially distributed crop fields, roads, shelterbelts, water bodies, and other land cover types. In addition to structural characteristics of habitat patches, abiotic or physical factors in the landscape and species behavioral characteristics can influence the distribution of a metapopulation. For example, soil properties and topography can influence insect distribution. The microhabitat of a preferred oviposition site for female corn rootworms is influenced by soil properties such as type, texture, moisture content, and compaction (Kirk et al. 1968, Ruesink 1986). Certain soil textures can also influence the mortality rate of corn rootworm larvae (Turpin and Peters 1971). In addition, corn rootworms are associated with microhabitats that result from differences in topography in the landscape (Hill and Mayo 1980). Therefore, to better understand some of the sources of variability in arthropod abundance, distribution, and diversity, it is important to view the agricultural mosaic at the landscape scale (Landis 1994).

To manage an insect metapopulation at the landscape scale, one must process spatial data layers. GIS are becoming increasingly more important in pest management programs because they can be used to create maps and conduct geostatistical analysis of spatial interactions that occur at much larger scales (Roberts et al. 1993). The use of

GIS to relate insect distributions to physiographic elements of the landscape is essential for pest managers to predict future pest metapopulation dynamics. This prediction is accomplished by analyzing map layers and field data to examine spatial relationships over time. In addition to using GIS to relate insect metapopulations to biological and physiographic elements of the landscape (Liebhold et al. 1993), GIS are used to analyze impacts of climate change on insect distributions (Williams and Liebhold 1995) and to improve pest scouting practices (Lefko et al. 1998).

There are many available spatial analytical techniques that can be employed to analyze the distribution of corn rootworms. To map populations over sampled and unsampled areas, a multitude of interpolation methods exist. The interpolation process calculates predicted values (unknown) within a site by using georeferenced (known) point locations and the associated table of population data (McCoy and Johnston 2002). To describe these mapped populations in spatial terms, some type of autocorrelation analysis can be used. This procedure determines the spatial distribution or dispersion pattern (i.e. random, uniform or regular, and aggregated or clumped) of the population in question by measuring the relationship between aspatial (i.e. soil type, land use class, and population densities) attributes of objects (i.e. trap sites) with the distance between the objects (Griffith 1987). For example, two objects that are close together and have very similar aspatial descriptors are highly spatially correlated (Goodchild 1986). To measure the relationships between physical factors and population abundance, contingency analysis can be used. Contingency analysis compares the values of one map layer with those of a second map layer and tabulates the frequency of each possible combination of both variables (McGrew and Monroe 2000).

In this paper, we describe the use of GIS and spatial analysis to interpret patterns of spatial variation in corn rootworm abundance. For the purpose of this paper, we considered the two common regional corn rootworm species (northern corn rootworm *Diabrotica barberi* Smith and Lawrence and western corn rootworm Diabrotica *virgifera virgifera* Leconte) as one metapopulation. We treat the two species as one metapopulation because management decisions are based on the cumulative numbers of both species where their distributions overlap, and we wish to emphasize our GIS techniques and not the biology of each species. Our analyses focuses on examining spatial relationships between corn rootworm metapopulation dynamics, soil texture, and elevation from 1997 to 2001 at the corn rootworm areawide pest management site in Brookings County, South Dakota. To analyze these relationships, we used several spatially explicit procedures within a GIS, which include an interpolation technique, spatial autocorrelation analysis, and contingency analysis (Figure 1). Finally, we discuss our preferences for using particular procedures compared to other available techniques and illustrate the use of these outputs in the further development of areawide pest management programs. We believe that a better understanding of the spatial interactions that occur with insect pests and the landscape can generate information for spatially explicit models to predict future metapopulation dynamics and formulate well-informed management decisions.

2 Methodology

2.1 Description of Study Area

Spatial dynamics of the corn rootworm were characterized over a five year period (1997 to 2001) at the South Dakota Areawide Management Site. This site was located

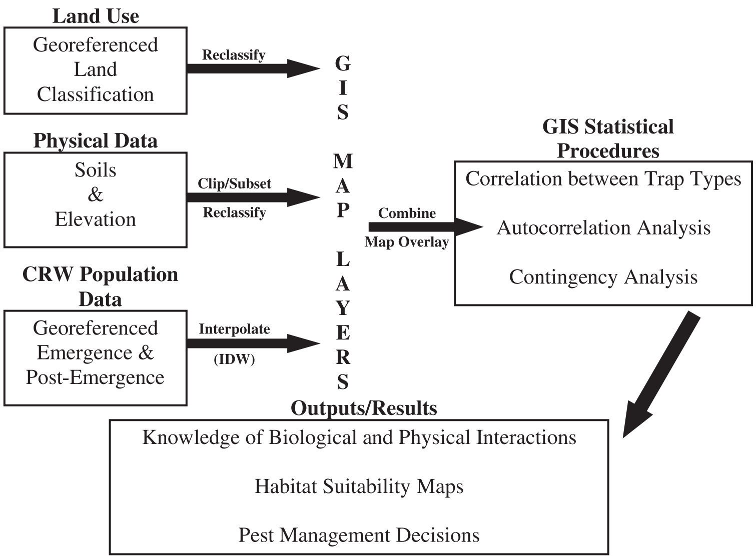

Figure 1 A schematic flow diagram of the spatial analytical techniques used and resulting outputs for this pest management application

in Aurora Township about 3.2 km east of Brookings, South Dakota. It encompasses 41.4 km^2 (16 square miles) and contains about 60 maize fields, depending on the year.

2.2 *Trapping Methodology*

We used different trapping procedures to collect adult corn rootworm beetles. To study the relationships between environmental and edaphic factors with corn rootworm population dynamics, an absolute population estimate was needed (Tollefson and Calvin 1994). Therefore, emergence traps were used to obtain an absolute estimate of the number of corn rootworms that completed development within a maize field. These traps (0.6 m × 1.0 m) were placed directly over five cut plants in the crop row to capture beetles as they emerged from the soil. We also used Pherocon AM® yellow sticky traps (post-emergence) to monitor adult populations throughout the growing season. The passive post-emergence traps (0.2 m × 0.3 m) were clamped onto wood lathes placed between crop rows within each field. We placed these traps at ear height of the maize plant, or approximately 1 m above the soil surface. As beetles flew through the field, they were captured on the adhesive surface of the trap.

The number of post-emergence and emergence traps used in each field varied with field size. Based on previous methods developed by Gerald Sutter (unpublished data), 12 traps were placed in fields of ≥47 ha, nine traps in fields of 25–46 ha, six traps in fields of 10–24 ha, and three traps in fields of ≤9 ha. The traps were placed along measured transects approximately 60 m apart in the field during mid-to late June each year, depending on weather conditions. All traps were collected weekly through vital stages of maize phenology (i.e. no further yield damage could occur from the beetles). The weekly totals were combined for each year from 1997 to 2001.

2.3 Land Use and Trap Location

Fields of maize and soybean (*Glycine max* L Merr) were first georeferenced in 1997 using handheld Trimble GeoExplorer II (Trimble, Sunnyvale, CA) Global Positioning System units. All land features (fields, roads, streams, etc.) were mapped between 1997 and 2000 and classified according to vegetation type. Trap locations were also georeferenced in 1998, 1999, and 2000 and classified by trap type. Trap locations were not georeferenced in 1997, and land features were not georeferenced in 2001; instead they were deduced from prior georeferenced trap locations and crop fields from the 1998, 1999, and 2000 maps. The georeferenced data were differentially corrected using Trimble Pathfinder Office 2.01 (Trimble, Sunnyvale, CA) and exported into shapefiles and projected to match other spatial datasets (i.e. population abundance, soils, and elevation maps). The projection used for all georeferenced data was Universal Transverse Mercator (UTM) Zone 14 using the Clarke 1866 Spheroid. The resulting shapefiles were exported into ArcGIS Desktop 8.x (ESRI, Redlands, CA) and converted to coverages. The computerized tables containing the number of corn rootworms captured were imported into the trap location tables.

2.4 Species Abundance Layers

The species population abundance maps were created using the 'Interpolate to Raster' tool in the ArcGIS 8.x Desktop Spatial Analyst extension to estimate corn rootworm abundance from the georeferenced trap locations. We used the Inverse Distance Weighted (IDW) method of interpolation to create the abundance maps. This method estimates the values of sample data points in the vicinity of each cell. The closer the point is to the cell center being estimated, the more influence it has in the averaging process. With IDW, the exponent or power value controls the significance of known georeferenced points upon the interpolated values, based upon the distance from the output point (McCoy and Johnston 2002). A high power value (3–5) emphasizes nearer points and smoothes local differences while a low value (0–2) emphasizes points further away, resulting in either a more detailed, less smooth output surface or a smoother surface with less detail, respectively (Krajewski and Gibbs 2001). We chose the most commonly used, and default, power value of 2. A search radius (fixed or variable) can also influence the characteristics of the interpolated surface or map layer by limiting the number of input points for calculating each interpolated cell (McCoy and Johnston 2002). The fixed search radius requires a distance and minimum number of points while the variable search radius requires the number of points and an optional maximum distance. We used the default variable search radius, with 12 input points to allow for variable search neighborhoods, depending on the density of measured points near the interpolated cell. The resulting maps were in a raster grid format with 26.4 m cell size.

2.5 Soil Texture

The five major soil textures found at the management site were extracted from the geographic soil survey (SSURGO) database for Brookings County, South Dakota provided by the USDA Natural Resource and Conservation Service data clearinghouse (www.ftw.nrcs.usda.gov/ssur_data.html). SSURGO consists of georeferenced digital map and attribute data in a 7.5-minute quadrangle format.

A soil coverage was created from the Brookings County SSURGO dataset to cover only the extent of the management site. The 'Clip' tool was used in ArcGIS Desktop 8.x to extract the SSURGO dataset. A surface texture item was added to the soil coverage and the surface texture attribute, found in the "COMP" table of the SSURGO dataset, was linked to each map unit (MUSYM). The soil texture coverage was reclassified into a raster grid with 26.4 m cell size and five major soil texture classes.

2.6 Elevation

The five major elevation classes found at the management site were extracted from United States Department of Interior Geological Survey digital elevation models provided by an online database (www.gisdatadepot.com). The dataset consists of georeferenced digital map and attribute data in a quadrangle format. The scale of the digital elevation model is 1:24,000 (30 m cell size) and the vertical accuracy is equal to or better than 15 m.

An elevation raster grid was created from the Brookings County dataset to cover only the extent of the management site. The 'Subset' tool was used in ERDAS Imagine 8.4 (Leica Geosystems, Atlanta, GA) to manipulate the digital dataset. The range of elevation was 494 m to 519 m. The clipped elevation raster grid was reclassified into a new raster grid with 26.4 m cell size and five equal-interval elevation classes.

2.7 Statistical Analysis

To measure corn rootworm spatial distribution, the Moran's *I* coefficient was used to determine the degree of autocorrelation for the interpolated species abundance maps. Using Idrisi 32.22 GIS software (Clark Labs, Worcester, MA), the 'Autocorr' command calculated a Moran's *I* coefficient for each raster grid. In a raster grid, the objects correspond to the cells and the aspatial attributes correspond to cell values. The Moran's *I* coefficient describes the degree to which values in any cell will be similar to the cells surrounding it. When adjacent cells are very dissimilar (negative or random spatial autocorrelation), the coefficient is –1, when they are very much alike (positive or aggregated spatial autocorrelation), the coefficient is +1 (Vasiliev 1996). The King's Case procedure was used, which examines the cells diagonally connected to each cell as well as those normally examined for the Rook's Case, which examines only cells to the left, right, above, and below each raster grid cell. Diagonal cells are given a weight of only 0.7071, relative to a weight of 1.0 to those vertically or horizontally adjacent (Eastman 2001).

Contingency analysis was used to analyze the relationship between corn rootworm populations, soil texture, and elevation. To do this, we had to determine whether to use emergence or post-emergence traps in the analysis. Corn rootworm emergence probably correlates with optimal conditions for oviposition and larval survival and should associate with edaphic factors like soil texture and topography (Tollefson and Calvin 1994). However, the number of emergence cages in the management site was much fewer than the number of post-emergence traps. Hence, the post-emergence traps covered a broader extent of the management site than emergence cages, and encompassed all elevation classes and soil types. These traps are also less cumbersome to handle and process than emergence cages, commercially available, and provide a relatively accurate estimation of population abundance (Hein and Tollefson 1984, 1985; but see Gray and Steffey 1995). In addition, the post-emergence traps were successfully used as a population control technique (i.e. triggered pesticide applications) in the South Dakota management site as well as corn rootworm management sites in Illinois/Indiana, Iowa, Kansas, and Texas (Chandler and Faust 1998, Tollefson 1998, Wilde et al. 1998). Therefore, a significant correlation between corn rootworm emergence and post-emergence would justify using post-emergence interpolated maps in determining relationships with soil texture and elevation.

The ArcInfo 8.x GRID module (ESRI, Redlands, CA) was used to compute a correlation coefficient that compared emergence and post-emergence population abundance raster maps. The 'Correlation' command calculates the cross correlation or degree of similarity between the cells of two input grids (emergence and post-emergence) and outputs a correlation coefficient. The resulting correlation coefficient will be a value ranging from –1 to +1. If the two grids are highly correlated the coefficient will equal +1, if they are independent, 0, and if there is a strong negative correlation the output value will equal –1 (Chou 1997). Significance of each correlation coefficient was determined from a table of critical values of the correlation coefficient (Zar 1984).

To run the contingency analysis, post-emergence abundance raster maps were classified by year into five classes (showing the number of WCR captured/trap). The natural breaks classification scheme was used to identify natural groupings of data based on breakpoints inherent in the data resulting in classes with varied class breaks, minimum values, and maximum values for each of the five years (Abler et al. 1971, Monmonier 1977, Hatakeyama et al. 2000). For each year, the data layers, soils, elevation, and population, were imported into Idrisi 32.22 GIS software and masked using the 'Query' command to display only those portions of map layers covering maize fields. The mask raster grid was created with ArcGIS 8.x Desktop Map Calculator using conditional statements. Within Idrisi 32.22 GIS software, the 'Crosstab' command created a contingency or cross-tabulation table and measures of association. The measures of association were a chi-square statistic and Cramer's V coefficient that measured the degree of association between the variables. The Cramer's V coefficient ranges from 0.0 indicating no correlation to 1.0 indicating perfect correlation (Ott et al. 1983, Siegel and Castellan 1988, Bonham-Carter 1994). Significance of each chi-square statistic was determined from a table of critical values of the chi-square distribution (Zar 1984).

3 Results

3.1 Map layers

Land use coverages were reclassified by vegetation type into continuous maize, first year maize, mixed maize, other maize, and soybeans for each year from 1997 to 2001 (see 1997 for example; Figure 2). The latter was classified and deemed important because of the prominent maize-soybean rotation in the management site. Continuous maize fields are fields that were planted to maize for two or more consecutive years. First year maize fields are fields that were planted to a crop other than maize the previous year (usually soybeans). Mixed maize fields are fields that were planted to two or more crops (i.e. maize and soybean) the previous year. Other maize fields are fields that include maize for human consumption or maize test plots and make up only a small portion of the maize planted in the management site. Over the five year period, the agricultural landscape was dominated by the maize-soybean crop complex. Figure 2 also illustrates the placement of the georeferenced locations of emergence cages and sticky traps

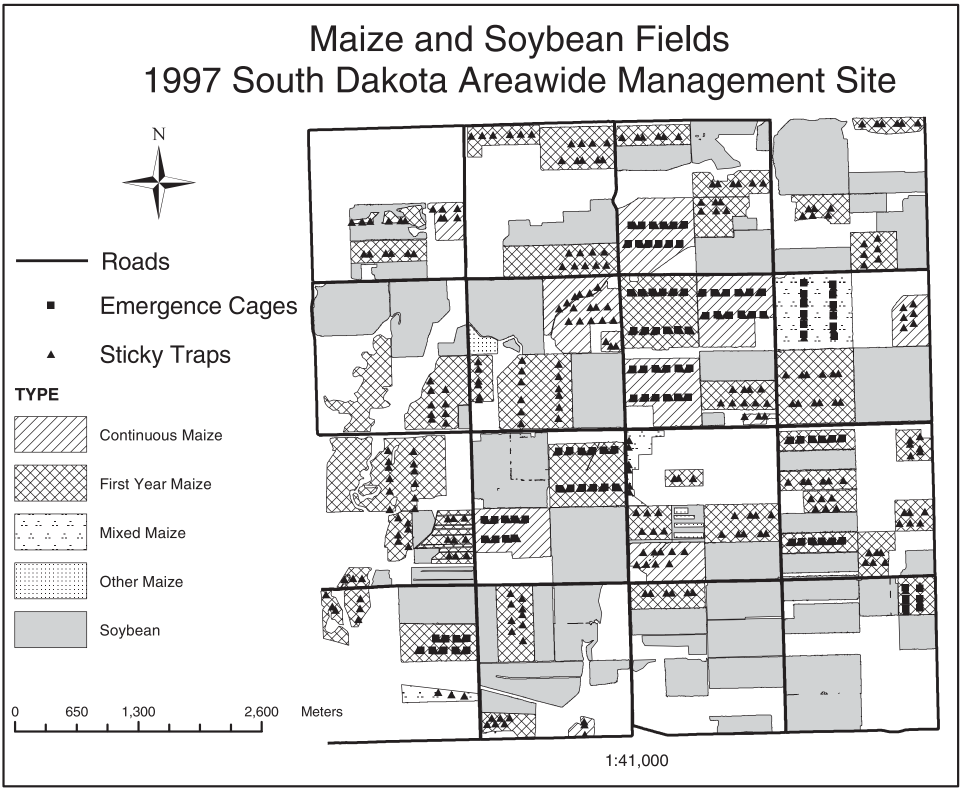

Figure 2 Vector map layer illustrating roads, emergence cages and sticky traps (post-emergence), and crop fields found at the South Dakota Areawide Management Site in 1997

(post-emergence) in 1997. The post-emergence traps were distributed much more widely compared to emergence traps, covering nearly all maize fields.

The soil texture raster map contains five major soil texture classes found at the management site. These include (with percent occupied in landscape) silty clay (0.3%), silty clay loam (31.4%), silt loam (17.7%), loam (47.7%), and sandy loam (2.9%). The elevation raster map contains five equal-interval elevation classes found at the management site. These include (with percent occupied in landscape) 494–499 m (24.1%), 500–504 m (34.6%), 505–509 m (22.4%), 510–514 m (17.7%), and 515–519 m (1.2%).

The interpolated corn rootworm map layers illustrate the spatial distribution of the corn rootworm emergence and post-emergence metapopulation over the management site (see 1997 for example; Figures 3 and 4, respectively). The raster maps illustrate the range of interpolated cell values with varying low and high values for each year. By visual inspection alone, the maps depict the nature of the clumped or aggregated spatial distribution of corn rootworms.

3.2 Autocorrelation Analysis

We used the interpolated population raster map layers to conduct autocorrelation analysis to determine cell value statistics and type of spatial distribution exhibited by the

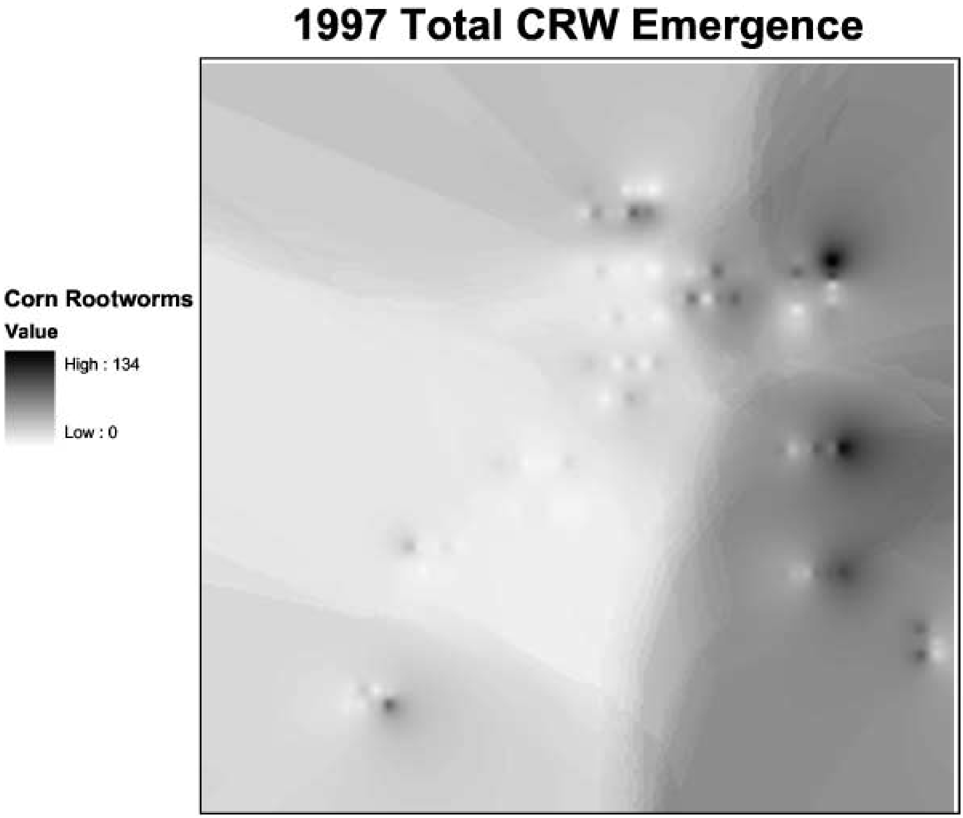

Figure 3 Raster map layer illustrating interpolated values of corn rootworm (CRW) emergence at the South Dakota Areawide Management Site

corn rootworm metapopulation (Table 1). Mean cell values and standard deviations based on the IDW interpolation indicate the average condition and variation for estimated population values in each map layer. Mean cell values of corn rootworm emergence decreased from 1997 to 1998 and increased again in 1999, followed by a decline from 1999 to 2001. Mean cell values of corn rootworm post-emergence increased from 1997 to 1999 and decreased from 1999 to 2001. There were large deviations from the mean for all map layers. In addition to general metapopulation fluctuations estimated by the cell statistics, the Moran's *I* coefficient indicated the dispersion pattern for each population map layer. Each of the corn rootworm emergence and post-emergence surfaces had Moran's *I* coefficients near +1, which indicates a highly aggregated metapopulation within the management site for all five years (Table 1).

3.3 Contingency Analysis

There were significant correlations between corn rootworm emergence and post-emergence interpolated maps for all five years (Table 2). Corn rootworm populations occurred most frequently on loam and silty clay loam soil textures (Table 3). Corn rootworms also occurred on silt loam soil textures, but in smaller proportions.

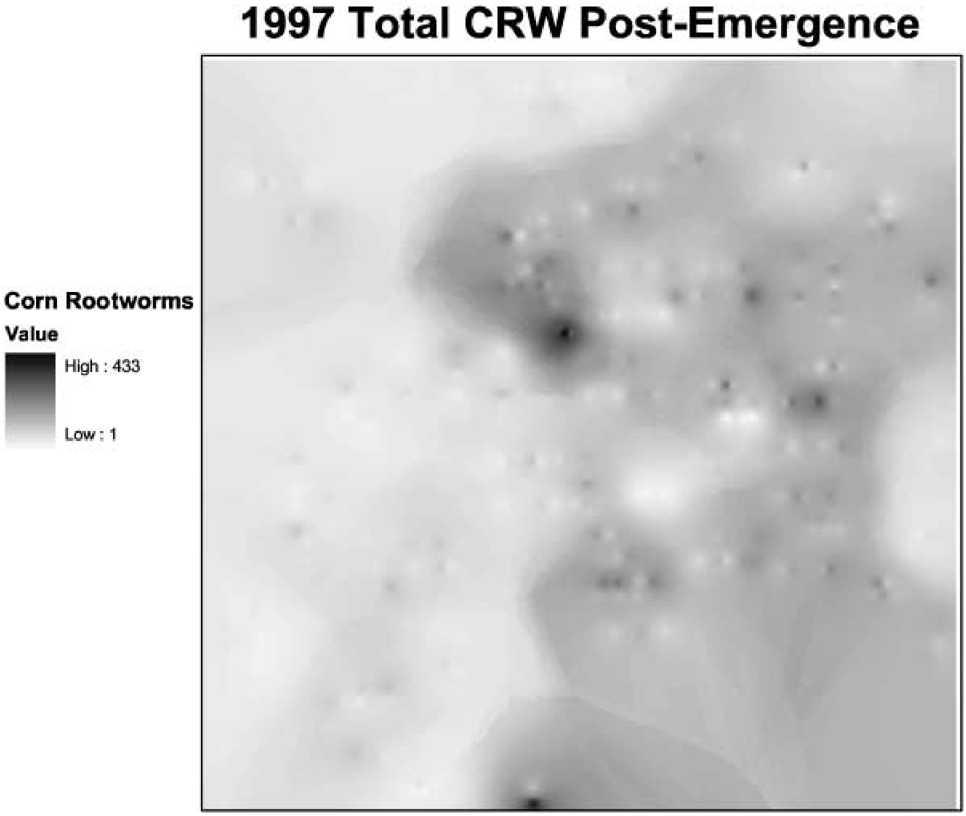

Figure 4 Raster map layer illustrating interpolated values of corn rootworm (CRW) post-emergence found at the South Dakota Areawide Management Site

Contingency analysis revealed highly significant associations between soil texture and corn rootworm abundance for each year, as indicated by chi-square values (Table 4). The strength of the association was greatest in both 1997 and 1999 and least in 1998 as indicated by Cramer's V coefficients (Table 4). Corn rootworms occurred most frequently on elevation classes at 500–504 m, 505–509 m, and 510–514 m (Table 5). Corn rootworms also occurred at 494–499 m, but in smaller proportions. Contingency analysis revealed highly significant associations between elevation and corn rootworm abundance for each year, as indicated by chi-square values (Table 6). The strength of the association was greatest in 1997, 1999, and 2001 and least in 2000 as indicated by Cramer's V coefficients (Table 4).

4 Discussion

Interpolation is central to many ecological field studies because it gives the researcher the ability to infer values over an entire plot, thus reducing overall sampling costs. A variety of interpolation methods exist, including weighted moving averages (e.g. the IDW method), kriging, spline, and trend surface analysis, among many others (Burrough

Table 1 Moran's *I* coefficients computed for corn rootworm emergence and post-emergence 1997 to 2001. The variables include type of raster layer (Layer), cell value (mean ± SD) of each map layer, and Moran's *I* coefficient (Moran)

Layer	Mean ± SD	Moran
	1997	
Emergence	30.91 ± 21.66	0.9993
Post-Emergence	83.01 ± 48.06	0.9947
	1998	
Emergence	24.12 ± 18.47	0.9976
Post-Emergence	105.80 ± 74.69	0.9979
	1999	
Emergence	27.45 ± 17.10	0.9899
Post-Emergence	175.09 ± 126.79	0.9846
	2000	
Emergence	21.58 ± 14.87	0.9991
Post-Emergence	120.85 ± 69.49	0.9843
	2001	
Emergence	22.82 ± 15.08	0.9972
Post-Emergence	119.05 ± 54.60	0.9882

Table 2 Correlation coefficients between corn rootworm emergence and post-emergence interpolated maps layers for 1997 to 2001. The variables include year, number of observations (N), correlation coefficient (r), calculated *t* value (*t* value), and probability value (*P*)

Year	N	r	*t*-value	*P*
1997	62,750	0.82	360	<0.001
1998	62,750	0.87	446	<0.001
1999	62,750	0.64	209	<0.001
2000	62,750	0.84	392	<0.001
2001	62,750	0.52	153	<0.001

1986). Each of these methods has traits (i.e. ease of use, execution time, accuracy of the interpolated values compared to actual data values, sensitivity to parameter changes and number of required inputs, and smoothness of the interpolated surface) that are conducive to certain applications (Heine 1986). Regardless of which interpolator is used, however, the more input georeferenced points and the greater their distribution, the more dependable the results (McCoy and Johnston 2002).

The most commonly used interpolation methods are kriging and weighted moving averages. As with any interpolation method, there are advantages and disadvantages for each technique used depending on the desired result. In the case of irregularly distributed trap locations, weighted moving averages or IDW is useful because it can use a

Table 3 Cell frequencies for contingency analysis between soil texture and corn rootworm abundance raster maps. Variables listed include classes of corn rootworm abundance (CRW Class) and soil texture classes, including silty clay (SiC), silty clay loam (SiCL), silt loam (SiL), loam (L), and sandy loam (SaL)

	Soil Texture Class				
CRW Class	SiC	SiCL	SiL	L	SaL
	1997				
5–51	0	839	817	4,458	456
52–94	0	785	920	1,524	65
95–135	53	3,013	886	1,272	0
136–186	66	2,034	434	731	18
187–426	4	195	138	335	16
	1998				
2–79	28	2,022	1,357	4,249	321
80–157	0	1,190	1,005	3,995	111
158–261	22	1,188	759	634	2
262–378	89	567	231	847	34
379–686	1	35	117	409	0
	1999				
10–126	46	745	1,197	3,841	760
127–213	77	2,758	1,270	2,467	13
214–341	2	2,409	225	817	0
342–777	0	920	22	451	0
778–1498	0	0	57	1	0
	2000				
17–86	22	619	1,630	3,682	219
87–135	64	1,709	541	2,487	87
136–197	12	1,721	342	2,992	13
198–422	0	987	100	1,150	0
423–903	0	1	57	0	0
	2001				
11–77	0	3,145	219	1,140	124
78–121	0	1,377	820	2,560	473
122–168	0	665	950	2,030	102
169–317	52	156	476	1,805	31
318–533	0	3	57	24	0

variable or fixed search radius to determine the interpolated value (McCoy and Johnston 2002). Kriging also allows for a variable search radius. At larger scales (i.e. landscape scale) however, kriging needs to be fitted to various data distributions instead of using just one semivariogram model for the entire surface (Burrough 1986). The IDW method is by definition a smoothing technique where maxima and minima in the

Table 4 Contingency statistics for soil texture and corn rootworm abundance. Variables listed include year, chi-square, degrees of freedom (df), Cramer's V coefficient, and probability value (*P*)

Year	Chi-Square	df	Cramer's V	*P*
1997	5,216	16	0.26	<0.001
1998	2,111	16	0.17	<0.001
1999	5,321	16	0.27	<0.001
2000	2,785	16	0.19	<0.001
2001	4,888	16	0.27	<0.001

interpolated surface can occur only at the data points. Unlike kriging, IDW does not include outlier data values such as negative numbers and exceptionally high values that do not match the actual data values collected at each trap location. Kriging provides more information about errors computed during the interpolation process and allows greater user-defined control over fitting data to the appropriate semivariogram model because it is based on the theory of regionalized variables (Oliver and Webster 1990). IDW does not compute errors and it does not allow user-defined inputs specific to the actual data distribution. However, fitting the data value distribution to the semivariogram can be difficult to ascertain without prior knowledge of the behavior of data values and a broad understanding of statistical theory (Burrough 1986). In general, the IDW algorithm allows for rapid calculations and generates quick contour plots for relatively smooth data values. Kriging requires more user inputs, more intense computing load, but gives more detailed estimates of interpolated values.

Analyzing the spatial pattern of individuals of a particular species has concerned ecologists and biologists because of the implications to metapopulation dynamics and physiographic influences. Traditional measures of aggregation are functions of the mean and sample variance (Taylor 1961, Lloyd 1967, Iwao 1968). These methods have been used extensively in population ecology, but are criticized because of the lack of any direct relationship with the movement of individuals, and because they do not use the available spatial information (Perry 1995). However, with the use of GIS applications, we are able to apply aggregation indices to metapopulations. Examples of aggregation indices include Negative Binomial k, Morisita's Index I δ, Mean Crowding, Moran's I coefficient, and Geary's c coefficient to determine the type of spatial distribution of organisms at all scales (Taylor 1984, Young and Young 1998, Koenig 1999). The most commonly used spatial autocorrelation techniques used in GIS applications are Moran's I and Geary's c coefficients (Johnston 1998). The Moran's I coefficient computes the degree of correlation between the values of a variable as a function of spatial locations (Fortin 1999). The Geary's c coefficient, on the other hand, measures the difference or distance among values of a variable at nearby locations. Two major weaknesses of these statistics include "topological invariance" (i.e. both indices disregard the spatial arrangement of sampling units) and measurement of spatial correlation between sampling units that are physically contiguous, which limits the knowledge of how the strength of the correlation changes over space (Young and Young 1998). However, these indices are relatively easy to use, interpret, and most GIS programs allow the computation of these two spatial autocorrelation techniques.

Table 5 Cell frequencies for contingency analysis between elevation and corn rootworm abundance raster maps. Variables listed include classes of corn rootworm abundance (CRW Class) and elevation classes, including Class 1 (494–499 m), Class 2 (500–504 m), Class 3 (505–509 m), Class 4 (510–514 m), and Class 5 (515–519 m)

	Elevation Class				
CRW Class	1	2	3	4	5
	1997				
5–51	2,004	2,252	1,797	517	0
52–94	285	955	1,238	764	52
95–135	13	1,206	1,657	2,233	115
136–186	14	753	1,215	1,253	48
187–426	38	47	428	175	0
	1998				
2–79	1,432	2,901	2,053	1,308	283
80–157	1,400	2,726	1,344	821	10
158–261	14	688	1,033	805	65
262–378	0	148	1,080	540	0
379–686	0	135	341	86	0
	1999				
10–126	1,928	1,870	2,032	759	0
127–213	261	1,998	2,203	1,996	127
214–341	74	997	1,105	1,187	90
342–777	14	344	156	879	0
778–1498	57	0	0	1	0
	2000				
17–86	848	2,791	2,048	458	27
87–135	707	1,614	1,355	938	274
136–197	949	1,549	1,101	1,447	34
198–422	561	571	312	793	0
423–903	57	0	0	1	0
	2001				
11–77	332	504	1,763	1,813	216
78–121	960	1,791	1,461	1,017	1
122–168	579	1,898	1,004	266	0
169–317	436	976	1,040	68	0
318–533	75	2	6	1	0

Our available GIS programs allowed computation of the Moran's *I* coefficient to measure spatial autocorrelation. High values of the Moran's *I* coefficients for all emergence and post-emergence raster grids showed highly aggregated metapopulations. Aggregated corn rootworm populations were also reported by Steffey and Tollefson

Table 6 Contingency statistics for elevation and corn rootworm abundance. Variables listed include year, chi-square, degrees of freedom (df), Cramer's V coefficient, and probability value (*P*)

Year	Chi-Square	df	Cramer's V	*P*
1997	5,113	16	0.26	<0.001
1998	3,321	16	0.21	<0.001
1999	4,370	16	0.25	<0.001
2000	2,465	16	0.18	<0.001
2001	3,998	16	0.25	<0.001

(1982), Midgarden et al. (1993), and Ellsbury et al. (1998). However, these studies were conducted at the field scale, and not at the larger landscape scale. In our study, the aggregated spatial distribution of the corn rootworm metapopulation at the landscape scale shows that structural characteristics of the landscape (i.e. vegetation configuration) and physiographic factors such as soil type characteristics and elevation influence their distributions.

Using GIS, we were able to test the strength of correlation between emergence and post-emergence traps for each year. Because the correlation was significant, we believe that post-emergence sticky traps may provide a reliable, accurate, and more cost-efficient sampling replacement for large, cumbersome emergence cages in describing the landscape scale distribution of corn rootworms. In addition, contingency analysis allows pest managers to effectively compare population abundance and physiographic map layers using GIS (McGrew and Monroe 2000). Contingency analysis was a useful technique to analyze the significance of spatial relationships between soil texture, elevation, and corn rootworm metapopulation dynamics at the landscape scale. The variability in soil texture at our site was comparable to a laboratory study that showed survival rate of corn rootworm larvae depended on the clay percentage of the soil and porosity, both of which are functions of soil texture (Turpin and Peters 1971). Knowledge about the interaction between different soil textures and corn rootworm survival, therefore, provides an additional measure of habitat suitability for this pest. The variability in elevation at our site is typical for eastern South Dakota and provided evidence of the prominence of corn rootworm abundance on several elevation classes.

Further research on other areawide sites that have a varying range of soil textures and elevation may be useful to determine the significance of the influence of these variables on corn rootworm metapopulation dynamics. However, the range of Cramer's V coefficients in our study was comparable to research that looked at the associations for site quality and stand characteristics with top kill severity due to defoliation by the jack pine budworm (Hall et al. 1998). The variations in our coefficients for both soil texture and elevation may be explained by the high mobility of corn rootworms, causing fluctuations in yearly population dynamics. Knowledge of factors like soil texture and topography that promote intense corn rootworm infestations allows pest managers to focus on problem areas within the landscape. Other factors such as temperature, precipitation, predators, and parasitoids not included in our study could affect the spatial distribution of corn rootworms and other agricultural pests.

5 Conclusions

There are many available spatial analytical approaches within GIS that can be used in pest management applications. Examples include basic map overlays to determine suitable habitat, contouring to determine location of varying concentration levels of attributes, and proximity analyses to determine locations of organisms in relation to buffers (Burrough 1986, Walker 1996). We applied several spatial analytical techniques using GIS, and the results provided information on the interactions between corn rootworm metapopulation dynamics and physical factors. The GIS operations were conducted with relative ease and in a timely manner. Thus, GIS may play a critical role in identifying and describing the interaction of physical variables at other sites with differing species, soil textures, elevation, and land use to improve pest management strategies.

The role of GIS techniques in pest management can provide descriptive information (i.e. knowledge of statistical spatial relationships) on physical and biological interactions with metapopulation dynamics as well as providing information on spatially explicit models to predict future pest populations by identifying suitable habitat conditions. To identify suitable habitat conditions, the raster map layers (population abundance, land use, soil texture, and elevation) can be combined with the use of a GIS compatible modeling program like RAMAS GIS (Applied Biomathematics, Setauket, NY). A habitat suitability function is created by assigning values to each of the various map layer categories. The relative values are determined by using information derived from the contingency analysis that illustrated preferences of corn rootworm abundance on various soil textures and elevation classes. The habitat suitability maps can then be coupled with corn rootworm fecundity rates and dispersal rates to analyze the behavior of metapopulation dynamics in the future. This information can then allow pest managers to make more well-informed decisions regarding control of pest populations at different locations and at much larger, regional scales.

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