Binomial sampling plans for estimating and classifying population density of adult *Bemisia tabaci* in cotton

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Abstract

We used an empirical relationship to develop models for estimating and for classifying the population density of adult *Bemisia tabaci* (Gennadius) (Homoptera: Aleyrodidae) in cotton based on the proportion of infested leaves. We examined models based on tally thresholds (the minimum number of insects present before a leaf is considered infested) of 1, 2, 3, 4, 5, and 6 adults per fifth mainstem node leaf from the terminal. For the estimation of density, sampling precision (SE/mean) increased with higher tally thresholds (T); however, there was negligible improvement in precision with $T \geq 3$ adults per leaf. Using $T = 3$ as few as 30 samples were necessary to achieve a precision of 0.25 over a wide range of population densities. To evaluate these binomial models for the classification of population density for pest management application, we used simulation analyses to determine operating characteristic curves (error probabilities), and to estimate average sample size and cost functions. Error probabilities and average sample sizes declined with higher values of T, but there was negligible decline in error probabilities using $T \geq 3$ adults per leaf, and the overall cost of sampling was lowest for $T = 3$. Wald's sequential probability ratio test was used to formulate sequential sampling stop lines for classifying population density relative to two nominal action thresholds, 5 or 10 adults per leaf. Simulation analysis indicated that by using $T = 3$, fewer than 30 samples, on average, were needed to classify populations relative to either action threshold. However, simulated error probabilities consistently exceeded the nominal error probabilities used to initially formulate sequential sampling stop lines regardless of the tally threshold. Comparing binomial models using $T = 1$ or $T = 3$ to independent data from four field sites, the model for $T = 1$ was generally biased towards overprediction of mean density, but the $T = 3$ model was a robust and relatively unbiased predictor of mean density. The binomial sampling plans presented here should permit the rapid estimation of population density and enhance the efficiency of pest management programs based on the prescriptive suppression of *B. tabaci* in cotton.

Introduction

Bemisia tabaci (Gennadius), the sweetpotato whitefly, occupies subtropical and tropical environments, is multivoltine and polyphagous, and vectors a number of economically important plant viruses (Brown & Bird, 1992). These characteristics underscore the destructive capacity of this insect to agriculture on a worldwide basis, and also emphasize the tremendous challenge to researchers in developing effective pest management strategies. The sweetpotato whitefly has recently become established as a key pest of various winter, spring and summer crops in Arizona and southern California. This insect has been present in Arizona and California since the 1920's (Russel, 1975) and outbreaks have been documented in the southwestern U.S. (Duffus & Flock, 1982; Natwick & Zalom, 1984; Butler & Henneberry, 1986). Recent problems, however, are throught to be associated with a new biotype (Biotype B) of *B. tabaci* (Brown et al., 1995) or possibly the appearance of a new species, *Bemisia argentifolii* Bellows & Perring (Perring et al., 1993; Bellows et al., 1994).

Progress has been made in developing efficient and reliable sampling plans for estimating the abundance of various life stages of *B. tabaci*, primarily for research purposes (Naranjo & Flint, 1994, 1995; Tonhasca et al., 1994a). There has been relatively little effort to devise viable sampling strategies for pest management applications. Sampling plans for this purpose must minimize both the error of making an incorrect decision regarding pest suppression and the cost of gathering the information. Binomial sampling has been successfully used in a number of pest management systems for a variety of pests (Binns & Nyrop, 1992). In this approach the mean density of an insect population is estimated from the proportion of sample units infested with a predetermined number of insects. Typically, the goal of binomial sampling is to classify populations relative to some action or economic threshold. However, binomial sampling may also be a useful method in estimating density for research purposes, particularly for an insect like *B. tabaci* that is small and has the potential to occur at high densities. The primary advantage of the binomial approach is that sampling can be completed with minimal cost. Binomial sampling plans are typically less precise than sampling plans based on complete enumeration. Thus, considerable effort is required in the development and testing of binomial sampling plans to ensure that they can accurately classify damaging populations or that they provide acceptable precision if used to estimate population density.

In a previous study we examined the spatial distribution of adult *B. tabaci* in cotton, *Gossypium* spp., determined the optimal sample unit, and devised sampling plans based on complete enumeration for estimating population density with fixed precision (Naranjo & Flint, 1995). In this study we evaluated and analyzed binomial models using different tally thresholds (the minimum number of insects present before a sample unit is considered infested) for sampling adult *B. tabaci* in cotton. Our goals were to evaluate the utility of binomial sampling for estimating population density and to develop sequential sampling plans for classifying population density of *B. tabaci* relative to two nominal action thresholds. We also evaluated the robustness of our binomial models by comparing them to independent data collected at four sites in central Arizona.

Materials and methods

Sampling data. Samples were collected weekly to biweekly on 16 dates from 8 June through 30 September 1993 from upland, *Gossypium hirsutum* L. cultivar Deltapine 50, and long-staple, *G. barbadense* L. cultivar Pima S-7 cotton. Cultivars were arranged in 24 0.1 ha plots (12 per cultivar) at the University of Arizona, Maricopa Agricultural Center (MAC). These plots were arranged using a split-plot design in a contiguous 2.4 ha area ($\approx$ 65 000 plants per ha, 1.02 m row widths) with half the plots receiving weekly irrigation and half receiving biweekly irrigation (Flint et al., 1994). Adult *B. tabaci* were counted on the underside of mainstem leaves from the fifth node from the terminal (Naranjo & Flint, 1995) on 15 randomly-selected plants along a diagonal transect in each plot. Counts from replicate plots of the same treatment were pooled, resulting in 64 treatment/date combinations with 90 individual leaf counts per observation for calculating means and proportion of leaves infested. All counts were completed between 06.00 and 10.00 h. Plots were planted on 10 April and maintained according to standard agronomic practices for the area. Insecticides (fenpropathrin and acephate mix) were applied to all plots for whitefly control on 7 and 13 August.

Sampling models and plans. We selected the empirical equation of Kono & Sugino (1958) and Gerrard & Chiang (1970) to model the relationship between mean density per leaf (m) and the proportion of leaves infested with at least T individuals (P_T). The model is:

$$\ln(m) = \alpha + \beta \ln(-\ln[1 - P_T]) \qquad (1)$$

where α and β are parameters estimated by linear regression. This model and one based on the negative binomial distribution have been widely used for insect sampling in pest management (Nyrop & Binns, 1991). The latter model requires the estimation of a nuisance parameter, k, that can change with mean density, whereas the former model is independent of the underlying distribution. We estimated model parameters for tally thresholds (T) of 1, 2, 3, 4, 5 and 6 adults per leaf.

First we evaluated and compared binomial models based on these six different tally thresholds in terms of their utility for estimating population density. We compared the variance of means (var[m]) predicted from the proportion of sample units infested. Several approximations of this variance have been proposed

(see Jones, 1994). We used the approximation given by Schaalje et al. (1991):

$$\text{var}(m) = m^2(c1 + c2 + [\text{MSE} - c3]) \qquad (2)$$

with

$$c1 = (\beta^2 P_T)/(n[1 - P_T]\ln[1 - P_T]^2)$$
$$c2 = \text{MSE}/N + \{\ln[-\ln(1 - P_T)] - \bar{P}\}^2 s_\beta^2$$
$$c3 = \exp\{a + (b - 2)[\alpha + \beta\ln[-\ln(1 - P_T)]]\}/n$$

where MSE is the mean square error term from the linear regression (equation 1), α and β are the intercept and slope parameters of the regression, s_β^2 is the variance of the slope, n is the number of sample units used to calculate the proportion of infested leaves, N is the number of sample points used in the regression, $\bar{P}$ is the average value of $\ln(-\ln[1 - P_T])$ used in the regression, and a and b are parameters from Taylor's (1961) power law, $\ln(S^2) = a + b\ln(m)$, describing the relationship between the variance and mean. These variance terms for estimating m include components representing prediction, sampling, and biological variance. The approximation of Schaalje et al. (1991) attempts to more accurately define the biological variance by eliminating a sampling variance component (c3). Defining precision (d) as the standard error to mean ratio (Cochran, 1977), $d = (s^2/n)^{0.5}/m$, and substituting equation 2 for s^2/n gives:

$$d = (c1 + c2 + [\text{MSE} - c3])^{0.5} \qquad (3)$$

We compared precisions among the different models as a function of mean density for sample sizes of 30, 50 and 200 leaves.

Second, we evaluated and compared binomial models based on these six different tally thresholds for the classification of population density through an analysis of sequential sampling plans based on Wald's (1947) sequential probability ratio test (SPRT). The SPRT is an efficient and widely-used method for classifying pest population density relative to an action or economic threshold. Four parameters are required to specify sequential sampling stop lines for a binomial model: p_0 and p_1, which are the lower and upper boundaries of the decision area, respectively, given as proportions, and alpha and beta error rates. These errors are defined as the probability of accepting the alternative hypothesis (control needed) when the null hypothesis is correct (no control needed) and the probability of accepting the null hypothesis when the alternative is correct, respectively. Formulae for constructing

sequential stop lines from these parameters have been detailed in several sources (e.g. Fowler & Lynch, 1987; Nyrop & Binns, 1991) and will not be repeated here. The simulation technique of Nyrop & Binns (1991) was used to estimate expected operating characteristic (OC) and average sample number (ASN) curves for sequential stop lines for each of the six tally thresholds and two action thresholds, 5 and 10 adults per leaf (Ellsworth & Meade, 1994). The OC is the probability of taking no action relative to a damage threshold given the true mean density, and the ASN estimates the average number of samples needed to make a terminal decision. For each action threshold we set the lower and upper bounds at the proportions corresponding to ± 2 adults per leaf estimated from equation 1 and used alpha = beta = 0.10 or alpha = beta = 0.01. These boundary values were chosen somewhat arbitrarily, but approximate the confidence limits expected from numerical sampling with a specified precision of 0.10–0.20 (Naranjo & Flint, 1995). In any case, the boundary values used here have no influence on the comparative performance of binomial models based on different tally thresholds. The simulation technique improves on the standard algorithms for OC and ASN curves (Fowler & Lunch, 1987) by taking into account the variability in predicting mean density from the proportion of infested sample units. The simulation requires the inverse regression of (1):

$$\ln(-\ln[1 - P_T]) = \gamma + \delta\ln(m) \qquad (4)$$

along with the variance of $\delta(s_\delta^2)$, the mean of $\ln m$ ($\bar{m}$), and the MSE and sample size of the regression. Basically, the simulation assumes that errors in predicting density from P_T are normally distributed about the regression line with mean equal to zero and variance equal to $\text{MSE}/N + (\ln[m] - \bar{m})^2 s_\delta^2 + \text{MSE}$. The OC and ASN values at any given density are then weighted according to this normal distribution to arrive at expected values for these functions. Finally, we calculated the cost of sampling using different tally thresholds by estimating the time required to count and record leaf samples in 12 plots on five separate dates during the collection of sample data at the MAC in 1993. Regression analysis was used to develop a relationship between adult density and the time required to complete a single sample.

On the basis of these analyses we determined the best tally threshold(s) and subsequently developed binomial sequential sampling plans based on the SPRT for the two action thresholds of 5 and 10 adults per leaf.

Validation. We evaluated the accuracy of mean density-proportion infested models using four independent data sets collected from 1992–1994 in central Arizona. In 1992, sampling data were collected from 24 0.1 ha plots of upland cotton (cultivars Deltapine 50 and Stoneville 506) at the MAC. On each of four dates between 16 June and 12 August we counted adults on the undersides of mainstem leaves from the top, middle, and bottom thirds of five randomly selected plants per plot. As before, these samples were pooled over replicate plots of the same experimental treatment. In 1993, adults were counted on a total of 75 fifth mainstem node leaves on each of 15 dates between 30 July and 22 October from a 1 ha field of upland cotton (cultivar Deltapine 90) at the Western Cotton Research Laboratory in Phoenix. Samples were also collected from this site in 1994 on a total of 17 dates from 1 July throught 17 October. Again, adults were counted on 75 fifth mainstem node leaves on each date. Finally, in 1994, samples were collected at the MAC in 24 0.1 ha plots of Deltapine 50 cotton. Adults were counted on 20 fifth mainstem node leaves per plot on a weekly basis from 31 May throught 23 August. Again these samples were pooled over replicate plots of the same treatment.

We evaluated whether data from the four sites fell within 95% confidence limits for the prediction model (equation 1). For each of the four data sets we also regressed mean density predicted from the proportion of sample units infested with at least T adults against actual mean density and then tested whether the slope and intercept were significantly different from unity or zero, respectively. Technically these regressions could lead to biased predictors of slope and intercept terms because of error in measuring the independent variable (Sokal & Rholf, 1981). However, we were careful to interpret conclusions based on these regressions in light of comparisons of fits of the data to the prediction model.

Results and discussion

Sampling models and plans. A total of 64 separate population estimates were collected in 1993, however, after eliminating proportion-infested values of 0 and 1 only 45 to 53 of the estimates were useful for binomial model development, depending on the tally threshold T. The empirical binomial model (equation 1) fit the field data well with r^2 values ranging from 0.92 to 0.97 (Table 1, Figure 1). Examination of the residual errors
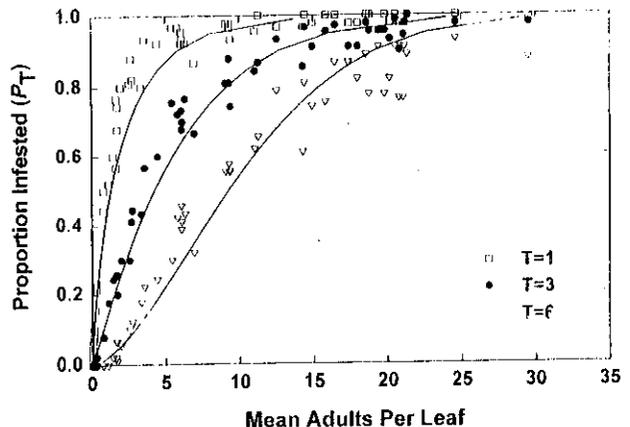

Figure 1. Empirical models (equation 1) relating mean density per leaf to the proportion of sample units infested with at least T adults (P_T). Models based on sample data collected at the MAC, Arizona, 1993.

from the regressions (MSE) indicated that model fits improved up to T = 3 and then declined slightly with T ≥ 4. An important limitation of binomial sampling models is that there are upper limits of mean density and that can be estimated before the models become asymptotic. For instance, the mean density at 95% infestation for T = 1 is about eight adults per leaf (Table 1) but about 22.6 with T = 6. Selection of the best tally threshold depends partly on the range of densities that are of greatest importance in pest management. However, proper selection of T can also reduce the variability and bias of the estimated mean and provide for acceptable error rates and average sample sizes when using sequential classification (Nyrop & Binns, 1991; Binns et al., 1992).

We examined the influence of using different tally thresholds on the estimation of mean density by determining sampling precision (SE/mean) as a function of density and the number of sample units examined (Figure 2) using equation 3 and parameters in Table 1. The parameters for Taylor's power law were taken from Naranjo & Flint (1995) with $a = 0.73$ and $b = 1.67$. In general, the number of sample units examined (n) had relatively little influence on sampling precision regardless of the tally threshold (Figure 2). This phenomenon is well known and derives from the fact that n influences the two components of the variance ($c1$ and $c3$) that carry relatively little weight in the overall estima-

Table 1. Parameters of an empirical binomial model (equation 1) relating mean adults per leaf to the proportion of leaves infested with at least T adults

T	α	β	r^2	n	$\bar{P}$	S^2_β	MSE	Mean density at 95% infested
1	0.7063	1.2511	0.96	53	−0.1250	0.0012	0.1735	8.0
2	1.4123	1.0103	0.97	52	−0.1260	0.0006	0.0989	12.4
3	1.7767	0.9178	0.96	48	0.1086	0.0008	0.0519	16.2
4	2.0893	0.7800	0.94	47	−0.0974	0.0008	0.0577	19.0
5	2.2982	0.6713	0.94	46	−0.3494	0.0006	0.0541	20.8
6	2.4487	0.6104	0.92	45	−0.5592	0.0007	0.0634	22.6

tion of the variance term (Nyrop & Binns, 1991; Jones, 1994). In contrast, increasing T had a dramatic effect on sampling precision, at least up to a point (Figure 2). Using T = 1, it was not possible to achieve a precision better than about 0.42 regardless of sample size. Doubling the tally threshold to two increased precision about 1.3-fold over all densities, however precision still never exceeded about 0.33. Using T = 3 increased precision roughtly another 1.3-fold, but further increase in T had little or no effect on precision, except at low densities ($P_T < 0.10$). This results primarily from relative stability in MSE at $T \geq 3$ (Table 1) and the fact that the MSE is the largest variance component (Nyrop & Binns, 1991; Jones, 1994). With $T \geq 3$ precision was equal to or better than 0.25 depending on sample size. Several other variance estimators have been suggested for the empirical model we used (see Schaalje et al., 1991) and each would have resulted in slightly different estimates of sampling precision. However, the relative variation between models with different values of T, and thus the relative ranking, would not have changed. Additional research and field validation are needed to test underlying assumptions and evaluate the accuracy of different variance estimators (Schaalje et al., 1991; Binns et al., 1992; Jones, 1994).

The relatively high levels of precision achieved with our binomial models, particularly those with $T \geq 3$, are unusual and suggest that binomial sampling could be a viable alternative to complete enumeration for estimating the density of *B. tabaci* in cotton for certain research purposes. For example, using a binomial model with T = 3 a sampling precision of 0.25 was possible with as few as 30 samples at mean densities from about 3 to 12 adults per leaf. For densities < about 5 adults per leaf this sample size requirement rivals that found for fixed-precision sampling plans based on complete leaf counts (Naranjo & Flint, 1995). In contrast, Tonhasca et al. (1994b) found that binomial
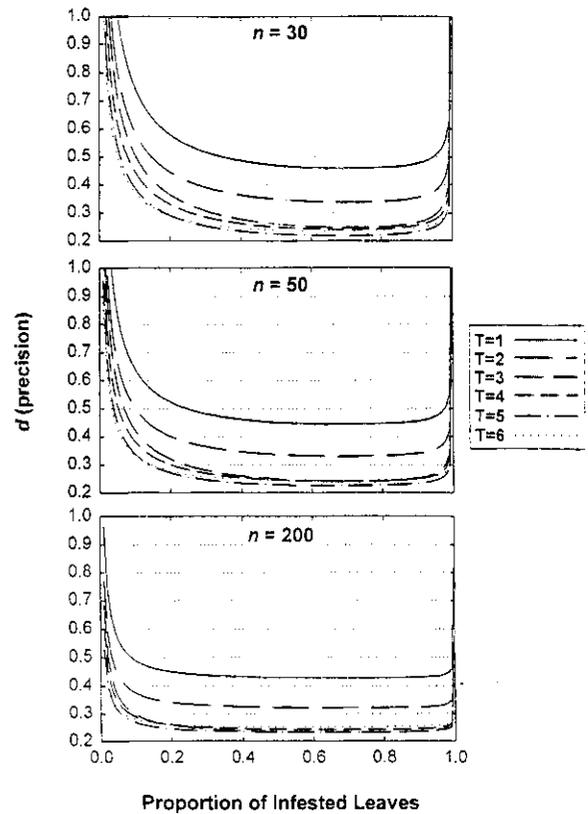

Figure 2. The precision (SE/mean) achieved when estimating mean density from the proportion of sample units infested with at least T adults (from equation 3). n refers to the number of sample units used to calculate the proportion infested.

sampling for *B. tabaci* on cantaloupe could not provide precision of mean density better than about 0.50, regardless of sample size or tally threshold. Binomial sampling is typically much less precise than complete

enumeration and this is the main reason why such plans are generally only used for the classification of density (Nyrop & Binns, 1991). Our results may be partially due to use of a carefully selected and optimized sample unit (Naranjo & Flint, 1995).

We evaluated models with different tally thresholds for use in the classification of population density by analyzing the operating characteristic and average sample size curves associated with sequential sampling stop lines derived from Wald's SPRT. The parameters necessary to carry out this analysis using the simulation method of Nyrop & Binns (1991) are given in Table 2. The expected OC curves for stop lines defined by 5 ± 2 adults per leaf were progressively steeper (indicating lower error probabilities relative to the action threshold) with increasing T up to three (Figure 3, top), but the OC curves differed relatively little with changes in T > 3. Changes in T had a more dramatic effect on OC curves based on stop lines defined by 10 ± 2 adults per leaf, but comparative results were the same: the OC curves became progressively steeper as T increased from one to three, but there was little, if any, improvement in the OC with T > 3 (Figure 3, bottom). In comparison with changes in T, reducing alpha and beta error probabilities had very little influence on the steepness of OC curves for either action threshold.

Examination of nominal OC curves clearly shows that because of variation in the mean density-proportion infested relationship, expected error probabilities exceeded nominal rates in all instances, with differences being greatest for T = 1 and an action threshold for 10 adults per leaf (Figure 3). Nominal OC curves were made markedly steeper by reducing alpha and beta error probabilities, however, as noted above, changing these error rates did little to improve expected OC curves. Nyrop & Binns (1991) suggest that alpha and beta should be considered parameters rather than fixed values in the development of sequential sampling stop lines, and that their values should be chosen on the basis of desired OC and ASN functions. Our results suggest that there is little to be gained by reducing alpha and beta. The result would be greater sample size requirements with little or no gain in the accuracy of decision-making.

With an action threshold of 5 adults per leaf, the average number of samples needed to make a control decision were very modest, regardless of the tally threshold (Figure 4, top left). For clarity, only ASN curves for T = 1, 3, and 6 are shown. At most, an average of about 15 samples were needed with T = 1 compared with about 10 samples at T = 3. However,

when the action threshold was increased to 10 adults per leaf there was a substantial change in sample size requirements (Figure 4, bottom left). Here, with T = 1, more than 80 samples were required on average to terminate sampling, whereas fewer than 35 or 20 samples were required, on average, with T = 3 or 6, respectively. Although the number of samples declines when the tally threshold is increased, more time is also required to evaluate the infestation status of an individual leaf. To account for this factor, we estimated the density (d) dependent time required to count an individual leaf in the field. The relationship is given by time (min) = $0.14 + 0.013d$ ($n = 144$; $r^2 = 0.80$). Assuming that T individuals must be counted on every sample unit, the average cost of sampling for each value of T can be estimated (Figure 4, right). In general, the differential costs of higher tally thresholds did not change the patterns seen for average sample number. Also, there was relatively little difference in sampling costs for an action threshold of 5 adults per leaf, regardless of T. Still, using T = 6 was most costly at densities near the action threshold, but T = 1 was most costly overall. Differences in sampling cost were greater for an action threshold of 10 adults per leaf. Near the threshold value more than 12 min were required, on average, to terminate sampling with T = 1. In contrast, fewer than 6 min was required with higher value of T. Further, these cost estimates for T = 3 and 6 are inflated because we assume that each sample unit took the same time (maximum) to assess. In reality, many of the leaves in a given sample would have fewer than T adults.

Based on results of the above analyses, we concluded that a binomial model with T = 3 was best. Error probabilities, and average sample sizes and costs declined from T = 1 to T = 3, but these qualities improved little or not at all with T > 3. Thus, a binomial model with T = 3 appears to be best for both the estimation of mean density and for the classification of density based on sequential sampling. The performance characteristics associated with using different tally thresholds have not been widely studied. Binns & Bostanian (1990) examined the behavior of binomial models based on the negative binomial distribution and found that values of T near the action threshold resulted in better OC and ASN curves and diminished the effects of incorrectly estimating the value of the nuisance parameter k. Based on the empirical model used here, Binns et al. (1992) and Feng et al. (1993) explored different values of T. In general they found, as we did, that the variance in estimating mean density declined with increasing T up to a point. The particular
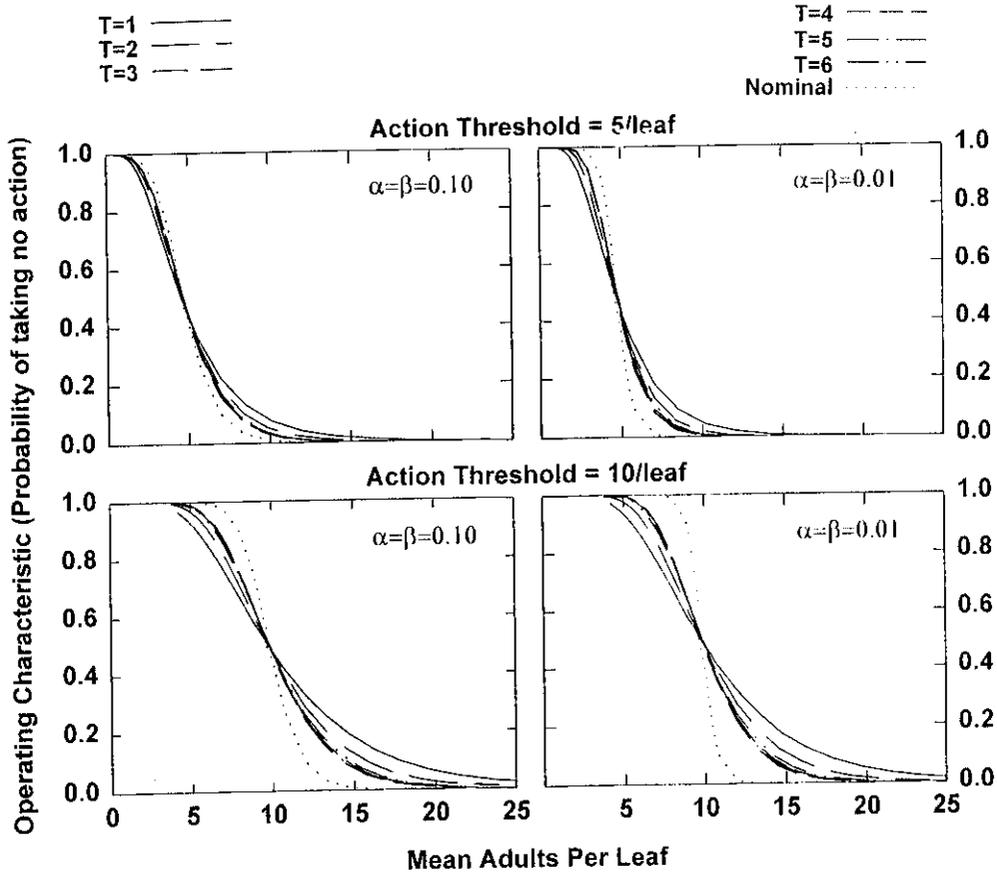
Figure 3. Expected and nominal operating characteristic (error probability) curves from Wald's sequential probability ratio test for two action thresholds, binomial-mean density models with different tally thresholds (T), and two rates of alpha and beta error. Expected curves were based on simulations which account for variability in the binomial-mean density regressions (Nyrop & Binns, 1991). There were no detectable differences in nominal OC curves for different tally thresholds for given alpha and beta errors and action thresholds, and so a composite curve is shown.

Table 2. Parameters of an empirical binomial model (equation 4) relating mean adults per leaf to the proportion of leaves infested with at least T adults. These parameters were used to estimate the OC and ASN functions using the simulation method of Nyrop & Binns (1991)

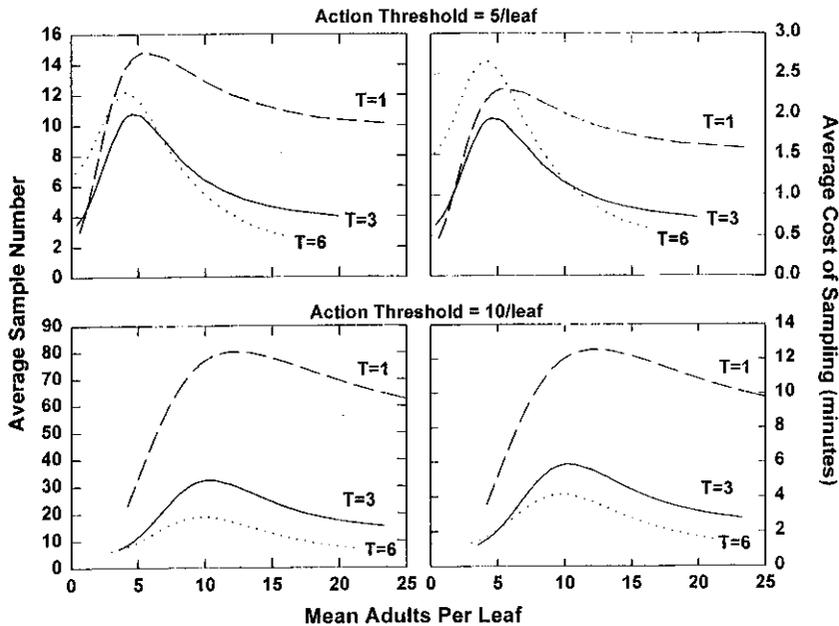| T	γ	δ	n	$\bar{m}$	s_δ^2	MSE
1	−0.5489	0.7709	53	0.5499	0.0004	0.1069
2	−1.3588	0.9594	52	1.2850	0.0006	0.0940
3	−1.8534	1.0456	48	1.8763	0.0010	0.0592
4	−2.5313	1.2089	47	2.0134	0.0020	0.0894
5	−3.2408	1.4011	46	2.0636	0.0028	0.1128
6	−3.7511	1.5146	45	2.1074	0.0044	0.1572

Figure 4. Average sample number curves and average cost curves based on Wald's sequential probability ratio test for two action thresholds, and binominal-mean density models with different tally thresholds (T). Results were based on simulations which account for variability in the binomial-mean density regressions (Nyrop & Binns, 1991). Nominal alpha and beta error were set at 0.10. Sampling costs were based on the per unit time needed to count T adults.

value of T that was best varied in relation to the size of the sample unit, the species under study, and the methods used to evaluate model performance. Recently, Tonhasca et al. (1994b) developed binomial sampling plans for adult *B. tabaci* on cantaloupe using T = 1 and T = 3. They found that the estimation variance was lower for T = 3, but concluded that gains in precision did not justify using T > 1. They did not examine decision error rates or sampling costs, but based their conclusion on a fairly low action threshold of three adults per leaf. In comparison with a higher action threshold, we also found relatively little difference in performance of sample plans using different values of T for the low threshold (5 adults per leaf). However, the lower error probabilities and lower sampling costs associated with T = 3, and the current uncertainty in the action threshold level justify use of T = 3 for decision-making in cotton.

Standard formulae were used to determine SPRT stop lines for action thresholds of 5 and 10 adults per leaf. For each action threshold we set the lower and upper bounds at the proportions corresponding to ±2

adults per leaf as discussed above, and set alpha and beta errors to 0.10. The stop lines are:

$y = 0.848x \pm 1.500$ (T = 1, action threshold = 5)

$y = 0.547x \pm 1.707$ (T = 3, action threshold = 5)

$y = 0.965x \pm 2.011$ (T = 1, action threshold = 10)

$y = 0.819x \pm 2.473$ (T = 3, action threshold = 10)

where x is the number of leaves examined and y is the corresponding number of infested leaves. Although we found that sampling plans with T = 3 would be most efficient, we also included plans based on presence/absence (T = 1) because this is the most common application of binomial sampling. The action thresholds and decision boundaries specified here are somewhat tentative and are the subject of considerable research at present. These sequential stop lines can be easily adjusted as new information becomes available.

Validation. Ultimately, the reliability of the sampling plans presented here is based on the accuracy of the empirical relationship between mean density and the proportion infested sample units. We compared predictions from binomial models with T = 1 and T = 3 to
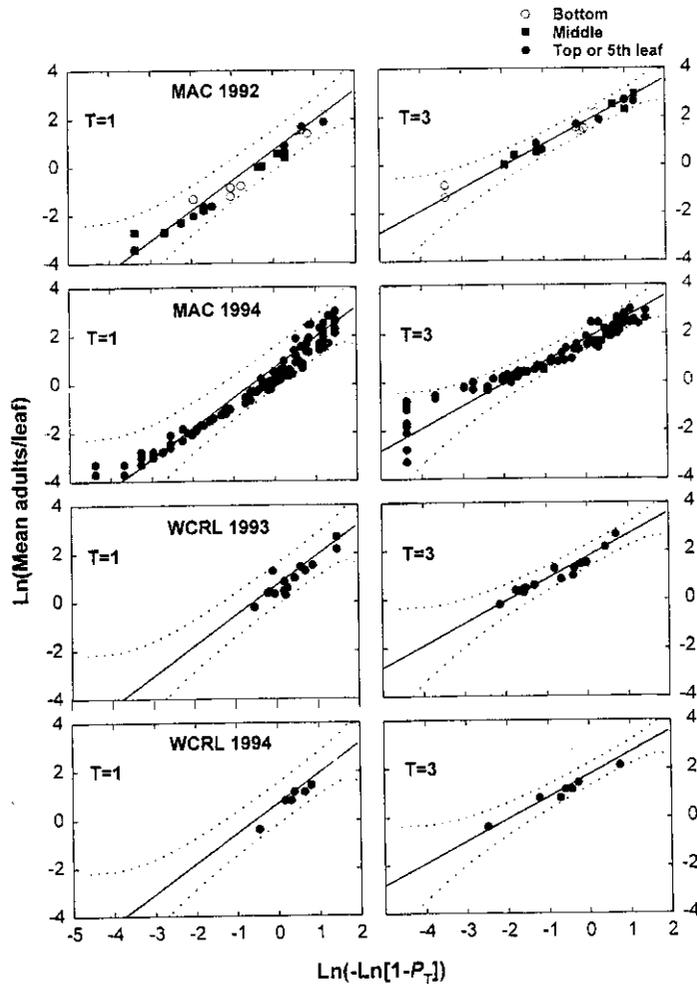
Figure 5. Comparison of independent sample data from four sites in Arizona to binomial-mean density models with tally thresholds of 1 or 3 (solid lines). The dotted lines represent 95% confidence intervals around the prediction equation. Samples in 1992 at the MAC were collected from leaves at three vertical strata within the plant; the sample unit at all other sites was the fifth mainstem node leaf from the terminal.

Table 3. Comparison of binomial models using tally thresholds of 1 and 3 to independent data sets from Arizona, 1992–1994

Site	T = 1				T = 3			
	Slope ± SE	Intercept ± SE	n	r^2	Slope ± SE	Intercept ± SE	n	r^2
MAC 1992	1.04 ± 0.03	0.20 ± 0.06*	34	0.98	1.06 ± 0.04	–0.06 ± 0.07	19	0.98
MAC 1994	1.08 ± 0.02*	0.19 ± 0.04*	120	0.97	1.13 ± 0.04*	–0.14 ± 0.05*	86	0.93
WCRL 1993	0.86 ± 0.11	0.32 ± 0.13*	15	0.83	1.00 ± 0.08	0.03 ± 0.09	15	0.93
WCRL 1994	0.84 ± 0.11	0.39 ± 0.11*	6	0.94	1.16 ± 0.09	–0.08 ± 0.11	7	0.97

Slope and intercept parameters estimated by regressing predicted ln(density) on actual ln(density). Asterisks indicate that the slope was significantly different from 1 or the intercept was significantly different from 0 ($P < 0.05$).

four independent data sets collected between 1992 and 1994 in central Arizona. Both models were relatively robust in that almost all of the independent observations fell within the 95% confidence band surrounding the prediction model (Figure 5). Furthermore, the empirical relationships were robust in relation to the sample unit observed. At the MAC site in 1992 (Figure 5, top panels), counts of adults were made on leaves from three different vertical strata within the plant, rather than being restricted to the 5th mainstem node leaf. Thus, although the density of adults varied between strata on any given sample date, the distribution of adults within the different strata were similar, and adequately described by our model. Regressing predicted ln(density) on actual ln(density) we found that the slope of this relationship varied significantly from unity in only one of the four comparisons for both T = 1 and T = 3 models (Table 3). However, the intercept was significantly different from zero in all comparisons for the T = 1 model but in only one instance for the T = 3 model. These results suggest that there is a high degree of correlation between predicted and actual values, but that there is also significant bias, particularly for the T = 1 model (Figure 5). The T = 1 model was consistently biased towards overprediction of mean density, whereas the T = 3 model was relatively unbiased with the exception that the model overpredicted mean density at densities above approximately 2–3 adults per leaf at the MAC in 1994. The overprediction of density at or near the action threshold would result in action being taken more often than necessary. That is, the alpha error rate would increase at the expense of the more critical beta error in which action is needed but none is taken.

Conclusions

The binomial sampling plans presented here should greatly enhance the efficiency of monitoring populations of *B. tabaci* for both research purposes and pest management decision-making. Typically, binomial sampling strategies are implemented by using the presence or absence of insects on the sampling unit to determine infestation. Although this may be the simplest approach to employ in the field it is not necessarily the most efficient and may sacrifice some reliability due to the relatively small amount of information collected per sample unit. We show that by increasing the tally threshold from one to three, both the efficiency and reliability of binomial sampling can be significant-

ly enhanced. The additional cost (time) of counting more insects per sample unit are more than compensated for by reduced sample size requirements and the increased accuracy of decision-making. Futhermore, increasing the tally threshold to three greatly improved the precision associated with estimating mean population density. It is impossible to achieve a sampling precision greater than 0.40 using a presence/absence scheme regardless of the sample size, whereas a precision of ≈0.25 could potentially be achieved with as few as 30 samples over a broad range of densities using a binomial model with a tally threshold of three. This approaches the performance of sampling plans for *B. tabaci* based on complete enumeration (Naranjo & Flint, 1995). Thus our binomial sampling model may also be applied to more research oriented problems that require more precise estimates of density.

Presently, our binomial sampling plan for classification of density is implemented for a tally threshold of three and a fixed sample size of 30 leaves collected from a minimum of two sites within a cotton field (Ellsworth et al., 1994). The performance of this plan and one based on the sequential selection of samples is currently under examination as part of a large scale implementation and validation study in Arizona.

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