Remote Sensing, Sampling and Simulation Applications in Analyses of Insect Dispersion and Abundance in Cotton

J. L. Willers, Research Entomologist, J. M. McKinion, Electronics Engineer, and J. N. Jenkins, Geneticist, USDA-ARS Genetics and Precision Agriculture Research Unit, Mississippi State, MS

Abstract—*Simulation was employed to create stratified simple random samples of different sample unit sizes to represent tarnished plant bug abundance at different densities within various habitats of simulated cotton fields. These samples were used to investigate dispersion patterns of this cotton insect. It was found that the assessment of spatial pattern varied as a function of sample unit size and was independent of large pest densities. Using this knowledge, it was demonstrated how remote sensing assists field scouts in estimating pest abundance and the pattern of dispersion within commercial cotton fields. For the majority of pest management decisions in commercial fields, both the simulation data and field results supported the robust assumption that cotton pests are randomly dispersed at different densities within homogenous habitats. Therefore, it was possible to estimate the boundaries of different pest densities by mapping habitat variability within cotton fields using high resolution, geo-referenced, remotely sensed imagery. Once boundaries for various densities of the pest were established, site-specific prescriptions of pesticides were implemented, reducing pest management costs and the amount of pesticide applied to the environment.*

Introduction

Analyzing the dispersion of many cotton insect pests in large commercial cotton fields is a challenging problem in applied ecology. Pest dispersion impacts sampling (Davis 1994; Trumble 1985), analysis of population ecology (Banerjee 1976; Dalthorp and others 2000; Fleischer and others 1999), the establishment of economic thresholds or injury levels (Byerly and others 1978; Stern and others 1959; Wilson 1994), the rate of habitat colonization (Southwood and others 1983), and the building of spatially-based prescriptions (Dupont and others 2000; Fleischer and others 1999; Seal and others 2001) to control cotton pests. The need to create efficient maps describing cotton pest dispersion patterns in commercial cotton fields provided the motivation for this study.

A simulation approach was stressed to avoid effects due to discrepancies in observer abilities, sampling error, management practices, location effects, or lack of enough sample time, all of which arise in field conditions and influence conclusions. Simulation methods to investigate relationships among sample unit size, clustering and infestation rate have already been described (Willers and others 1990). These initial results are built upon in this work, where simulation methods now explore the relationship between infestation rate and measures of dispersion for sample units of different sizes if pests are randomly dispersed. Knowledge of these relationships is necessary in order to employ (Willers and others 1999) remote sensing to stratify cotton fields into various habitats according to the phenology of the crop. Willers and others (1999) have previously found that tarnished plant bugs (TPB; *Lygus lineolaris* [P. de B.] (Heteroptera: Miridae)) distribute themselves at different infestation rates in these habitats. Information about how dispersion patterns relate to sample unit size, pest density, and habitat quality therefore creates the foundation for spatial approaches toward cotton insect control. These simulation results are applicable to the tarnished plant bug. Results are relevant to field data and can apply to other pest species (Willers, unpublished), particularly for pests that attack the floral structures of the cotton plant.

The various methods utilized in the analysis of spatial patterns have been presented by Dalthorp and others (2000), Davis (1994), Kuno (1991), Ludwig and Reynolds (1988), Patil and Stiteler (1974), Pielou, (1977, 1978), Southwood (1978), Taylor (1984) and Waters (1959). The analysis approach employed here does not follow the traditional testing of the goodness of fit of sample data to expected frequencies estimated from the Poisson, or any other probability distribution (Davis 1994; Ludwig and Reynolds 1988; Poole 1974; Steel and Torrie 1960). The reason for choosing to not use this classical approach was the deliberate choice to study estimator performance and assessment of dispersion when the sample size is usually small (< 30 sample units/sample). The goodness of fit test does not apply when sample size is small. Therefore, use is made of Lloyd's mean crowding and patchiness indices (Lloyd 1967) to test for random dispersion. Also, choices for sample unit size are known to influence the assessment of dispersion, particularly when artificial (as opposed to natural (see Ludwig and Reynolds 1988)) units are employed (Davis 1994; Ludwig and Reynolds 1988; Pielou 1977, 1978; Poole 1974). The indices developed by Lloyd (1967) are not influenced by sample unit size.

The information discovered through use of simulation was used to assess pest dispersion in large commercial cotton fields during the production season.

Methods and Materials

The sample design used in the simulations has been previously described (Willers and others 1999; Willers and Akins 2000) and a sensitivity analysis has been presented in Willers and others (2000). However, several points must be recalled from these previous studies. The first is that the fundamental sample unit size is a quadrat (cell) with a length of 0.9144 m and a width equal to half the row spacing (commonly, 1.016 m) between rows of cotton. Therefore, 0.404 ha (or 1 land ac) of field area will contain 4,359.526 units of this size (at 0.9290 m^2 each). These units provide the main link between the simulated system and field conditions. Specifically, the total number of these units (or small areas centered upon the crop row) in a cotton field is the finite population size (Thompson 1992) at risk to be sampled, and can be apportioned amongst one or more habitats (Willers, unpublished). Also, the individual pixel in a geo-registered, high spatial resolution (1 m^2), multi-spectral image of the field of interest conceptually corresponds to one of these quadrats.

The second point is that these quadrat sampling units can be arranged into a series of consecutive units to span the cotton rows at right angles to the row direction, and form a larger sampling unit called a belt transect (Ludwig and Reynolds 1988; Thompson 1992; Willers and others 1999; Willers and Akins 2000). A single transect constitutes a sample and a diagram of a transect is provided in Willers and Akins (2000). In the field, the number of insects of a particular species are counted, along with ancillary data (such as the size or age of each individual observed), within each quadrat sample unit. The quadrat sample unit results are totaled for each transect sample. In the simulated system the model generates and tallies these counts.

The third point is that these transects (using a simple random sampling strategy) are placed at consultant/producer determined locations within habitats based upon maps derived by classified imagery (Richards and Jia 1999; Willers and others 1999; Willers, unpublished) of the cotton field. In the simulated system, different habitats are modeled by changing the infestation rate parameter (see below).

Simulation Model Development and Assumptions

The development of the simulation model to study dispersion in the presence of different pest densities and sample unit sizes was based upon the negative binomial distribution (NBD) (Anscombe 1949; Davis 1994; Ludwig and Reynolds 1988; Pielou 1977, 1978; Southwood 1978). Willers and others (1990) describe most modifications necessary to simulate impacts of different sample unit sizes, densities, and dispersion patterns using the NBD. Counts of numbers of insects per row for simulated belt transects of different lengths (L) and infestation rates (λ) were obtained using the NBD with its dispersion parameter (k) set to 50 so that random variates could be generated at different pest infestation rates and sample unit sizes, under the assumption of a Poisson (random) dispersion pattern. The simulated sample unit size for each quadrat (or crop row length) of the belt transect was fixed at 10 plants/quadrat (Willers and others 1990; Willers, unpublished). The number of insects (events) per quadrat for a belt transect of length L was generated by the inverse transformation method (Pritsker and Pegden 1979) and used to sample a simulated area of field having a particular mean infestation rate (or number of insects/100 plants, λ). To create transect lines of different lengths (or a sample unit of length L) a 'do-loop' was employed to repeat the process and simulate the sample results for a specified number of 'crop rows'. The simulation model was programmed in SAS® (SAS Institute 1990).

The question in this study was to determine how assessment of dispersion differs with changes in (1) the pest density (infestation rate) and (2) the length of the primary sample unit within a cotton habitat class. Therefore, various lengths (L = 4, 8, 16, 24, or 396 rows) of belt transects were employed and the dispersion pattern of insect pests at different densities was investigated. Comparisons of simulated results with actual TPB counts were obtained by comparison with transect lines sampled in a commercial cotton field (Willers and others 1999; Willers, unpublished). This published data set can be examined and compared to these simulated results (available online at http://www.jcotsci.org).

Analysis of Dispersion

Lloyd's indices of patchiness and mean crowding (Lloyd 1967) judged performance of the random dispersion assumption for simulated combinations of different infestation rates (densities) and transect sample unit sizes. The index of patchiness is a measure of random dispersion when equivalent to unity (Davis 1994; Lloyd 1967; Southwood 1978). The index of mean crowding (Lloyd 1967; Pielou 1977) is a description of the mean number of individuals occupying the same habitat space as another individual. In this study, this index applies to the quadrat sample unit and not the belt transect sample unit.

Results

The various combinations of pest density and transect length were studied using 10,000 simulation runs. Estimates of mean crowding and patchiness were obtained for each combination and summarized by histograms. Figs. 1 through 3 show results for estimates of Lloyd's index of patchiness at several infestation rates and several different (short) transect lengths. Simulation results where the transect length is fixed for a long distance (396 crop rows) while varying the infestation rate (λ = 0.01, 0.08, 0.16, 0.24, and 0.40) are presented in figures 4 (mean crowding) and 5 (patchiness).

Analyses of Simulation Data Using Lloyd's Indices

The index of patchiness is derived from the mean crowding index (Davis 1994; Lloyd 1967). This index indicates random dispersion for values equivalent to 1. Patterns of results are shown for λ = 0.01, 0.08 and 0.24 (figs. 1 through 3). For brevity, only a few of the many possible graphs from simulation runs estimating dispersion statistics are shown. For patchiness, as belt transect length and infestation rate increased, the index decreases in multi-modality and increasingly centers about a modal value of 1. This index is sensitive to choices for sample unit size, 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 supports the assumption that a random dispersion pattern is plausible for most densities estimated with a belt transect sampling technique. Consistency in estimating this index is most doubtful if too short of a transect was employed and the density was close to zero, which means that field samples would most likely be so variable as to obscure any discernment of relationships. Trends are most clear if very long transects are utilized; however, very long transects require too much time in commercial fields.

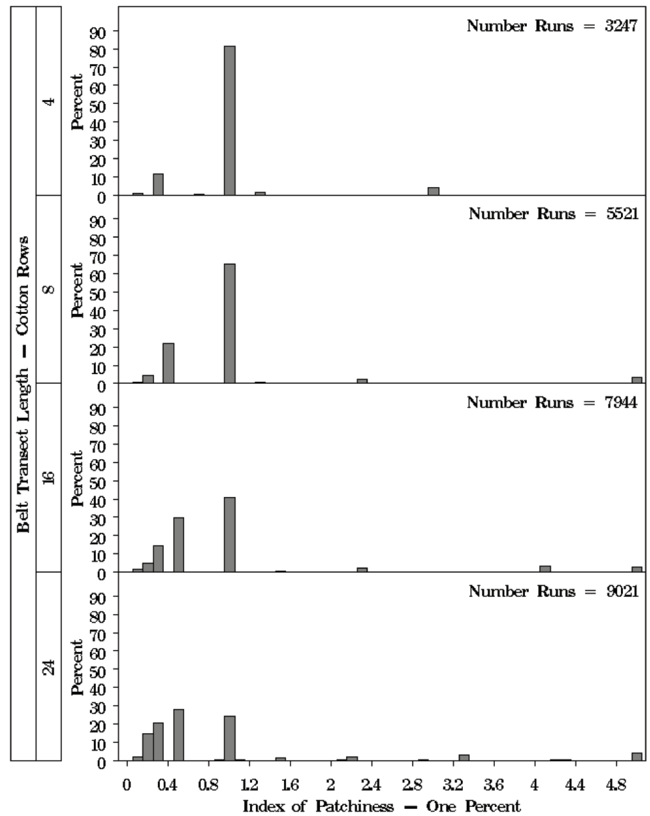

Figure 1. Histograms of results for Lloyd's (1967) index of patchiness for 4 different transect lengths at a simulated infestation rate of 1 percent. The index has a value < 1 for regular dispersion patterns.

Analysis of Simulation Data Using A Long Transect

The pattern of response between pest density and very long transects is presented in figs. 4 and 5. While many lengths could be chosen, we selected one that was ca. 0.4 km (0.25 mi) long. This distance is often encountered in large fields and within similar habitat classes of cotton growth and phenology as captured by remote sensing imagery.

The analysis of results at this large size (or distance) of sample unit reveals an interesting finding about increases in pest numbers per unit area. Mean crowding is a noisy parameter when belt transects increasingly shorter than 24 rows are employed and lower infestation rates exist (data not presented). Mean crowding estimates for long transects (L = 396 rows), on the other hand, are well separated with increases in density (fig. 4). This result is reasonable and could be important for assisting the development of better logic for spatial simulation

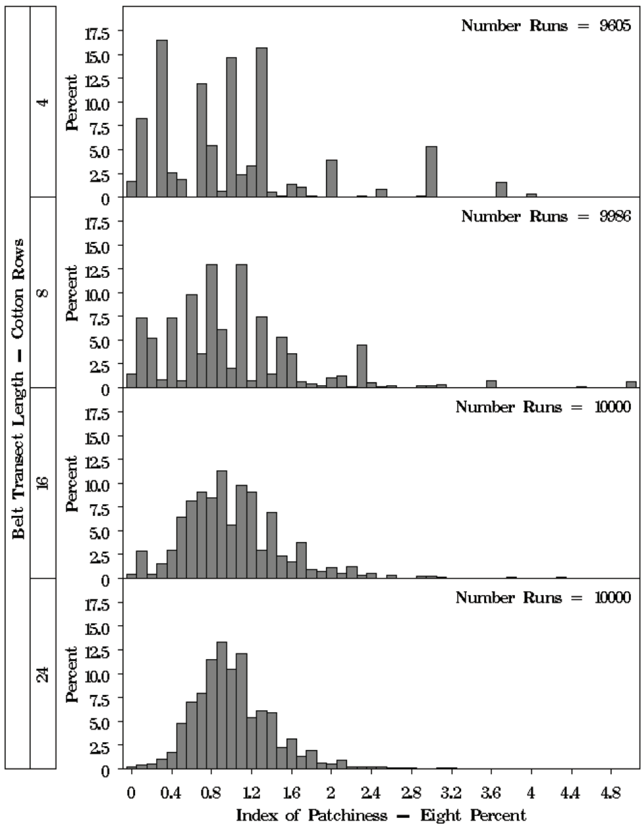

Figure 2. Histograms of results for the index of patchiness for four different transect lengths at a simulated infestation rate of 8 percent. The index has a value > 1 for aggregated dispersion patterns.

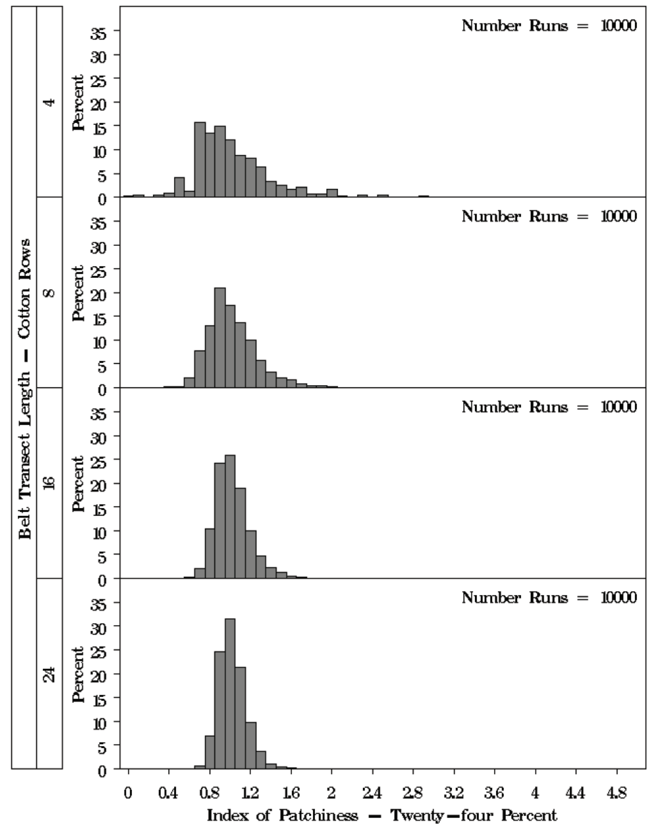

Figure 3. Histograms of results for the index of patchiness for four different transect lengths at a simulated infestation rate of 24 percent. The index is equivalent to one for random dispersion patterns.

models of pest damage to cotton. Wagner and others (1996) reviewed many models of damage to plants by cotton pests. A flaw of many was the failure to correctly model pest damage at high densities. The mean crowding value could provide a metric to better allocate damage amongst groups of plants in simulation models, especially if spatial allocations of different pest densities (within an individual simulated field) were also incorporated.

For all densities, except $\lambda = 0.01$, the index of patchiness for the longest transect converged about a value of 1 (an indicator of random dispersion) (fig. 5). The lack of stability at low densities (as shown in the top panel of fig. 5) was previously found by Byerly and others (1978; p. 262). The effect was attributed to the proportionately large effect that errors in estimating the standard error of a small mean could cause. Similar effects are likely to be at work for the index of patchiness when a short belt transect samples a habitat having a low pest population. The effect is particularly obvious when smaller lengths (recall figs. 1 through 3 and compare across increasing densities at similar transect lengths) are used to sample simulated populations in homogenous habitats. Furthermore, for low population densities there may not be enough individuals to occupy all available habitat spaces, which also would cause deviations from a random dispersion index of 1. However, the patchiness index is independent of density (fig. 4) once there is a departure from very low infestation rates (fig. 5) (Myers 1978).

The behavior of convergence about a patchiness of 1 for large sample unit sizes (fig. 5) shows most clearly the validity of a random dispersion pattern over a large spatial extent (or distance), particularly for increases in infestation. While it is impractical to sample large sized sample units, it is practical to apply simple random sampling within homogenous habitat classes and select widely spaced sample sites. If the estimate of pest density is similar at the widely spaced sites within a habitat class, it is reasonable to infer that other unsampled locations between these sites are also infested at a similar rate. Therefore, a habitat classification map derived from imagery can effectively be used to estimate pest severity in commercial fields without large sample sizes, because the pest is most likely randomly dispersed throughout the habitat. Other works are in preparation to verify with field observations this conclusion derived by use of simulation.

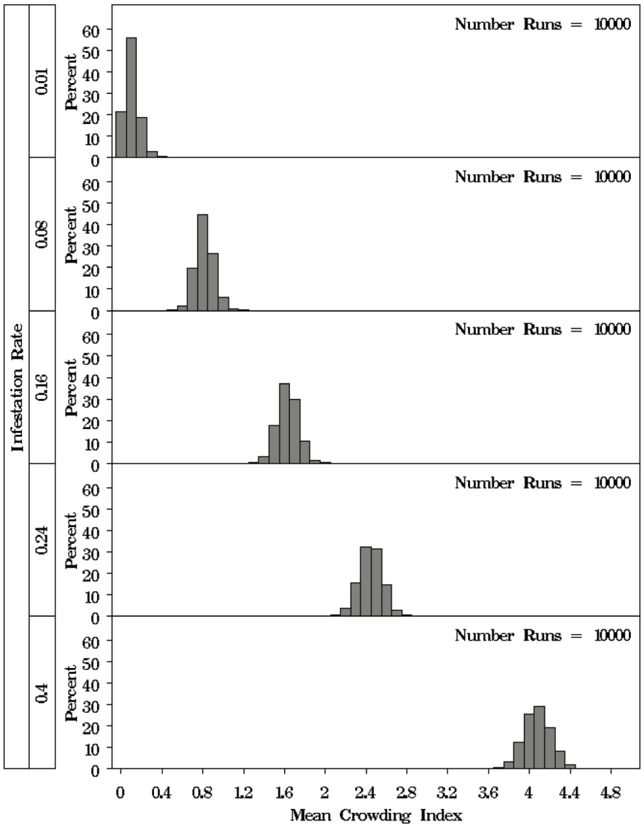

Figure 4. Histograms of results for Lloyd's (1976) mean crowding index for 5 different simulated pest densities where the belt transect length is 396 crop rows.

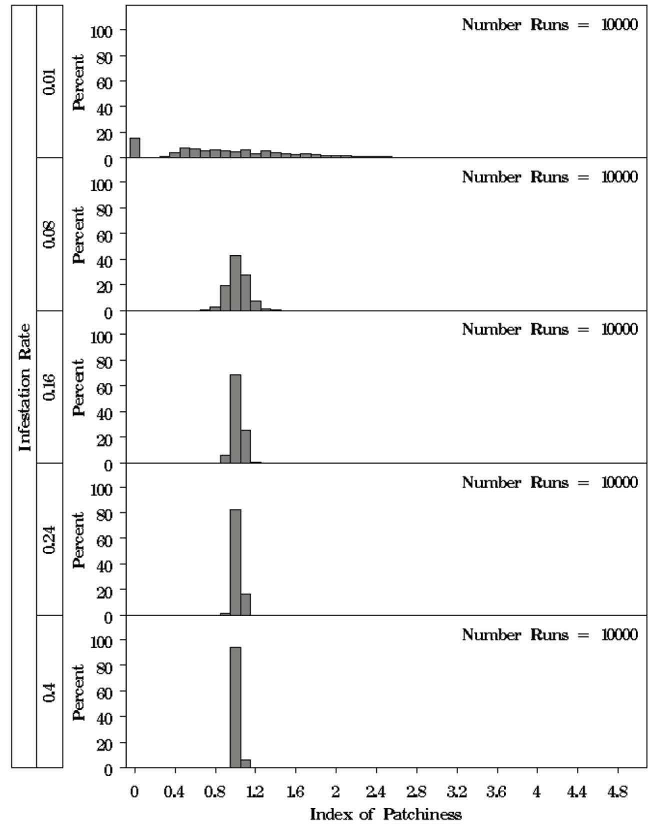

Figure 5. Histograms of results for the index of patchiness for five different simulated pest densities across a belt transect length of 396 crop rows.

Discussion

Stern and others (1959) first presented the concept of an economic threshold (ET), or economic injury level (EIL). They discussed several ecological concepts and considered the impact of changes in pest density in both space and time (Fleischer and others 1999). It is reasonable to consider that the ET and EIL strongly imply the presence of a consistent density on a spatial scale until an edge of a habitat class is encountered. Across this edge, the pest density will decrease or increase as the habitat and/or environmental conditions within these other additional regions vary. These effects will persist during a small increment of time so that management decisions can be made. Remote sensing can provide the delineation of edges of cotton habitats (Willers and others, 1999; Willers, unpublished). These technologies, along with the use of appropriate ecological assumptions combined with density estimates (with small sample sizes) and experience (Willers, unpublished), permit the building of plausible maps of pest density in cotton. The five key concepts driving the creation of these pest density maps are (1) the assumption of a random dispersion pattern amongst (2) small units of area for (3) characteristic densities occurring within (4) different habitats in cotton fields over (5) time.

Many investigators consider regular and random dispersion patterns to be rare in natural contexts (Dalthorp and others 2000; Ludwig and Reynolds 1988; Taylor 1961; Wilson 1994). For insects that are distributed across natural units (Ludwig and Reynolds, 1988) such as a plant, a leaf, or a cotton bud (square, flower, or boll) one can easily envision (in fact, demonstrate) that an aggregated dispersion pattern is common. Using sample units that are small in size, we can, in these cases, agree with traditional thinking. In this study, a measure of dispersion examined the assumption that a random dispersion pattern could be assumed for many fruit feeding cotton insect pests when large arbitrary (rather than natural (Ludwig and Reynolds 1988)) sampling units are employed. Based upon the use of these practical, but arbitrary, sampling units, we disagree with traditional thinking that random dispersion patterns are rare. Furthermore, the conclusion of random dispersion found amongst belt transects should apply to other sampling techniques (for example, whole plant visual samples, drop cloth, or sweep net) provided that sample units are constructed to constitute more than a single plant. The intent should be to focus searching within 'small' sizes of area, rather than over a wide scattering of individual plants across a large area or along a single, short length of row (Willers, unpublished) as traditionally done in cotton.

Several authors have used simulation as a tool to answer various questions about either aggregation or dispersion (Myers 1978; Pielou 1960; Sawyer 1989). The findings of this simulation study have also produced useful results. Obtaining a field data set as comprehensive as those obtained here by use of simulation would have been quite expensive. The customized form of the NBD that generated much of the data used in this study has been quite useful in cotton sampling research (Willers and others 1990, 1999; Willers and Akins 2000; Williams and others 1995). The results provided insight useful for the application of site-specific approaches to cotton insect control. The assumption that a random dispersion pattern occurs within large sized sample units (fig. 5) (also found by Sawyer (1989)) derived from a series of contiguous, secondary sample units placed in homogenous habitats has value. The finding can be exploited for (1) redefining economic injury levels (EILs), (2) simulating pest damage to the crop, or (3) refining sample design efficiency. All these goals have relevance for additional discoveries that provide decreases in sample size or sampling time in commercial cotton applications. 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 densities and small sample sizes is desirable. The utilization of information from remote sensing imagery along with the simulation and sampling methods described here can reduce sample time in commercial cotton fields. The same information provides the template for spatial applications of pesticides, reducing costs and providing environmental benefits (Dupont and others 2000; Frigden and others 2002; Seal and others 2001; see also www.gointime.com).

Summary

The simulation analyses indicate that the assumption of random dispersion of a pest within crop habitats occupied at different characteristic densities is useful for commercial scouting and decision making purposes. The assumption strengthens continued use of simple random sampling (SRS) or line-intercept (LIS) estimators (Thompson 1992; Willers and others 1999; Willers and Akins 2000) for pest or plant densities within habitats. Boundaries (or edges) of different pest densities in commercial fields can be determined from appropriately classified (Richards and Jia 1999), high resolution, remotely sensed imagery to create a mosaic (Pielou 1977, 1978) of habitat classes. The pest density estimate for a habitat stratum geographically applies to each class within the mosaic (whether sampled or not) if other conditions such as planting date or other agronomic influences are also similar.

Acknowledgments

We thank Drs. Eric Villavaso and Wes Burger as reviewers for their comments of the initial draft. The Advanced Spatial Technologies for Agriculture Program of Mississippi State University has partially provided funds for the work described. The assistance of Mr. Kenneth Hood, Mr. John Freeman, Mr. John Bassie, Sr., and Mr. M. Doug Cauthen and other staff of Perthshire Farms, Gunnison, MS, is also appreciated.

References

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

Banerjee, B. 1976. Variance to mean ratio and the spatial distribution of animals. Experientia 72: 993-994.

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.

Dalthorp, D.; Nyrop, J.; Villani, M. G. 2000. Foundations of spatial ecology: The reification of patches through quantitative description of patterns and pattern repetition. Entomologia Experimentalis et Applicata 96: 119-127.

Davis, P. M. 1994. Statistics for describing populations. In: Pedigo, L. P.; Buntin, G. D., eds. Handbook of Sampling Methods for Arthropods in Agriculture. Boca Raton, FL.: CRC Press: 33-54.

Dupont, J. K.; Campenella, R.; Seal, M. R.; Willers, J. L.; Hood, K. B. 2000. Spatially variable insecticide applications through remote sensing. Proc. Beltwide Cotton Conf., Vol. 2: 426-429.

Fleischer, S. J.; Blom, P. E.; Weisz, R. 1999. Sampling in precision IPM: When the objective is a map. Phytopathology 89: 1112-1118.

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. Proc. Beltwide Cotton Conf. 13 pp. (unpaginated CD).

Karandinos, M. G. 1976. Optimum sample size and comments on some published formulae. Bull. Entomol. Soc. Am. 22: 417-421.

Kuno, E. 1991. Sampling and analysis of insect population. Ann. Rev. Entomol. 36: 285-304.

Lloyd, M. 1967. Mean crowding. J. Anim. Ecol. 36: 1-30.

Ludwig, J. A.; Reynolds, J. F. 1988. Statistical Ecology: A primer on methods and computing. New York: John Wiley and Sons. 337 p.

Myers, J. H. 1978. Selecting a measure of dispersion. Environ. Entomol. 7: 619-621.

Patil, G. P.; Stiteler, W. M. 1974. Concepts of aggregation and their quantification: a critical review with some new results and applications. Res. Popul. Ecol. 15: 238-254.

Pielou, E. C. 1960. A single mechanism to account for regular, random and aggregated populations. J. Anim. Ecol. 48: 574-584.

Pielou, E. C. 1977. Mathematical ecology. New York: John Wiley and Sons. 384 p.

Pielou, E. C. 1978. Population and community ecology: Principles and methods. New York: Gordon and Breach. 416 p.

Poole, R. W. 1974. An introduction to quantitative ecology. New York: McGraw-Hill. 532 p.

Pritsker, A. B.; Pegden, C. D. 1979. Introduction to simulation and SLAM. New York: Halsted Press, John Wiley and Sons.

Richards, J. A.; Jia, X. 1999. Remote sensing digital image analysis. An introduction (3rd ed.). Berlin: Springer-Verlag. 363 p.

Sawyer, A. J. 1989. Inconstancy of Taylor's b: Simulated sampling with different quadrat sizes and spatial distributions. Res. Popul. Ecol. 31: 11-24.

SAS Institute, 1990. SAS® Language: Reference, Ver. 6, 1st ed. Cary, NC: SAS Institute.

Seal, M.; Dupont, K.; Bethel, M.; Lewis, D.; Johnson, J.; Willers, J.; Hood, K.; Hardwick, J.; Leonard, R.; Bagwell. R. 2001. Utilization of remote sensing technologies in the development and implementation of large-scale spatially variable insecticide experiments in cotton. Proc. Beltwide Cotton Conf., Vol. 2: 1010-1018.

Southwood, T. R. E. 1978. Ecological methods with particular reference to the study of insect populations. New York: Halsted Press, John Wiley and Sons. 524 p.

Southwood, T. R. E.; Brown, V. K.; Reader, P. M. 1983. Continuity of vegetation in space and time: A comparison of insects' habitat templet in different successional stages. Res. Popul. Ecol. Suppl. 3: 61-74.

Steel, R. G. D.; Torrie, R. H. 1960. Principles and Procedures of Statistics. New York: McGraw-Hill. 481 p.

Stern, V. M.; Smith, R. F.; van den Bosch, R.; Hagen, K. S. 1959. The integrated control concept. Hilgardia 29: 81-101.

Taylor, L. R. 1961. Aggregation, variance and the mean. Nature 189: 732 – 735.

Taylor, L. R. 1984. Assessing and interpreting the spatial distributions of insect populations. Ann. Rev. Entomol. 29: 321-358.

Thompson, S. K. 1992. Sampling. New York: Wiley-Interscience.

Trumble, J. T. 1985. Implications of changes in arthropod distribution following chemical applications. Res. Popul. Ecol. 27: 277-285.

Wagner, T. L.; Olson, R. L.; Willers, J. L.; Williams, M. R. 1996. Modeling and Computerized Decision Aids. In: King, E. G.; Phillips, J. R.; Coleman, R. J., eds. Cotton Insects and Mites: Characterization and Management. No. 3. Memphis, TN: The Cotton Foundation Reference Book Series: 202-250.

Waters, W. E. 1959. A quantitative measure of aggregation in insects. J. Econ. Entomol. 52: 1180-1184.

Willers, J. L; Akins, D. S. 2000. Sampling for tarnished plant bugs in cotton. Southwest. Entomol. Supp. No. 23: 39-57.

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. Appl. Stat. in Agric. Conf.: proceedings; 1990 April 29-May 1; Manhattan, KS. Kansas State Univ.: 33-45.

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. Appl. Stat. in Agric. Conf.: proceedings; 2000 April 30-May 2; Manhattan, KS. Kansas State Univ.: 119-133.

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. [Online]. J. Cotton Sci. 3(4): 160-170. Available at http://www.jcotsci.org (verified 26 Aug. 2004).

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.

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. Boca Raton, FL: CRC Press: 475-514.