Application of Remote Sensing in Integrated Pest Management

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3.1 Introduction

Analysing the dispersion of insect pests in any ecosystem is a challenging problem for many applied ecology investigations, especially when considering the spatio-temporal dynamics of habitat conditions and pest preferences. Pest dispersion impacts sampling efforts (Davis, 1994; Trumble, 1985), rate of habitat colonization (Southwood et al., 1983) and the establishment of economic thresholds or injury levels (Byerly et al., 1978; Stern et al., 1959; Wilson, 1994) as well as a host of population ecology-related analyses (Banerjee, 1976; Dalthorp et al., 2000; Fleischer et al., 1999). Previously, Willers et al. (1999, 2005, 2009) and Willers and Riggins (2010) described some site-specific sampling strategies for tarnished plant bug (TPB) (*Lygus lineolaris* [P. de B.] (Heteroptera: Miridae)) detection aided by remotely-sensed imagery of commercial cotton fields. Other complementary works have developed the initial capacity for site-specific pesticide applications (Dupont et al., 2000; Seal et al., 2001). As these efforts expand and become more mainstream in the management of commercial cropping systems, it is necessary to make continued improvements in methodology.

One important issue with image-based sampling is focused on understanding how sample unit size choices and habitat-related differences in pest density affect a field scout's assessment of pest dispersion in commercial cotton fields. To examine this question, two general courses of investigation are available: (i) conduct a detailed field-scale study or (ii) conduct a simulation study. Under commercial conditions, influences due to discrepancies in observer ability, physiographic location of arable parcels and cropland-hedgerow adjacencies, field heterogeneity, management practices, sampling error, and/or lack of

sufficient time (cost efficiencies) to conduct thorough field sampling efforts heavily influence outcomes, interpretations, conclusions, and subsequent management actions. However, a simulation model can generate large numbers of observations useful for discerning patterns and trends to make better informed choices about the most economically efficient sample unit size as related to pest infestation rates and dispersion under heterogeneous field conditions. Various methods utilized in the analysis of species-specific spatial patterns have been described in the literature (Davis, 1994; Ludwig and Reynolds, 1988; Pielou, 1960, 1977, 1978). With field data, the goodness of fit test (Davis, 1994; Poole, 1974; Steel and Torrie, 1960) is traditionally employed. In this investigation, Lloyd's mean crowding and patchiness indices (Lloyd, 1967) are used to examine relationships among pest density, dispersion pattern and sample unit size. These indices developed by Lloyd (1967) were based on the use of quadrats (a cell or small sized unit of area) and, thus, appear to correspond well with the characteristics/conditions of the two choices of simulation models used in this study. Previous work by Willers et al. (2005) assumed that the dispersion of TPBs in various cotton habitat classes was random. The main objective of the current study is to further examine this assumption by application of additional simulation modelling efforts. If a parametric random pattern is established as a condition, the null hypothesis is that there is no relationship between sample unit size and pest density. Estimates for mean crowding or patchiness (Lloyd, 1967) are used to test this hypothesis. The practical utility of the computer simulations is underscored by other simulation experiments with dice, and a real-world example involving several adjacent cotton fields during the 2006 production season.

3.2 Methods

The simulation model is comprised of two parts. The first part models a simple random sample (SRS) obtained from a simulated habitat. The second part models the characteristics of a randomly dispersed pest insect population set to only one of the several choices 'available' for an infestation rate describing the mean number of insects per plant (Willers et al., 2005) in a simulated habitat.

3.2.1 Simulation of a Simple Random Sample Design

The quadrat-based SRS design modeled here has been previously described (Willers and Akins, 2000; Willers et al., 1999, 2005). The simulation model employs two different sampling unit sizes. The smallest sampling unit is called the quadrat, whose dimensions are a crop row length of 0.914m (which emulates one drop cloth sample from that row) and a width set equal to two row spacings (as typically used in actual Mid-South (USA) cotton fields and is either 0.762m or 1.016m). For the simulation model, this single quadrat is assumed to bisect these two drills of each crop row. These quadrat units provide the main link between the simulated system and actual field conditions. Therefore, 0.4047ha (or 1ac) of field area will contain 4356.3 units of this size (at 0.9290m2 when the row spacing is 1.016m). It is important to emphasize that the total number of quadrat units in a cotton field constitute a countable number of sampling units (Thompson, 1992). These units are nested within different sizes, selected at random and assessed for counts of a particular insect. If these quadrats are apportioned amongst one or more habitats of crop growth and development (Willers et al., 2005) using remote sensing information, a SRS plan by habitat class is constructed. Since the spatial resolution of individual pixels (often 1m2) in a geo-registered multi-spectral image of a cotton field conceptually corresponds to the size of one of these quadrats, the practical linkage between the computer simulation model and field applications with remote sensing is demonstrable. The larger sized sampling unit, referred to as a belt transect, consists of a sequential arrangement of n quadrats joined together (Willers et al., 1999) for a variable length (L). For different runs, each quadrat outputs a random variate of insect counts for a simulated habitat class assigned one of several simulated insect infestation rates. An additional programming module collects the counts of simulated insects from each quadrat of a belt transect sample of a particular size and summarizes the total number of insects found in each simulated sample**.** Under field conditions, each belt transect sample is selected by consultant/producer determined preferences within meso-scale habitat maps derived from classified imagery (Richards and Jia, 1999) of the cotton field (Willers et al., 1999, 2005, 2009, 2012). To represent these field practices in the simulated system, different pest densities for various habitat classes were modelled by changing the infestation rate parameter (λc, as explained in the following section) and by aggregating (or stacking) adjacent belt transects to create larger areas that approximate the size of individual

sprayer polygons contained in a field grid. For spatial pesticide applications in a commercial cotton field, each cell of the field grid can be assigned an application rate to apply a spatial pesticide prescription. These very large-sized sample units matched to sprayer traits represent another construct that enables the simulation model to be applicable to real-world field conditions. Since the boom width of the sprayer determines the length of each belt transect (L) in a stack of transects, the breadth of the simulated stack of transects is determined by the variable-rate controller's response time. However, the model does not account for other spatial relationships (e.g. the distance, direction or proximity to edges or differences in the sharpness of gradient effects) among simulated samples within a simulated habitat during a given simulation run.

3.2.2 Insect Infestation of Habitats Simulation Model

The basic approach to model infestation rate was to employ the negative binomial distribution (NBD) (Anscombe, 1949; Davis, 1994). Other detailed modifications have been described in Willers et al. (1990). The model generates integer values of counts to simulate numbers of insects per quadrat for simulated belt transects of different sizes and infestation rates (λc), while setting the dispersion parameter (k) to a constant value of 50. (Note: If k is set to very small values (e.g. 1, 2 or 3), the model would generate clustered or aggregated variates for a simulated belt transect sample, while for increasingly larger values of k, the NBD converges to the Poisson (or random) distribution.) The number of insects (or events (counts)) per quadrat for a belt transect of size L was subsequently generated by the inverse transformation method (Pritsker and Pegden, 1979) using the probability values presented in Table 3.1. The simulation model was programmed in SAS® (SAS Institute, 1990). The primary objective of this simulation study is to investigate how the assessment of insect dispersion differs with changes in (i) the pest density (or infestation rate, where λc = 0.01, 0.04, 0.08, 0.24 and 0.40) and (ii) belt transect sizes within a simulated cotton habitat class. The various lengths of belt transects employed were L = 4, 8, 16, 24 crop rows (for 1.016m row spacings) or L = 315 crop rows in a stack (for 0.7620m row spacings). The infestation rate parameter (λc) is linked to assumptions about the number of plants contained in a quadrat (Willers et al., 1990). For simplicity, the

plant density was 'fixed' at a value of 10 cotton plants/quadrat in the simulation model, although other values could be specified.

Table 3.1 Probability of observing Various Counts of Insects Per Quadrat (Simulated Sample Units)

Insects/SU	$\lambda_c = 0.01$	$\lambda_c = 0.04$	$\lambda_c = 0.08$	$\lambda_c = 0.16$	$\lambda_c = 0.24$	$\lambda_c = 0.40$
0	0.9049278	0.6713877	0.4521834	0.2070213	0.0959259	0.0213212
1	0.0903122	0.2664237	0.3560499	0.3209633	0.2196776	0.0789675
2	0.0045967	0.0539191	0.1429807	0.2537850	0.2565701	0.1491609
3	0.0001590	0.0074174	0.0390288	0.1364012	0.2036892	0.1915152
4		0.0007800	0.0081438	0.0560408	0.1236129	0.1879686
5		0.0000669	0.0013851	0.0187672	0.0611459	0.1503749
6		0.0000049	0.0001999	0.0053343	0.0256720	0.1021064
7			0.0000252	0.0013232	0.0094065	0.0605075
8			0.0000028	0.0002923	0.0030697	0.0319345
9				0.0000584	0.0009061	0.0152445
10				0.0000107	0.0002448	0.0066624
11				0.0000018	0.0000612	0.0026919
12					0.0000142	0.0010136
13					0.0000031	0.0003581
14					0.0000006	0.0001194
15						0.0000377
16						0.0000114
17						0.0000033
18						0.0000009

The plant sample size per quadrat is 10 cotton plants (0.9144 m length of row for different infestation rates (λ_c) (see text)).

3.2.3 Dispersion Analyses of Simulated Conditions

Lloyd's mean crowding and index of patchiness (Lloyd, 1967) was used to assess the random dispersion assumption for various simulated combinations of infestation rate (λc) and belt transect size (L) under the conditions of the model to generate a parametric random dispersion pattern. Lloyd's mean crowding index (Davis, 1994; Lloyd, 1967) is estimated (without correction for bias (Pielou, 1978, p. 151)) as

$$\overset{*}{x} = \bar{x} + \frac{s^2}{\bar{x}} - 1 \qquad (3.1)$$

The index of mean crowding describes the mean number of individuals occupying the same habitat space (here, a quadrat sample unit of a particular size) (Lloyd, 1967; Pielou,

1977, 1978). Lloyd's patchiness index (or the ratio of mean crowding to the mean) is expressed as

$$\overset{*}{x}/\bar{x} \qquad (3.2)$$

where: <1 corresponds to regular dispersion, =1 random dispersion, and >1 aggregated dispersion. The index of patchiness is derived from the mean crowding index (Lloyd, 1967; Southwood, 1978) and is dependent upon quadrat size (Davis, 1994). Choices for sample unit size are known to influence the assessment of dispersion, particularly when artificial units as opposed to natural units are employed (Pielou, 1977, 1978; Poole, 1974). See discussion in Ludwig and Reynolds (1988) for additional details. The index of patchiness was estimated for the larger belt transect sample units of different sizes. Patterns of these statistics, generated over 10,000 simulation runs for each combination of infestation rate and belt transect size, were summarized by histograms. A single run represents a single belt transect sample at a particular combination of L (i.e. aggregated quadrat units) and λc (i.e. pest density).

3.2.4 Simulation Experiments with Dice

The purpose of the dice simulations is to enable the reader to better grasp the 'geographical' and 'statistical' correspondences between the computer simulation model and field applications. The particular aim is to understand how the sample size (or sample time) may be reduced without compromising precision for management decisions about insect control. The first sampling 'universe' (Ash, 1993) assigned one of five colours (red, orange, yellow, green, and blue) to each face of each die. The color assignment of the countable events (the integers 1–6) (Table 3.2) corresponds to a SRS scheme for each colour. Each face of a die represents the count of insects found for adjacent quadrats of different belt transect lengths assigned to a colour (i.e. habitat class) where the mean infestation rate of each colour is similar. To add some variability to this system, the event 3 was assigned twice to the color 'Red' and was not assigned to the color 'Blue' (Table 3.3). Table 3.4 presents the frequency count of the outcomes of the events for 30 rolls by color. The second sampling 'universe' was established from 10 new dice, where the events 1–6 were assigned to one of five colors.

These color assignments correspond to a SRS scheme where the mean infestation rate is not equivalent over the colours, since the mean ranks of events are Red < Orange < Yellow < Green < Blue. The belt transect length is determined by the number of times a particular color occurred on a roll of the 10 dice. All color and event combinations were not observed in every roll. This corresponds to the situation under field conditions when the sampler chooses to *not* sample a habitat class. The outcomes observed by color for seven rolls of these 10 dice are summarized in Table 3.4.

Table 3.2 Event list for Sampling Universe with Dice with Similar Mean Values among the Colors

Colour	Lists of Face Values per Die per Colour
Red	(5) (3, 4) (1, 2, 3, 6)
Orange	(4) (6) (1, 3) (2, 5)
Yellow	(1) (3, 6) (2, 4, 5)
Green	(5) (6) (1, 3) (2, 4)
Blue	(1) (6) (2, 4, 5)

Table 3.3 Table of frequencies for 30 Rolls of five Dice for the Sampling Universe Presented in Table 3.2

	Face Value					
Colour	**1**	**2**	**3**	**4**	**5**	**6**
Red	3	6	5	6	5	7
Orange	5	8	2	6	3	5
Yellow	6	7	6	4	6	4
Green	2	6	6	4	6	5
Blue	6	5	0	5	5	5

Table 3.4 outcomes for Seven Rolls of 10 Dice for Another Sampling Universe Where the Expected Mean by Color is Ranked as Red < orange < Yellow < green < Blue

	Colour				
Roll	Red	Orange	Yellow	Green	Blue
1	1, 1	–	1, 3	3, 4, 4	5, 5, 6
2	–	3	1, 3	4, 4, 5, 6	6, 6, 6
3	1	2, 2	3, 3	3, 4, 4, 5	5
4	1	2, 2	3, 3, 3, 4	4, 4	5
5	1, 1	2	3, 3	5, 5, 6	6, 6
6	1, 1	–	3	4, 4, 5, 5, 5, 6	6
7	1, 1	1, 2, 2	1, 3, 4	4	6

3.2.5 Field Data Illustrations

The field data originally used to validate the model consisted of insect counts obtained from 48 transect lines across a large commercial cotton field in Bolivar County, MS. Quadrat-based samples (0.9144m) were collected across eight successive rows (L = 8.128m) on 17 July and 22 July 1997. For each row at each sample site, the number of plants and total number of TPB were recorded. A partial listing of these data is included in Table 3.5; the complete dataset may be examined in Willers et al. (1999).

The sample locations of the 2006 field datasets (collected in June, July and August) from a farm in Noxubee County, MS, were consolidated onto a single classified map (Figure 3.9). Row spacing for each cotton field was 0.7620 m (30 in). Coordinates for insect collection loci (n = 104 sites) were obtained using a Garmin Model 12 GPS unit (Olathe, KS) and overlain on a classified image using ESRI® ArcMap (Ver. 9.1 (Redlands, CA)) using various geoprocessing techniques similar to those described by Nelson et al. (2005). The classified image layer (accomplished with ERDAS® Imagine software (NorCross, GA)) represents the categorical change in vegetation vigour of the cotton crop, including other surrounding features (i.e. corn, grasses, trees, pond, soybean and roads) detected between early June and July 2006. Higher class values represent the most change in cotton plant vigour between these two months. The details of each scouting site, how the imagery of cotton fields was processed and classified into habitats, and the subsequent preparation of any pesticide prescription maps (based on sprayer polygons built using a custom application programmed for ERDAS® Imagine, Ver. 8.7) are not described here. (Interested readers may consult Dupont et al., 2000; Frigden et al., 2002; McKinion et al., 2009; Richards and

Jia, 1999; Seal et al., 2001; Theobald, 2003; Willers and Riggins, 2010 and Willers et al., 1999, 2005, 2009, 2012 for details).

3.3 Results

This study improves prior simulation efforts (Willers et al., 1990, 2000, 2005) to further explore emergent details of relationships among different infestation rates and patterns of dispersion as sampling unit size changes. Simulated results were first compared with actual TPB counts obtained from belt transects sampled in commercial cotton fields to test the model's ability to generate variates by quadrat similar to field data (see Willers et al., 1999). Only one of these comparisons (for 1.016m row spacing) is presented here, for reasons of brevity. These simulation runs were based on an 8-row long belt transect using an infestation rate of λ c = 0.20 distributed across a uniform stand of 10 plants per row. Examining the counts by quadrat (or crop row) between the simulated runs and the actual field sample, it is observed that the simulation runs provide similar estimates of insect abundance. On occasion, however, the number of insects 'observed' per quadrat in the simulated runs was much larger than that obtained from field data for a comparable density (e.g. run 4593, with eight insects counted in quadrat 5).

Table 3.5 Comparison of a Sample Transect from a Cotton field of Tarnished Plant Bug Counts per Quadrat with Seven Random Selections from a Total of 10,000 Simulation Runs

	Crop row (Quadrat)									
	1	2	3	4	5	6	7	8	Density/0.405 ha[1]	Infestation rate[2]
Totals	2	2	2	0	2	0	2	3	7085	0.20
Stand	8	10	6	7	11	11	6	7	35,937	–
ILLUSTRATIVE SIMULATION RUNS										
Run 328	2	1	1	3	1	2	2	1	7085	0.16
Run 607	1	2	2	3	1	0	0	2	5995	0.14
Run 2880	5	1	0	1	4	0	3	3	9265	0.21
Run 4593	0	0	3	3	8	2	2	0	9810	0.22
Run 5378	1	1	4	0	3	3	4	0	8720	0.20
Run 7627	1	3	2	0	1	2	3	1	7085	0.16
Run 8573	2	2	2	1	4	3	4	3	11,445	0.26
Stand (Model)	10	10	10	10	10	10	10	10	43,600	–

Equivalent densities/0.405 ha, infestation rates (near 0.20) and numbers of insects per quadrat are obtained irrespective of the variability of numbers of plants per quadrat for the field data vs. the fixed number of 10 plants per quadrat used by the model (see text).

1 These values were determined using a line-intercept sampling estimator (Willers et al., 1999; Williams et al., 1995).

2 Infestation rate is determined by dividing the insect density estimate by the stand density estimate.

Patterns of dispersion using estimates of Lloyd's index of patchiness at infestation rates of λ c = 0.01, 0.08 and 0.24, simulated for several relatively short transect lengths, are summarized in Figures 3.1–3.3. Only a few of the many possible graphs from these simulation runs are shown. As belt transect length and pest density increased, the patchiness index decreased in its range and centred about a value of 1.0. These trends indicated increasing 'opportunities' for random dispersion and decreased capacity for aggregated dispersion pattern tendencies within a homogeneous habitat. Therefore, this index is sensitive to choices for belt transect length, but not to values for infestation rate, once the rate departs from small values close to zero. Despite this sensitivity, the convergence of results about a mode of 1.0 supports the assumption that a random dispersion pattern is plausible for most pest densities estimated with larger sample unit

sizes. Consistency in estimating this index is most doubtful with a pest density close to zero (Figure 3.1) and if too short a belt transect has been employed (see the uppermost panels in Figures 3.2 and 3.3). Mean crowding tended to be a noisy parameter when belt transects shorter than 24 crop rows were used and lower infestation rates (<8%) were modelled. Mean crowding results are presented for a partial collection of sample unit size and pest density combinations (Figures 3.4–3.6). Emergent trends are most clear if very long transects (e.g. 315 quadrats or crop rows) are utilized (as shown in Figures 3.7 and 3.8); however, sampling these very long (stacked) belt transects would require an excessive amount of scouting time in commercial field settings. The practicality of the mean crowding trends detected does provide an advantage when preparing site-specific pesticide prescriptions for application by a variablerate sprayer. Thus, patterns of simulated dispersion responses at selected pest densities (λc = 0.01, 0.04, 0.16, 0.24, and 0.40) while using a large stacked belt transect are very consistent in contrast to the shorter transects of 24 or fewer quadrats. This stacked transect (approximately 219.456m2) corresponds to a practical polygon size that matches the characteristics of a variable-rate sprayer (i.e. its boom length and controller response time). Additional analysis of the simulated outcomes for this large belt transect revealed an interesting insight about increases in pest numbers per unit area. Unlike results shown for transect samples smaller than 24 quadrats (Figures 3.4–3.6), mean crowding estimates for a large stacked transect (L = 315 rows) were well separated as pest density increased (Figure 3.7). However, even for a very large sample unit size, if the pest density is low (see Figure 3.8, top panel), wide discrepancies in the patchiness index still occurred. For several runs when the pest density was 1%, the index of patchiness was estimated to be >1, indicative of an aggregated dispersion pattern. The lack of stability at very low pest densities (λc = 0.01 as shown in the top panel of Figure 3.8) was previously reported by Byerly et al. (1978), and was attributed to the proportionately large effect that sampling errors contribute to estimation of standard error for a mean based on a small sample size. Similar influences are also likely to be at work on the outcomes observed for Lloyd's index of patchiness when a short belt transect is used to sample a habitat class having a low pest density. At low population densities, there may be insufficient numbers of pests to occupy all 'available habitat units' within a given class (or state of plant vigour) captured by the

classified image. This scenario would also result in deviations from a random dispersion index of 1.0. However, the patchiness index is independent of population density once there is a departure from low infestation rates and when the sample unit size is very large. (Compare Figures 3.7 and 3.8 at infestation rates of 0.04, 0.08, 0.16, and 0.40.) This decoupling of Lloyd's index of patchiness from the mean crowding index was first reported by Myers (1978).

Convergent behavior about a patchiness value of 1.0 for the largest belt transect length (315 quadrats) used in the simulation study reinforces the validity of a random dispersion pattern over a large, consistent, spatial extent, particularly when pest density (or infestation rate) is large enough to take action. A map of sample site allocations based upon a classified, remotely-sensed image of several nearby cotton fields during the 2006 season typifies a real-world application of these simulation results. While it is impractical to sample very long belt transects in a commercial field setting, it is practical to apply SRS within homogeneous habitat classes (as determined by classified colour infrared (CIR) aerial imagery), select a few widely-spaced sampling locations (Figure 3.9) within a particular field over the course of a production season (Willers et al., 2005), and use belt transect lengths shorter than 4–8 crop rows (McKinion et al., 2009).

If the estimate of pest density is similar at the widely spaced sites within a particular habitat class, it is reasonable to infer that other unsampled locations between these sites are also infested at a similar rate. This pattern in the selection of scouting sites is strongly evident in Figure 3.9. The different habitats were repeatedly sampled at similar locations over time while other regions of the various habitat classes were never sampled during the 2006 production season. A habitat classification map derived from crop imagery (and based on some measure of plant vigour – such as Normalized Difference Vegetation Index (NDVI)) has been effectively used by field scouts to select sites for estimating infestation severity in commercial cotton fields without resorting to large sample sizes (e.g. Willers et al., 2005). Once the scout has learned that a particular habitat class (Figure 3.9) is occupied by the pest above the economic threshold, he/she can conclude that the entire habitat class needs treatment because, in all likelihood, the pests will be randomly dispersed throughout. He/she will come to know from sampling other habitat classes whether they demonstrate tendencies to be above or below an economic threshold.

However, if the conclusion is that pest insect abundance is low (say, 1%), localized collections of pests in that habitat may occur, because simulation results indicated that, for low pest densities, clustered dispersion patterns are probable at times for even the largest sample unit size (recall top panel, Figure 3.8). For very low pest densities, the pattern of dispersion is unimportant because the cost of control would exceed the probable benefits of an application.

For each sampling date shown in the case study (Figure 3.9), only a small number of scouting sites (3–7) were required to make decisions 'not to spray', 'wait and see one more week', or 'spray now here' for TPB management during any given week of the production season. Likewise, the histogram series (Figures 3.1–3.8) reflects this phenomenon of random dispersion because as sample unit size increased and pest density increased, the required sample unit size could become smaller. This concept learned from a simulation analysis provides information highly useful for refining pest sampling efforts in commercial cotton fields.

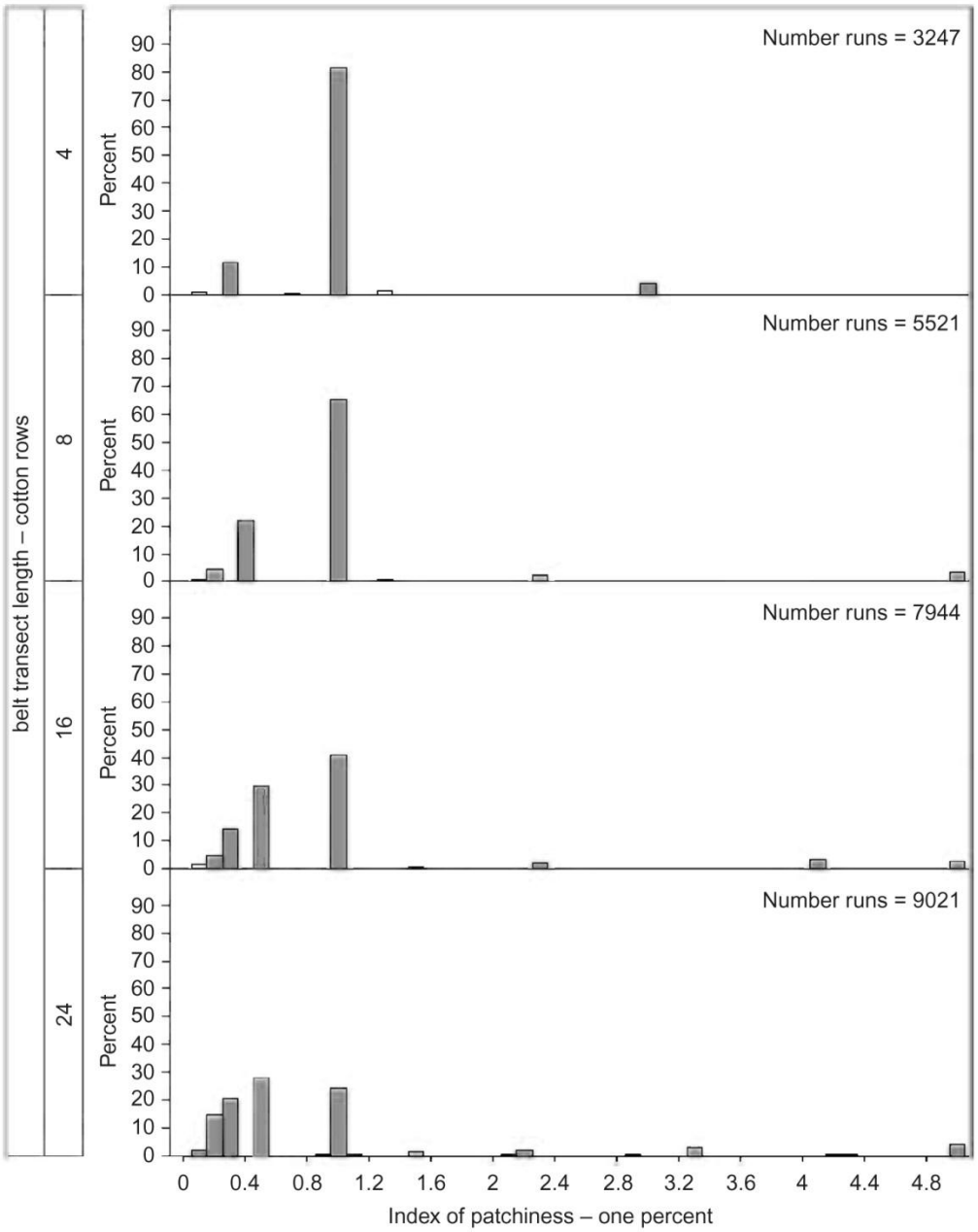

Figure 3.1 Histograms of results for Lloyd's (1967) index of patchiness for four different transect lengths at a simulated infestation rate of 1%. The index has a value <1 for regular dispersion patterns.

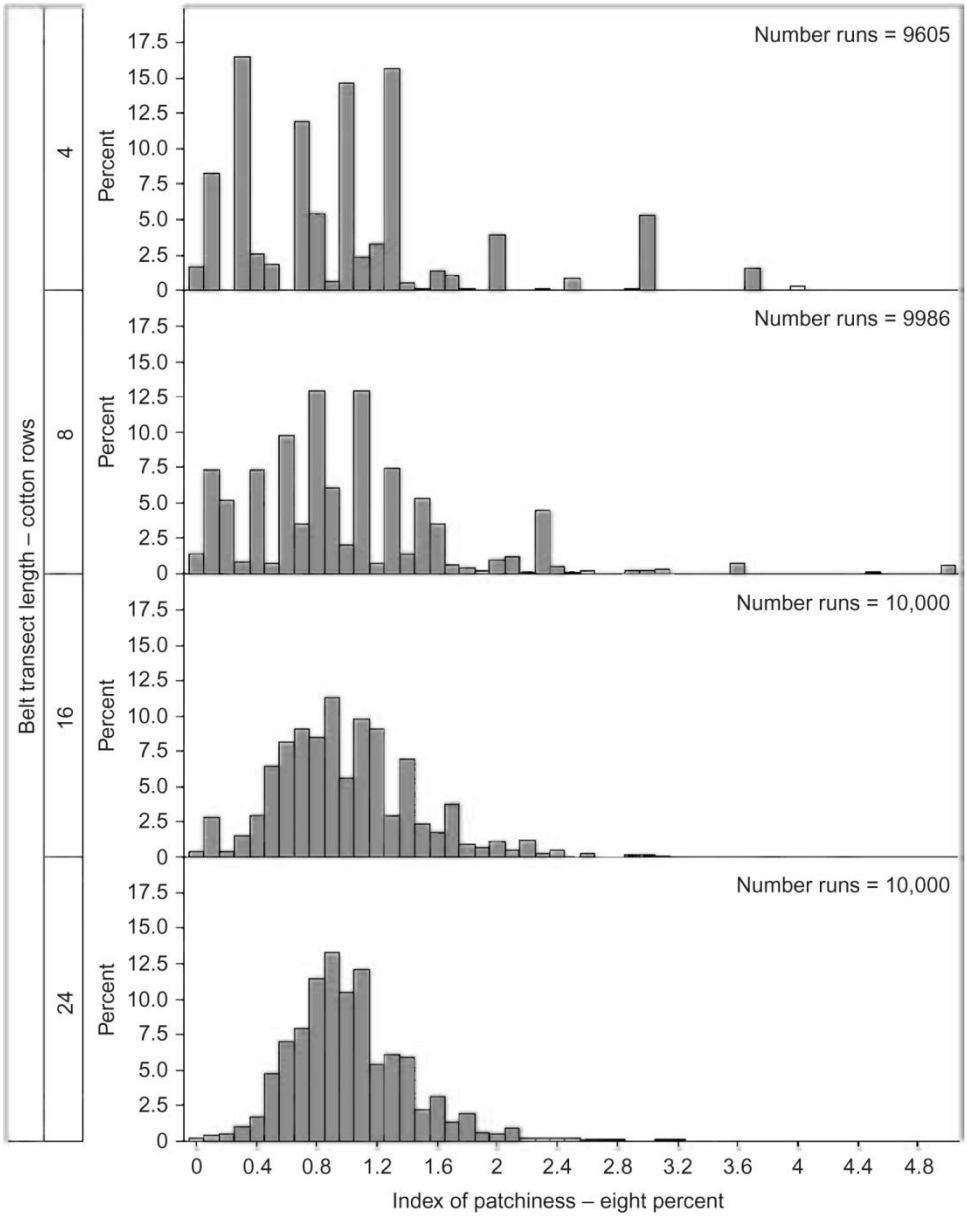

Figure 3.2 Histograms of results for the index of patchiness for four different transect lengths at a simulated infestation rate of 8%. The index has a value >1 for aggregated dispersion patterns.

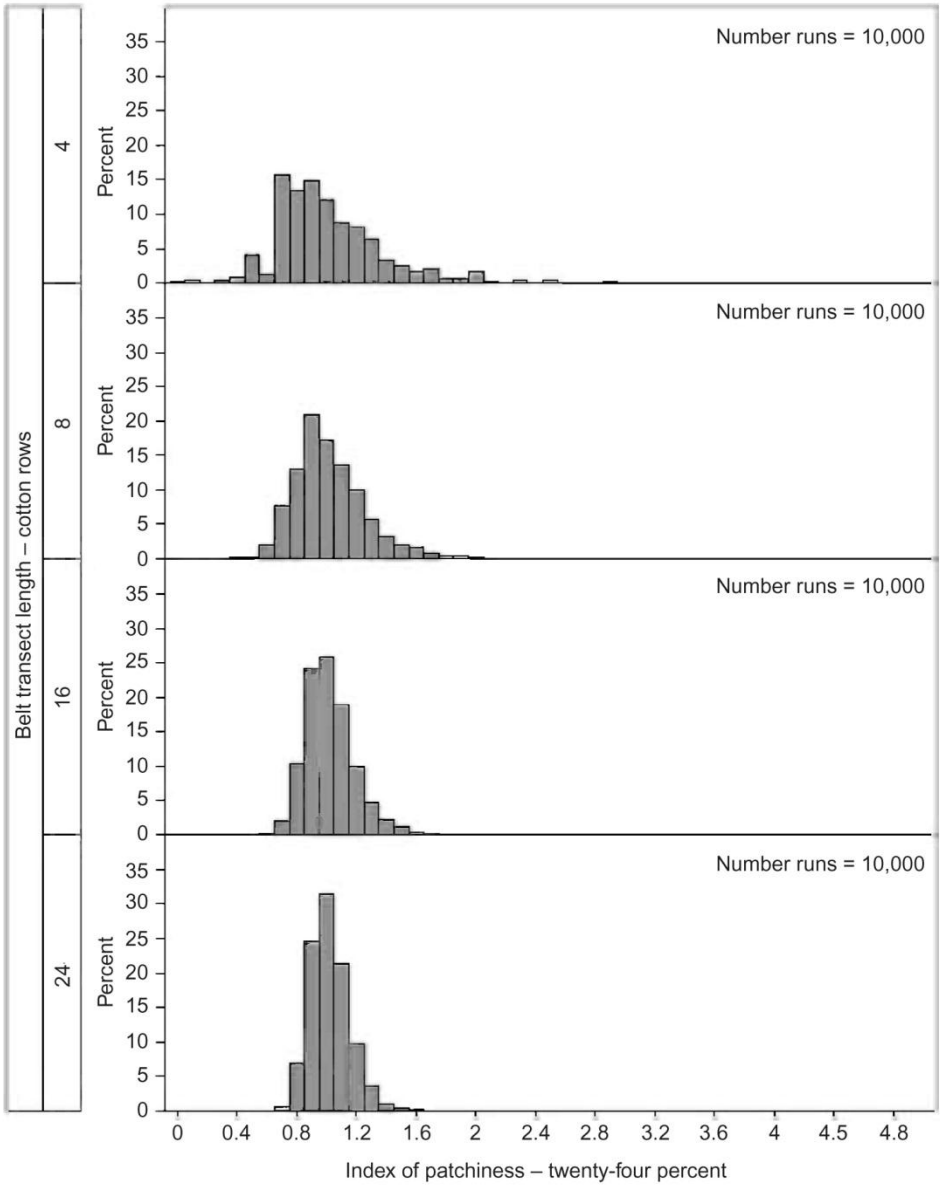

Figure 3.3 Histograms of results for the index of patchiness for four different transect lengths at a simulated infestation rate of 24%. The index is equivalent to 1 for random dispersion patterns.

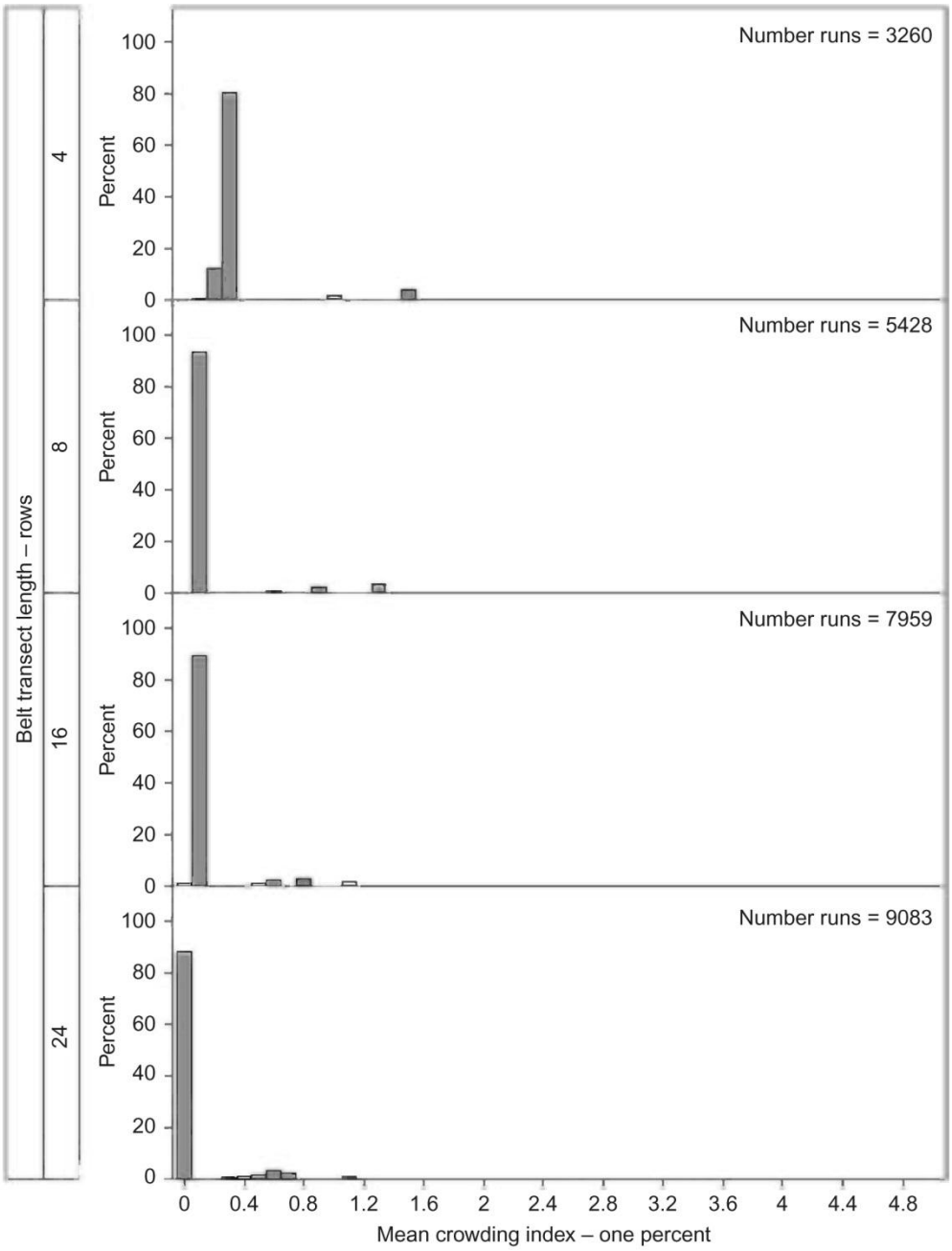

Figure 3.4 Histograms of results for mean crowding for four different transect lengths at a simulated infestation rate of 1%. Compare to Figure 3.7 for a sample unit size of 315 units.

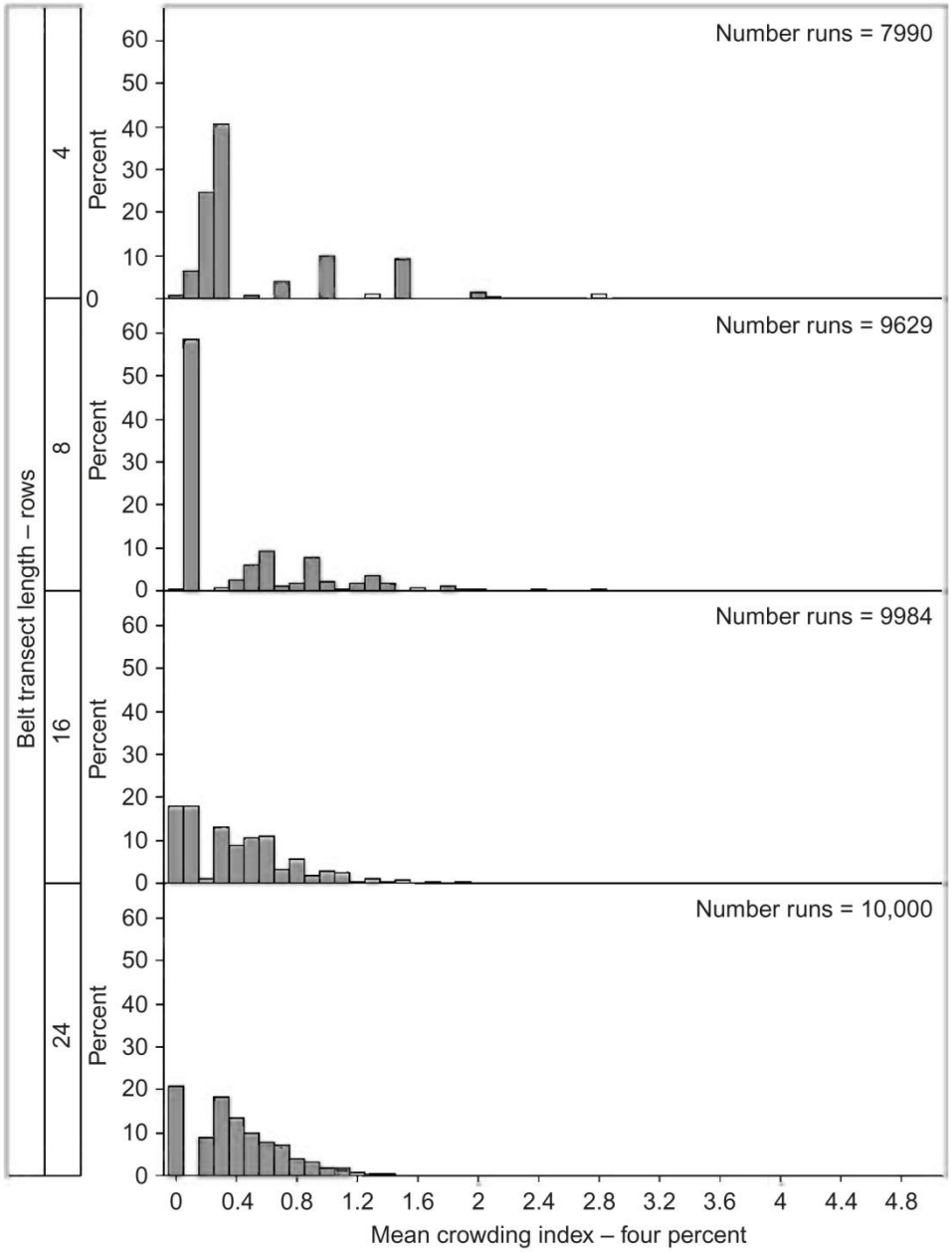

Figure 3.5 Histograms of results for mean crowding for four different transect lengths at a simulated infestation rate of 4%. Compare to Figure 3.7 for a sample unit size of 315 units.

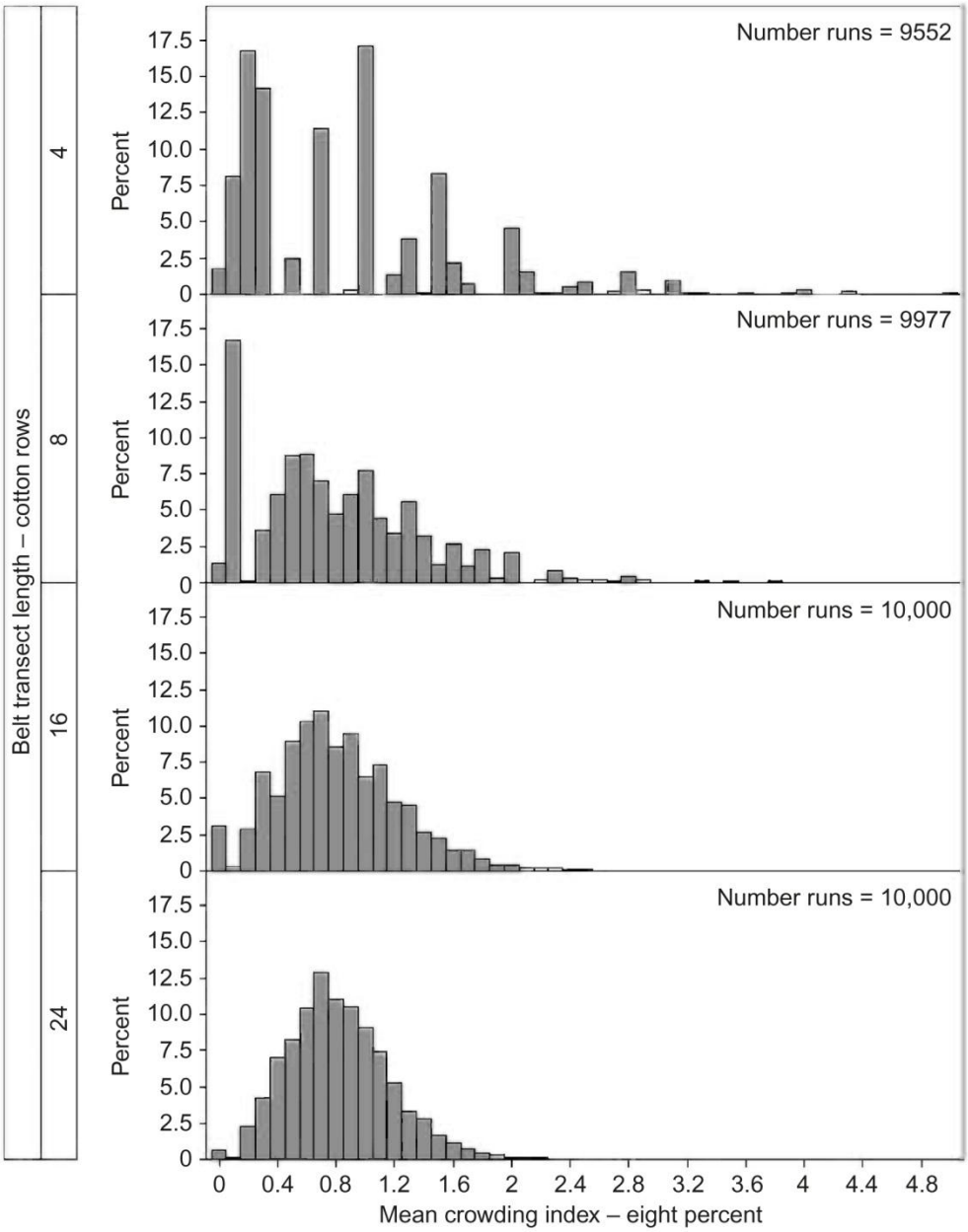

Figure 3.6 Histograms of results for mean crowding for four different transect lengths at a simulated infestation rate of 8%. Infestation rates larger than 8%, but less than 40% (not shown) would show less variability for different transect sizes. Compare to Figure 3.7 for a sample unit size of 315 units.

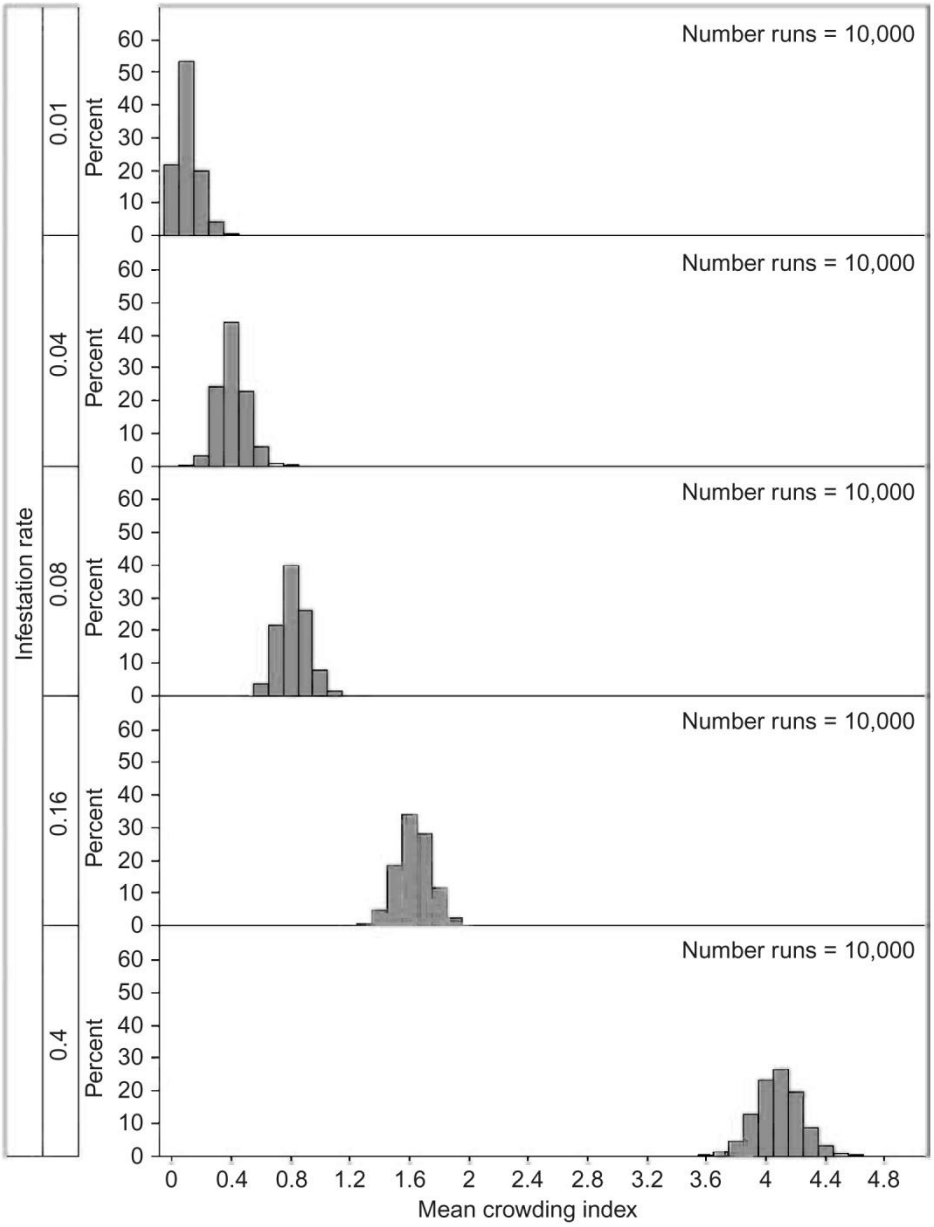

Figure 3.7 Histograms of results for Lloyd's (1967) mean crowding index for five different simulated pest densities where the belt transect length is 315 crop rows.

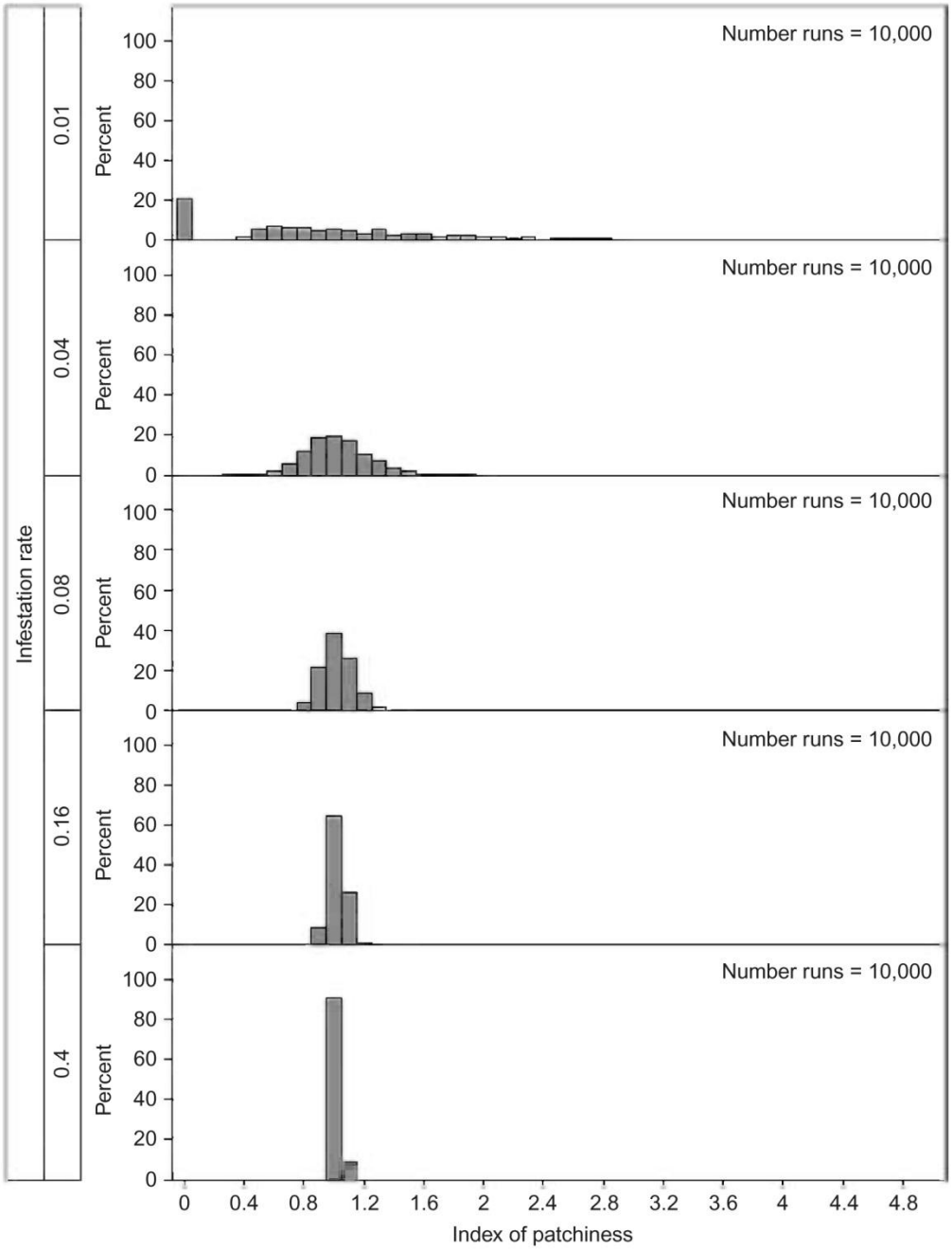

Figure 3.8 Histograms of results for the index of patchiness for five different simulated pest densities across a belt transect length of 315 crop rows.

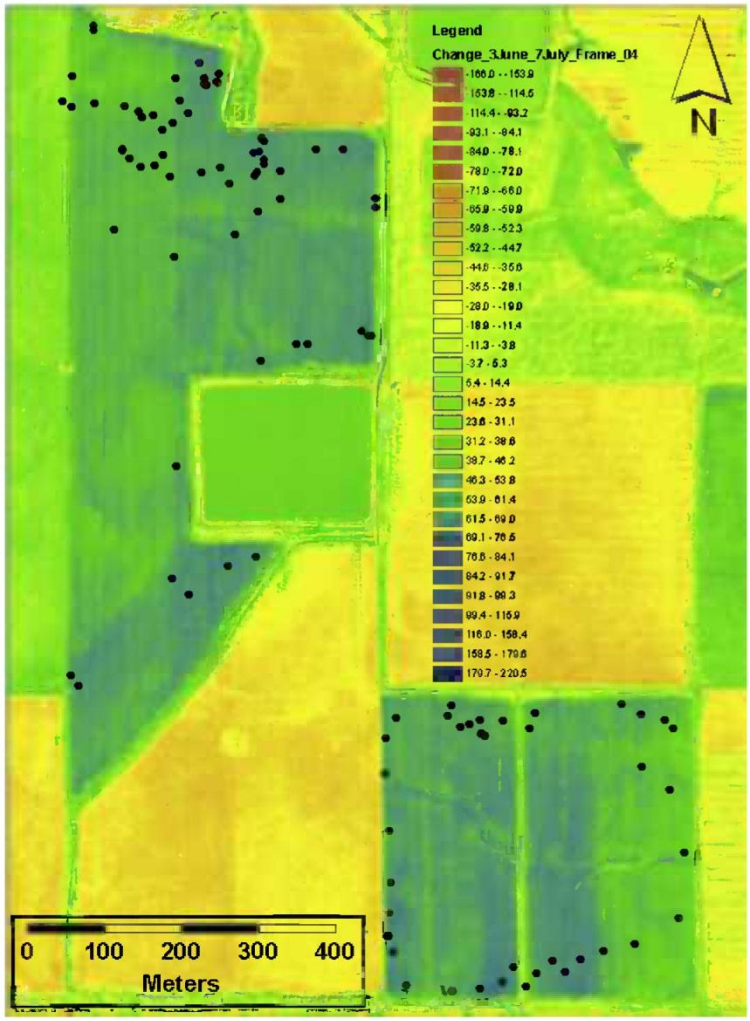

Figure 3.9 Example of scouting sites selection by a field scout for the entire 2006 production season for three cotton fields in Noxubee County, MS.

3.4 Discussion

Stern et al. (1959) first presented the concept of an economic threshold (ET) or economic injury level (EIL). They elaborated on several key ecological concepts and discussed the impact of changes in pest density in both space and time (Fleischer et al., 1999). The simulation results presented here indicate that when a pest population exceeds an ET as low as four insects per 100 plants, it is plausible and practical to conclude that the pest persists at that density until the 'edge' of another habitat class is encountered. Across this edge or habitat boundary, pest density will either decrease or increase in response to shifts in environmental conditions encountered within these adjacent areas. These effects

are stable during a small increment of time so that crop management decisions can be made. From this perspective, the chief value of remote sensing is the delineation of edges of cotton habitats (Willers et al., 1999, 2005; Willers, unpublished data) that are due to variability in edaphic or hydropedologic conditions as well as nutrient availability (Daubenmire, 1974; DeFauw et al., 2006; Gish et al., 2005).

In this study, Lloyd's indices evaluated the plausibility of an assumption (see also Willers et al., 2005, p. 438) that a random dispersion pattern occurs within a habitat class for many fruit feeding cotton insect pests if sufficiently sized sampling units are geographically nested. To link this finding to field applications, other small experiments, based upon discrete probability applications with dice, were also conducted. These transitional experiments convey how the linkages between the spatial resolution of image pixels and the spatial resolution of a variable-rate equipped ground sprayer combine to create sample units of various sizes that represent the entities actually sampled. Consequently, the perspective that pests follow a random dispersion pattern, in homogeneous habitat classes, whenever the infestation rate is large enough to require action, leads to simplicity in field applications. Here are the salient points. First, the field can be apportioned into distinctive habitat classes, similar to the use of colour in the experiments with dice. Second, these habitat classes can be apportioned into discrete sample units according to characteristics of variable-rate sprayer equipment. This is the same as the face of each side of any one die. Third, the intersections of these sprayer unit polygons with the pixel ground spatial distances of the classified remote sensing imagery comprise a population of countable sampling units (Figure 3.10) from which a SRS scheme can be employed to assess the risk of pest infestation in the habitat classes. Once a location in a field is sampled and its locus mapped by GPS, the collection of counts of insects using a quadrat-based construct generates a list of values from each location, just as lists can be generated from the simulations using dice. If the insect is ubiquitous throughout the field, then the lists of counts will behave similarly to those found in Tables 3.3 and 3.4. On the other hand, if the insect is only ubiquitous in some habitat classes and not others, then the list of sample counts from the field will behave similarly to that found in Table 3.5. And, if a count does not arise (for example, the absent 3 for the colour blue (Table 3.4)), it will show up promptly as occurrences of zeros in just a few samples (n<30). Interestingly, however,

for a count such as the 3, which was doubled up for the red colour, it requires a very large number of samples to assess a subtle pattern involving nonzero counts. But, if there is a pattern of counts strongly associated with a spatial structure, such as colour (Table 3.5), then that reality is quickly noticed and can be determined with very, very small sample sizes (for example, seven rolls or less). These points, for example, are further confirmation of the idea that there are patterns in the counts from a geo-referenced SRS plan as first investigated by a sensitivity analysis using resampling methods (Willers et al., 2000) and a second work comparing resampling and count model regression approaches of field samples obtained by two persons (Willers et al., 2009). Thirdly, the effects of sample unit size on these patterns is also strengthened as described in Willers et al. (1990, 2005). Therefore, all of these sources of evidence indicate that it is not necessary to sample all patches of habitat in any given field, as far too many people believe necessary to do with a site-specific sampling plan employing classified imagery products.

In commercial applications, it is not possible to satisfy the sample number sizes often required by theory (Karandinos, 1976); therefore, discovering new estimators accurate at low pest densities while using small sample sizes is advantageous. Armed with an understanding of the relationships gleaned from this and previous simulation efforts (Willers et al., 2005), numerous seasons of fieldwork confirm that it is possible to use smaller numbers of field samples. The samples can be obtained more effectively and better interpreted if remotely-sensed imagery is available (Willers and Riggins, 2010). Information derived from timely and frugal sampling methods linked to remote sensing imagery of row crop landscapes provides the template for sitespecific applications of pesticides, reducing costs and providing environmental benefits (Dupont et al., 2000; Frigden et al., 2002; Seal et al., 2001). This additional benefit of classified imagery for field sampling was also demonstrated in the experiments with coloured dice. Opportunities exist to further refine the computer simulation model. For instance, the model may be too heavily influenced by values of abundance from the upper tail of the NBD. It may be more realistic to assume that biological populations within a homogeneous habitat (Willers et al., 1999, 2005) class are less likely to exhibit the higher count values with respect to their population mean for a particular habitat class. In other words, sample count distributions may be more restrictive within habitat classes under field conditions, such that the higher

extremes predicted to occur by a fit to a particular probability density function may actually not occur. Other possibilities to consider are that the classification procedure (e.g. Backoulou et al., 2013; Willers et al., 2012) applied to the imagery may not have been the most appropriate choice for a particular pest species or that the information captured by a particular sensor type is erroneous due to inadequate calibration or sensor failure.

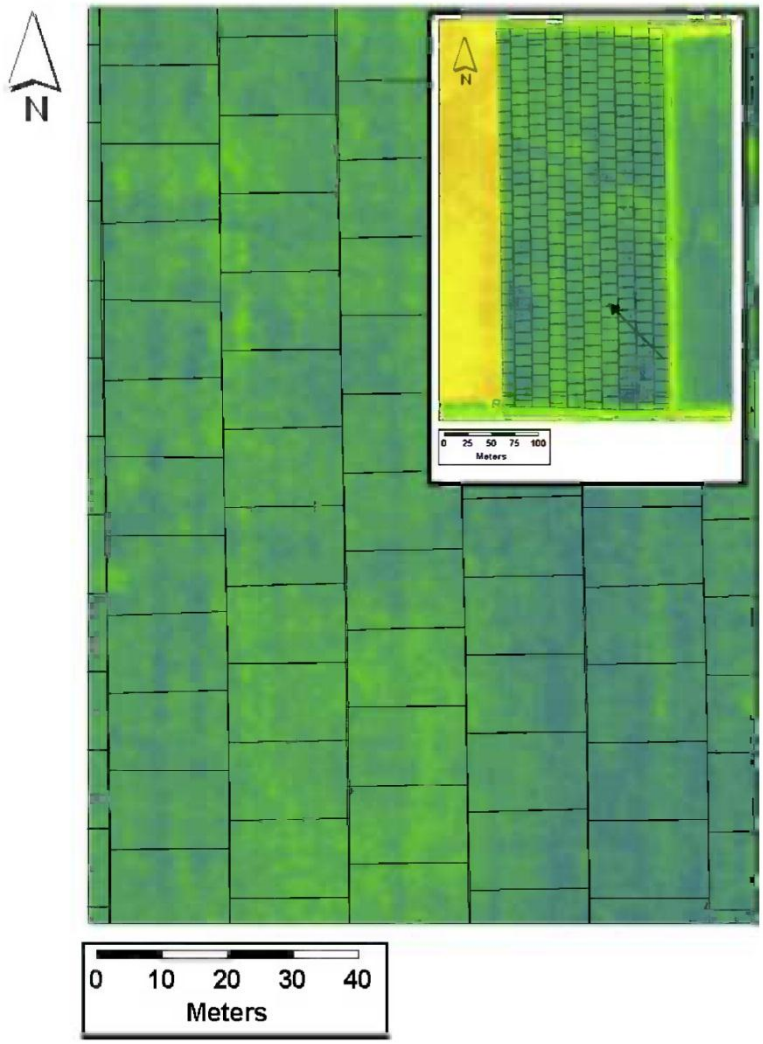

Figure 3.10 Example spray grid showing the polygons within sprayer paths that are the basis of assignments for different pesticide rates to build a spatial prescription. Each polygon of the grid is equivalent in area to a stacked belt transect sample of 315 units (or 219.456m2).

3.5 Conclusions

The simulation analyses indicate that the assumption of random dispersion of a pest within crop habitats (based on remotely-sensed phenologic indicators that correlate well with pest density differences) is practical and prudent for commercial scouting and decision making purposes. The assumption strengthens continued use of SRS or line intercept (LIS) estimators for pest densities within habitat classes established by the geoprocessing of remote sensing images acquired during key cropspecific stages of the growing season. The findings reported here, when linked to outcomes presented in our earlier works (Willers and Akins, 2000; Willers and Riggins, 2010; Willers et al., 1990, 1999, 2005, 2009, 2012) and other investigators (e.g. Carrière et al., 2006; Dammer and Adamek, 2012; Karimzadeh et al., 2011; van Helden, 2010) build up a body of knowledge helpful for assessing pest dispersion and abundance in large, remotely-sensed, commercial production fields. These concepts and methods on image-based, geographical SRS sampling procedures are expected to change the future of insect pest control once further research is accomplished.

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References

1. Anscombe, F.J., 1949. The statistical analysis of insect counts based on the negative binomial distribution. Biometrics 5, 165–173.

2. Ash, C., 1993. The probability tutoring book. An Intuitive Course for Engineers and Scientists. IEEE Press, New York.
3. Backoulou, G.F., Elliott, N.C., Giles, K.L., Rao, M.N., 2013. Differentiating stress to wheat fields induced by *Diuraphis noxia* from other stress causing factors. Comput. Electron. Agric. 90, 47–53.
4. Banerjee, B., 1976. Variance to mean ratio and the spatial distribution of animals. Experientia 72, 993–994.
5. Byerly, K.F., Gutierrez, A.P., Jones, R.E., Luck, R.F., 1978. A comparison of sampling methods for some arthropod populations in cotton. Hilgardia 46, 257–282.
6. Carrière, Y., Ellsworth, P.C., Dutilleul, P., Ellers-Kirk, C., Barkley, V., Antilla, L., 2006. A GIS-based approach for areawide pest management: the scales of *Lygus Hesperus* movements to cotton from alfalfa, weeds, and cotton. Entomol. Exp. Appl. 118, 203–210.
7. Dalthorp, D., Nyrop, J., Villani, M.G., 2000. Foundations of spatial ecology: The reification of patches through quantitative description of patterns and pattern repetition. Entomol. Exp. Appl. 96, 119–127.
8. Dammer, K.-H., Adamek, R., 2012. Sensor-based insecticide spraying to control cereal aphids and preserve lady beetles. Agron. J. 104 (6), 1694–1701.
9. Daubenmire, R.R., 1974. Plants and Environment: A Textbook of Autecology, third ed. John Wiley and Sons, New York.
10. Davis, P.M., 1994. Statistics for describing populations. In: Pedigo, L.P., Buntin, G.D. (Eds.), Handbook of Sampling Methods for Arthropods in Agriculture. CRC Press, Boca Raton, FL, pp. 33–54.
11. DeFauw, S.L., English, P.J., Harris, F.A., Willers, J.L., 2006. Field-scale stability assessment of cotton productivity zones using NDVI imagery, soils, TDR, Veris and yield data. Proceedings of the Beltwide Cotton Conference, vol. 8, pp. 2092–2099d.
12. Dupont, J.K., Campenella, R., Seal, M.R., Willers, J.L., Hood, K.B., 2000. Spatially variable insecticide applications through remote sensing. Proceedings of the Beltwide Cotton Conference, vol. 2, pp. 426–429.
13. Fleischer, S.J., Blom, P.E, Weisz, R., 1999. Sampling in precision IPM: when the objective is a map. Phytopathology 89, 1112–1118.

14. Frigden, J.J., Seal, M.R., Lewis, M.D., Willers, J.L., Hood, K.B., 2002. Farm level spatially-variable insecticide applications based on remotely sensed imagery. Proceedings of the Beltwide Cotton Conference. 13 pp. (unpaginated CD).
15. Gish, T.J., Walthall, C.L., Daughtry, C.S.T., Kung, K.-J.S., 2005. Using soil moisture and spatial yield patterns to identify subsurface flow patterns. J. Environ. Qual. 34, 274–286.
16. van Helden, M., 2010. Spatial and temporal dynamics of arthropods in arable fields. In: Oerke, E., Gerhards, R., Menz, G., Sikora, R.A. (Eds.), Precision Crop Protection – the Challenge and Use of Heterogeneity, first ed. Springer, pp. 51–64.
17. Karandinos, M.G., 1976. Optimum sample size and comments on some published formulae. Bull. Entomol. Soc. Am 22, 417–421.
18. Karimzadeh, R., Hejazi, M.J., Helali, H., Iranipour, S., Mohammadi, S.A., 2011. Assessing the impact of sitespecific spraying on control of Eurygaster integriceps (Hemiptera: Scutellieridae) damage and natural enemies. Prec. Agric. 12, 576–593. Lloyd, M., 1967. Mean crowding. J. Anim. Ecol. 36, 1–30.
19. Ludwig, J.A., Reynolds, J.F., 1988. Statistical Ecology: A Primer on Methods and Computing. John Wiley and Sons, New York.
20. McKinion, J.M., Jenkins, J.N., Willers, J.L., Zusmanis, A., 2009. Spatially variable insecticide applications for early season control of cotton insect pests. Comp. Electron. Agric. 67, 71–79.
21. Myers, J.H., 1978. Selecting a measure of dispersion. Environ. Entomol. 7, 619–621.
22. Nelson, T., Wilson, H.G., Boots, B., Wulder, M.A., 2005. Useof ordinal conversion for radiometric normalization and change detection. Int. J. Rem. Sens. 26, 535–541.
23. Pielou, E.C., 1960. A single mechanism to account for regular, random and aggregated populations. J. Anim. Ecol. 48, 574–584.
24. Pielou, E.C., 1977. Mathematical Ecology. John Wiley and Sons, New York.
25. Pielou, E.C., 1978. Population and Community Ecology: Principles and Methods. Gordon and Breach, New York.
26. Poole, R.W., 1974. An Introduction to Quantitative Ecology. McGraw-Hill, New York.
27. Pritsker, A.B., Pegden, C.D., 1979. Introduction to Simulation and SLAM. Halsted Press, John Wiley and Sons, New York.

28. Richards, J.A., Jia, X., 1999. Remote Sensing Digital Image Analysis. An Introduction, third ed. Springer-Verlag, Berlin.
29. SAS Institute, 1990. SAS® Language: Reference, Ver. 6, first ed. SAS Institute, Cary, NC. Seal, M., Dupont, K., Bethel, M., Lewis, D., Johnson, J., Willers, J., et al., 2001. Utilization of remote sensing technologies in the development and implementation of large-scale spatially variable insecticide experiments in cotton. Proceedings of the Beltwide Cotton Conference, Vol. 2, 1010–1018.
30. Southwood, T.R.E., 1978. Ecological Methods with Particular Reference to the Study of Insect Populations. Halsted Press, John Wiley and Sons, New York. Southwood, T.R.E., Brown, V.K., Reader, P.M., 1983.
31. Continuity of vegetation in space and time: a comparison of insects' habitat templet in different successional stages. Res. Popul. Ecol. (Suppl. 3), 61–74.
32. Steel, R.G.D., Torrie, R.H., 1960. Principles and Procedures of Statistics. McGraw-Hill, New York.
33. Stern, V.M., Smith, R.F., van den Bosch, R., Hagen, K.S., 1959. The integrated control concept. Hilgardia 29, 81–101.
34. Theobald, D.M., 2003. GIS Concepts and ArcGIS® Methods. Conservation Planning Technologies, Fort Collins, CO. Thompson, S.K., 1992. Sampling. Wiley-Interscience, New York.
35. Trumble, J.T., 1985. Implications of changes in arthropod distribution following chemical applications. Res. Popul. Ecol. 27, 277–285.
36. Willers, J.L., Akins, D.S., 2000. Sampling for tarnished plant bugs in cotton. Southwest. Entomol. (Suppl. 23), 39–57.
37. Willers, J.L., Riggins, J.J., 2010. Geographical approaches for integrated pest management of arthropods in forestry and row crops. In: Oerke, E., Gerhards, R., Menz, G., Sikora, R.A. (Eds.), Precision Crop Protection – the Challenge and Use of Heterogeneity, first ed. Springer, pp. 183–202.
38. Willers, J.L., Boykin, D.L., Hardin, J.M., Wagner, T.L. Olson, R.L., Williams, M.R., 1990. A simulation study on the relationship between the abundance and spatial distribution of insects and selected sampling schemes. Proceedings of the Conference on Applied

Statistics in Agriculture, 29 April–1 May 1990, Kansas State University, Manhattan, KS, pp. 33–45.

39. Willers, J.L., Seal, M.R., Luttrell, R.G., 1999. Remote sensing, line-intercept sampling for tarnished plant bugs (Heteroptera: Miridae) in Mid-south cotton. J. Cotton Sci. 3 (4), 160–170.
40. Willers, J.L., Ladner, W.L., McKinion, J.M., Cooke, W.H., 2000. Application of computer intensive methods to evaluate the performance of a sampling design for use in cotton insect pest management. Proceedings of the Conference on Applied Statistics in Agriculture, 30 April–2 May 2000, Kansas State University, Manhattan, KS, pp. 119–133.
41. Willers, J.L., Jenkins, J.N., Ladner, W.L., Gerard, P.D., Boykin, D.L., Hood, K.B., et al., 2005. Site-specific approaches to cotton insect control. Sampling and remote sensing analysis techniques. Prec. Agric. 6, 431–452.
42. Willers, J.L., Jenkins, J.N., McKinion, J.M., Gerard, P., Hood, K.B., Bassie, J.R., et al., 2009. Methods of analysis for georeferenced sample counts of tarnished plant bugs in cotton. Prec. Agric. 10, 189–212.
43. Willers, J.L., Wu, J., O'Hara, C., Jenkins, J.N., 2012. A categorical, improper probability method for combining NDVI and LiDAR elevation information for potential cotton precision agricultural applications. Comput. Electron. Agric. 82, 15–22.
44. Williams, M.R., Wagner, T.L., Willers, J.L., 1995. Revised protocol for scouting arthropod pests of cotton in the Midsouth. Miss. Agric. For. Exp. Stn. Tech. Bull. 206.
45. Wilson, L.T., 1994. Estimating abundance, impact, and interactions among arthropods in cotton agroecosystems. In: Pedigo, L.P., Buntin, G.D. (Eds.), Handbook of Sampling Methods for Arthropods in Agriculture. CRC Press, Boca Raton, FL, pp. 475–514.