Cascading tripartite binomial classification plans to monitor European red mite (Acari,Tetranychidae) through a season; development and evaluation of a new methodology for pest monitoring

by

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Cascading tripartite binomial classification plans to monitor European red mite (Acari,Tetranychidae) through a season; development and evaluation of a new methodology for pest monitoring

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ABSTRACT

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A monitoring protocol that schedules future sample bouts based on the outcome of density classification and expected population growth has been developed and applied to monitoring European red mite (*Panonychus ulmi* Koch) through a growing season. The monitoring protocol is based on concatenating through time tripartite sequential classification sampling plans that use binomial counts in lieu of complete enumeration. Binomial counts are scored positive when the number of organisms (mites) on a sample unit (leaves) exceeds a tally number. At each sample occasion the monitoring procedure leads to one of three possible decisions; intervene when the density is high, sample at the next sample occasion (after one week) when the density is intermediate, and sample at the second next sample occasion (after two weeks) when the density is low. Evaluation of the monitoring protocol under field conditions showed that the protocol with constituent tally 0 binomial count sampling plans was quite successful in timing intervention at the moment when population densities were about to exceed an established threshold that dictated intervention. The performance of this monitoring protocol and another protocol in which constituent sampling plans used binomial counts with a tally number of 4 were compared using simulation. Sampling plans that used a tally number of 4 were more precise than plans that used a tally number of 0. However, the overall performance of the monitoring protocol based on tally 0 sampling plans did not greatly differ from the monitoring protocol based on tally 4 sampling plans. Simulated performance of the tally 0 protocol was corroborated by field evaluation. The monitoring protocol based on tripartite classification required

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30 to 45 percent fewer sample bouts than a protocol based on conventional sequential classification at weekly intervals. The monitoring protocol based on tripartite classification was also better able to schedule intervention when needed compared to a protocol based on conventional classification at two week intervals. Using the tally 0 protocol and current thresholds for *P. ulmi*, cumulative mite density was kept below 300 mite-days per leaf, which is well below levels regarded damaging. A tally 0 protocol with raised thresholds, developed on the basis of this finding, gave the best simulated performance of all protocols evaluated.

INTRODUCTION

Cornerstones of most integrated pest management programs are decision-making protocols that allow determination of when a pest population is so abundant as to require control. Most of these protocols consist of at least two items: (1) a threshold pest density, which, when exceeded by a local population, dictates management intervention (usually a pesticide application), and (2) a reliable and efficient method for estimating or classifying pest abundance. Much work has been devoted to devising and analyzing sampling methods that maximize precision while minimizing sampling costs (Kuno, 1991; Nyrop and Binns, 1991; Binns and Nyrop, 1992).

Most sampling procedures used in pest management have only been concerned with classifying or estimating pest density at a single point in time. This reflects the primary purpose of these procedures; to determine whether a chemical pesticide is needed. There are, however, instances when it is desirable to know whether population density remains below some critical threshold(s) over a period of time. For example, when biological control is substituted for a chemical pesticide, it may be necessary to monitor the population over a period of time to be sure that control by natural enemies is effective. It might be possible to predict the outcome of a natural enemy – pest interaction based on the ratio of pest to natural enemy and thereby obviate the need for monitoring (Nyrop, 1988). However, a number of factors such as uncertainty in the understanding of natural enemy – pest dynamics, errors in initial population estimates, and the influence of biotic and abiotic factors can obviate such predictions.

When a pest population is monitored through time, two questions must be answered: (1) Does the pest density exceed a threshold that dictates management intervention now? (2) If the density is below the threshold now, when should the population be sampled again? A simple solution to the second question is to sample very frequently; however, this will be unnecessarily costly. A better solution would be to use information about population density in conjunction with knowledge about population growth to schedule future sampling bouts (Wilson, 1985).

European red mite (*Panonychus ulmi* Koch) is a worldwide pest of apples. This mite usually achieves pest status as a result of its natural enemies being destroyed by pesticide applications. Biological control of *P. ulmi* can be successful; however, it is also often necessary to monitor populations to insure that densities remain below levels that cause injury to foliage. Even when natural enemies of *P. ulmi* are present, biological control may not result because abiotic factors or pesticide applications may differentially influence prey and predators. Furthermore, several natural enemies may attack *P. ulmi* simultaneously making it difficult to predict the natural enemy – pest interactions. Thus, biological control of European red mite populations often requires monitoring pest density through time.

In this paper we describe a method that can be used to efficiently monitor a population through time to determine whether density remains below a critical threshold(s) and apply this procedure to monitoring *P. ulmi*. We also describe how the performance of any protocol used to monitor a population can be assessed. It is important to distinguish a monitoring method from a sampling plan. We will use the term sampling plan to denote a scheme for classifying pest density at a specific point in time. We will use the term monitoring protocol to refer to the way in which one or more sampling plans are concatenated to assess population density repeatedly through time. The paper is divided into four sections. In the materials and methods section we describe the monitoring protocol by specifying in a general way what it is designed to do, how constituent sampling plans are constructed, and how the performance of constituent plans and the monitoring method can be assessed by the use of computer algorithms. Next, we describe those algorithms as developed for monitoring European red mite. The algorithms incorporate the fact that because counting spider mites in the field is laborious and not practical, records of the presence or absence of spider mites on a sample unit (binomial counts) are substituted for complete enumeration. Thirdly, we present a specific monitoring protocol, field evidence for its effectiveness in monitoring European red mite, and its simulated performance when applied to a set of fictitious and observed populations. Finally, it is shown how some parameters of constituent sampling plans affect the performance of the monitoring protocol.

MATERIALS AND METHODS

Principles of the monitoring protocol

The monitoring method consists of tripartite sequential classification plans that are cascaded through time (Fig. 1). Tripartite classification sampling plans are used to classify density each time a population is sampled. The classifications are: (1) low density indicating that damaging pest levels are unlikely to occur in the near future and hence resampling can be delayed; (2) intermediate density showing that densities are not currently at a damaging level, but the population should be sampled again soon to make sure this is still the case; and (3) high density prompting immediate intervention. If the first or second decisions are reached, the population is sampled again using either the same or a different tripartite classification protocol. Several tripartite classification procedures are thus cascaded through time (Fig. 1). Depending upon the population dynamics process, sample occasions are scheduled more or less frequently. The process stops either at the end of the season or when an "intervene" decision is made.

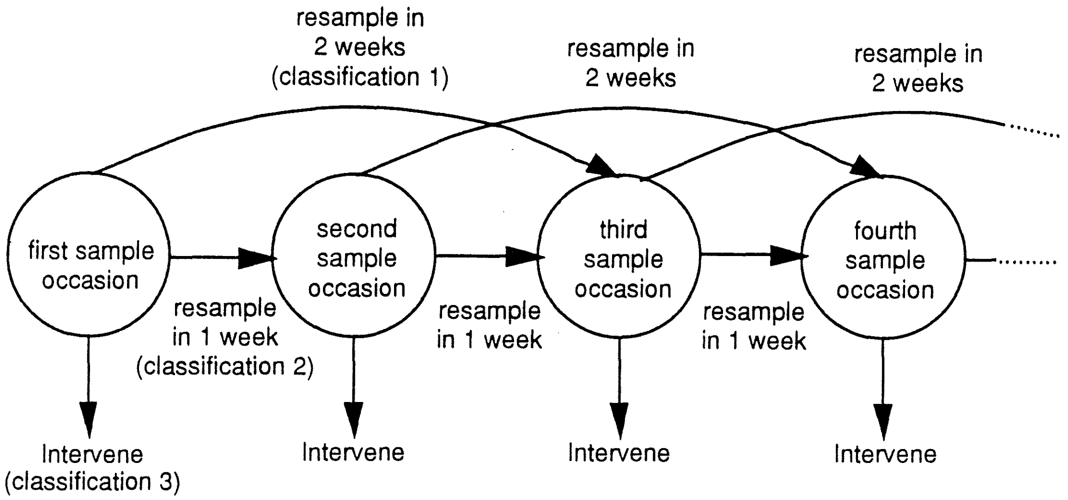

Fig. 1. Illustration of a monitoring scheme based on cascaded tripartite classification of population density. Large circles are points in time a population is sampled. Each sampling session can result in one of three classifications with concordant decisions.

Each tripartite sequential classification sampling plan is constructed by combining two dichotomous classification protocols (Binns, 1994; Fowler and Lynch, 1987). Suppose one wishes to classify density (μ) into one of three regions defined by two critical densities cd_1 and cd_2; $\mu \leq cd_1$, $cd_1 < \mu \leq cd_2$, and $\mu > cd_2$ where $cd_1 < cd_2$. Using the two critical densities two dichotomous plans would be constructed: Plan 1; $\mu \leq cd_1$ or $\mu > cd_1$. Plan 2; $\mu \leq cd_2$ or $\mu > cd_2$. Construction of these plans using Wald's sequential probability ratio test (Wald 1947) and placement of the stop lines for both plans in one figure would result in a composite figure as Fig. 2. If, in this figure, the plotted cumulative sample counts cross into region 1 density is classified as $\mu \leq cd_1$ (decision 1), if the sample data cross into region 2, density is classified as $cd_1 < \mu \leq cd_2$ (decision 2), and if the sample path enters region 3, density is classified as $\mu > cd_2$ (decision 3).

Tripartite classification sampling plans are cascaded by scheduling future sampling based on the current density classification. If density is classified as intermediate ($cd_1 < \mu \leq cd_2$; decision 2), then the next sample should be taken after time interval Δt. If density is classified as low ($\mu \leq cd_1$; decision 1) the next sample should be taken after time interval $m\Delta t$. We have always set $m = 2$; however, other multipliers could be used. One way of determining the critical densities cd_1 and cd_2 is to let cd_2 be an intervention threshold (a density that triggers a management action) and let cd_1 be a density which, if allowed to grow unchecked for $m\Delta t$ time steps, would result in cd_2. It is in the computation of cd_1 that knowledge about population growth is incorporated into the sampling protocols.

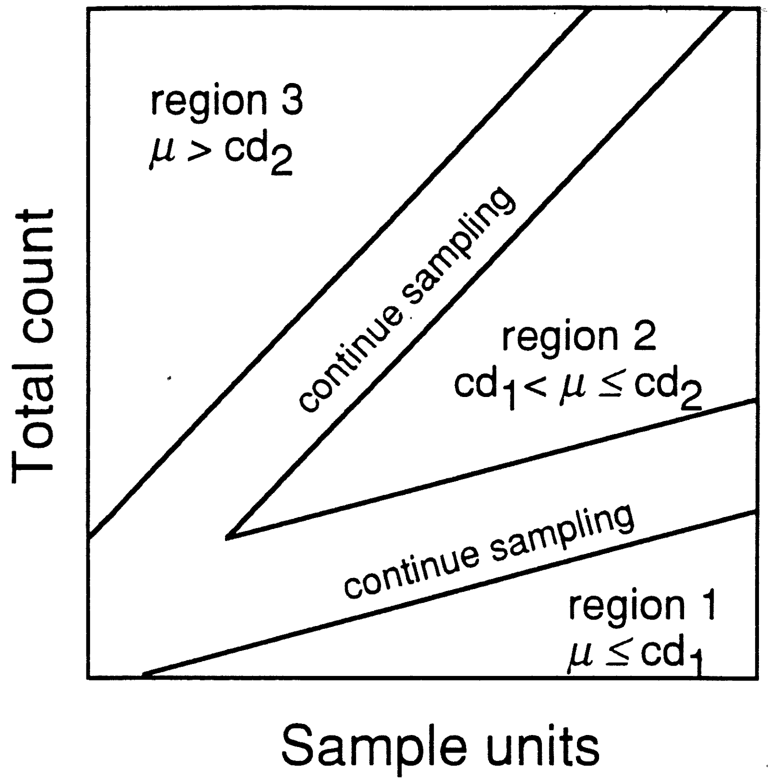

Fig. 2. Stop lines for a tripartite sequential classification sampling plan.

Evaluating the monitoring protocol by simulating the sampling process
To evaluate the monitoring protocol two steps are followed. First, performance of each tripartite classification procedure is determined. Second, the monitoring protocol is evaluated for specific population trajectories on the basis of the performance of its constituent sampling plans.

Dichotomous classification plans have two performance criteria; the OC function which is the probability of accepting the low density hypothesis (*i.e.;* $\mu \leq cd_1$) as a function of the true mean, and the average number of sample units (ASN) required to make a classification, also as a function of the true mean. With a tripartite classification scheme there are three possible classifications (Fig. 2) and three corresponding probabilities of making these classifications (PC^i, $i = 1,2,3$). Tripartite classification schemes also have an ASN function; however, it usually has two peaks instead of one.

Probability of classification (PC^i, $i = 1,2,3$) and average sample number (ASN) functions for tripartite classification sampling plans must be determined using simulation, unlike dichotomous plans for which these functions can be approximated analytically. The simulation entails generating random variables from probability distributions and then simulating sampling by subjecting these random variables to stop boundaries of a tripartite plan as if the random variables were actual sample observations (Binns, 1994; Nyrop and van der Werf, 1994).

The performance of tripartite classification sampling plans cascaded through time to monitor an entire population trajectory can be evaluated using five criteria: (1) The probability of intervening at some time during the season, (2) the expected number of occasions (bouts) on which samples are taken; (3) the expected total sample size (*e.g.* number of leaves) taken in all bouts; (4) the expected density at which intervention occurs and some indication of variability; and (5) the expected loss and again some indication of variability. Because the relationship between mite density and damage is not well defined, we use cumulative mite density per leaf until a decision to intervene is made as a measure of loss. As an indication of variability we use the value of density at intervention, or loss, that is greater than $\alpha \times 100$ percent of possible densities or losses. This is a useful measure for risk to a grower. A mathematical description of these performance criteria is provided in the appendix and FORTRAN programs that make the calculations are available from the authors.

Parameterization of the monitoring protocol for European red mite in apple
During the course of the study, several sampling plans were constructed and evaluated for use in monitoring European red mite populations. We will first describe the plan for which a field evaluation was done and then present modifications made to this plan based on later simulation studies.

Three tripartite sequential classification plans were constructed for use at different times during the period 1 June to 31 August. The upper arm of each plan (Fig. 2) was based on the critical densities (cd_2) 2.5 motile mites (*i.e.* anything but eggs) per leaf for the period 1 June to 30 June, 5.0 motiles per leaf for 1 July to 31 July, and 7.5 motiles per leaf thereafter. These thresholds were expert judgements based on the need to prevent a cumulative density (mite-days) of more than 500–600 from occurring during this period (Nyrop et al. 1989), while also minimizing the risk of letting dense populations of more than approximately 15 mites per leaf establish, as such dense populations are sometimes difficult to control. The critical densities (cd_1) defining the lower set of dichotomous plans were chosen in such a way that, after 14 days with an exponential growth rate of 0.065 d^{-1}, densities cd_1 would grow to densities cd_2: $cd_2 = cd_1 \exp(0.065 \times 14) = 2.5 \times cd_1$, approximately. The growth rate of 0.065 d^{-1} was an average determined by fitting an exponential model to 14 data sets on *P. ulmi* dynamics (Nyrop, unpublished data). Seven days was chosen as a natural and practical time interval between potential sample bouts ($14 = 2 \times 7 = 2\Delta t$).

Because counting spider mites in the field is difficult at best and often not even possible, binomial sampling plans were used. These are founded on a relationship between the proportion of sample units with more than T organisms (p_T), $T = 0, 1, 2, \ldots$, and the density (d) of organisms per sample unit. The parameter T is called a tally number. Based on Nyrop and Binns' work (1992), we used a negative binomial probability model to describe the $p_T - d$ relationship.

We constructed binomial count sampling plans based on T equal to 0 and 4 using

Wald's sequential probability ratio test (SPRT). The parameter k for the negative binomial distribution was estimated via Taylor's power law, variance = $a(\text{mean})^b$ and the relationship $k = (\text{mean})^2/(\text{variance-mean})$ (Nyrop and Binns, 1992). The critical proportions of leaves with more than T mites corresponding to the critical densities cd_1 and cd_2 were based on the negative binomial distribution using values of k derived from the above formula. The four parameters of the SPRTs were selected so that ASN functions remained below 100. We also set an upper limit of 100 to the sample size because the stop boundaries do not guarantee a decision will be reached within any given sample size. If 100 samples are taken without making a classification, the estimated proportion of occupied sites is compared with the two threshold proportions (cd_1 and cd_2 converted to proportions) and density classified accordingly. Parameters for the sample plans are shown in Table 1.

The only parameter that has to be known when using the negative binomial distribution is k. A value for k must be specified in order to compute p_T for a particular critical density. Functional dependency of k on mean density and/or

TABLE 1

Parameters used to construct "standard" tripartite sequential classification sampling plans for use with P. ulmi.

	Critical density			Sprt parameters			
Plan[a]	cd_i^b	k[c]	Proportion[d]	H_0[e]	H_1[e]	α[f]	β[g]
Tally 0							
1.1	1.0	0.301	0.356	0.306	0.406	0.075	0.075
1.2	2.5	0.467	0.578	0.529	0.628	0.075	0.075
2.1	2.0	0.418	0.520	0.48	0.56	0.1	0.1
2.2	5.0	0.667	0.760	0.72	0.80	0.075	0.075
3.1	3.0	0.513	0.627	0.587	0.667	0.1	0.1
3.2	7.5	0.827	0.852	0.812	0.892	0.05	0.05
Tally 4							
1.1	1.0	0.301	0.061	0.031	0.091	0.075	0.075
1.2	2.5	0.467	0.187	0.137	0.237	0.1	0.1
2.1	2.0	0.418	0.146	0.106	0.186	0.1	0.1
2.2	5.0	0.667	0.368	0.318	0.418	0.1	0.1
3.1	3.0	0.513	0.227	0.176	0.276	0.1	0.1
3.2	7.5	0.827	0.507	0.457	0.557	0.1	0.1

[a] For each plan there are two thresholds and two sets of SPRT parameters. The number following the decimal point signifies whether it is plan 1 or 2 of the tripartite scheme.

[b] The first value for each plan is cd_l and the second is cd_2.

[c] k parameter for negative binomial distribution computed using moments and based on a predicted variance calculated using the model $s^2 = 4.32d^{1.42}$.

[d] cd_i expressed as the proportion of sample units with > tally number.

[e] H_0 and H_1 reflect two hypothetical true proportions of occupied leaves an arbitrary 'distance' at both sides of the threshold proportion.

[f] Probability of erroneously classifying proportion = H_1 when H_0 is true.

[g] Probability of erroneously classifying proportion = H_0 when H1 is true.

variation in k independent of mean density introduces variability into the $p_T - d$ relationship. When there is variation in k, a specific p_T corresponds to a range of densities instead of to a single value, which in turn affects the performance of sampling procedures that classify density based on a classification of p_T. In general, if a particular value of k is used for $T = 0$, then the OC and ASN functions for k values less than the nominal k (*i.e.* the population is more aggregated) tend to be flatter and shifted to the right along the mean density axis. OC and ASN for k values greater than the nominal value (*i.e.* the population is less aggregated) tend to be steeper and shifted to the left along the mean density axis. What this means is that is that if aggregation is greater than expected, populations with density much in excess of the intervention threshold are liable to be classified as needing no action. Likewise, if aggregation is less than expected, populations with density much less than the intervention threshold are liable to be classified as requiring intervention. Clearly, sampling plans for which modest changes in k of the sampled population result in wide variation in the outcome of sampling are not robust. The robustness of the sampling procedure with respect to the effect of variability in k can be improved by careful selection of the tally number (Binns and Bostanian, 1990). Nyrop and Binns (1992) showed that binomial sequential classification sampling plans for European red mite having a tally number of four or six were significantly more robust than plans with a tally number of zero. However, sampling plans with such high tally numbers are more time-consuming because they require some mite counting. PC and ASN functions were computed using simulation methods described by Nyrop and Binns (1992). The functions presented in this paper are averages that incorporate variation in k. A FORTRAN program that performs these computations is available from the authors.

Evaluation of the monitoring methods using field data and computer simulation

The sampling plan based on tally 0 binomial counts was used to monitor 42 European red mite populations from 42 apple orchard blocks located at the New York State Agricultural Experiment Station, Geneva, NY, USA. The tally 0 plans were used for the field evaluation because we have found that practitioners are reluctant to use sampling plans based on higher tally numbers. The study was conducted during the summer of 1992 between 15 June and 26 August. Apple leaves were collected for observation by removing 5 intermediately-aged leaves from the outer portion of the mid-crown of each tree sampled. Before making comparisons to stop lines, at least 4 trees were sampled. Furthermore, when additional samples were required, leaves were collected in batches of five and comparisons to stop boundaries were based on these totals. Based on the outcome of the classification procedure, each population was either sampled again after one or two weeks or treated with a miticide. If a miticide was applied the population was not sampled further. After each classification, an additional 100 leaves were collected and *P. ulmi* density was estimated by brushing mites from these leaves onto a single glass plate and counting the mites with a microscope.

For each intervention threshold, the distribution of estimated *P. ulmi* density that corresponded to each classification decision (resample in two weeks, resample in 1 week, treat) was plotted. Box plots (Systat, 1992) were constructed of cumulative mite density that corresponded to the final decisions of; (1) not intervening, (2) applying a miticide when the threshold was 5 mites per leaf, and (3) applying a miticide when the the threshold was 7.5 mites per leaf.

Performance of the monitoring schemes based on tally 0 and tally 4 sampling plans was studied using simulation by applying the monitoring protocols to a set of 15 artificial populations described by logistic growth and a further seven actual population trajectories. The populations with logistic growth were meant to broadly represent mite population growth under a range of conditions where the shapes of the population trajectories were similar. The latter condition was required so that we could use cumulative density as a reasonable index for each population. The growth rate r ranged from 0.03 to 0.14 and the maximum density was set to 60. When density approached the maximum it was not allowed to decline as would happen in the real world due to degradation of the plant because in the simulations it allowed the accumulation of mite-days at the maximum to be a surrogate for the relatively greater damage that would be done by such large populations early in the season. The seven actual population trajectories were all influenced by predaceous mites; however, biological control was not always realized. Sampling plans with intervention thresholds of 2.5, 5.0 and 7.5 were used from day 1–30, 31–60 and 60 to the last sample time, respectively, counting 1 June as day 1.

We compared the performance of the monitoring scheme based on tally 0 sampling plans to a monitoring protocol based on tally 0 dichotomous sampling plans that resulted in decisions to either intervene or sample the population again after one week or after two weeks. These comparisons were made for two reasons. First, to determine the savings in sampling costs and errors that might result from using the tripartite schemes compared with sampling each week. Second, to determine the improvements in scheduling intervention when tripartite classification sampling plans were used compared with dichotomous plans used every two weeks. The dichotomous plans were constructed using the parameters for the plans based on cd_2 shown in Table 1.

Based on outcomes from the experiments described thus far, two additional simulation experiments were conducted with monitoring protocols based on tally 0 tripartite sampling plans. In the first of these ("short term plans") we reduced the values for cd_1 (Table 2). This was done because region 2 of the stopping boundaries for the original sampling plans were very narrow and we wished to determine the effect of making these areas larger. We hypothesized that doing so would increase the expected number of sample bouts and reduce expected density at intervention and expected loss.

In the second experiment we applied the monitoring protocols to a population trajectory that exactly followed the cd_2 values and to a set of population trajectories that were 10, 20, 30, 40, and 50 percent less than the cd_2 values. This was done to

TABLE 2

Parameters for tripartite classification plans with increased probability of decision 2: "short term plans".

	Critical density			Sprt parameters			
Plan	cd_i	k	Proportion	H_0	H_1	α	β
1.1	0.50	0.224	0.231	0.201	0.261	0.15	0.15
1.2	2.5	0.467	0.578	0.529	0.628	0.075	0.075
2.1	1.25	0.334	0.405	0.355	0.455	0.075	0.075
2.2	5.0	0.667	0.760	0.720	0.800	0.075	0.075
3.1	2.0	0.418	0.520	0.470	0.570	0.075	0.075
3.2	7.5	0.827	0.852	0.812	0.892	0.05	0.05

TABLE 3

Parameters for tripartite classification sampling plans with higher values of cd_1 and cd_2 than those shown in Table 1: "long term plans".

	Critical density			Sprt parameters			
Plan	cd_i	k	Proportion	H_0	H_1	α	β
1.1	2.0	0.418	0.520	0.480	0.560	0.100	0.100
1.2	5.0	0.667	0.760	0.720	0.800	0.075	0.075
2.1	3.0	0.513	0.627	0.587	0.667	0.100	0.100
2.2	7.5	0.827	0.852	0.812	0.892	0.050	0.050
3.1	4.0	0.594	0.703	0.663	0.743	0.100	0.100
3.2	10.0	0.934	0.904	0.874	0.934	0.075	0.075

determine how the monitoring protocol behaved when population levels were close to levels requiring control but the intervention thresholds had not been exceeded. This situation could arise when *P. ulmi* population growth was being constrained by natural enemies. We then constructed new sampling plans ("long term plans") in which we increased the values of cd_2 from 2.5, 5.0 and 7.5 to 5.0, 7.5, and 10.0 respectively (Table 3) and applied them to these artificial populations as well as to the set of populations described by logistic growth.

RESULTS

Performance of constituent sampling plans

Probability of classification (PC^i) and average sample number (ASN) functions for the tally 0 and tally 4 tripartite "standard" classification plans are shown in Fig. 3. Probability of classification functions for the tally 4 sampling plans are steeper than those for the tally 0 sampling plans indicating that the tally 4 procedures produce

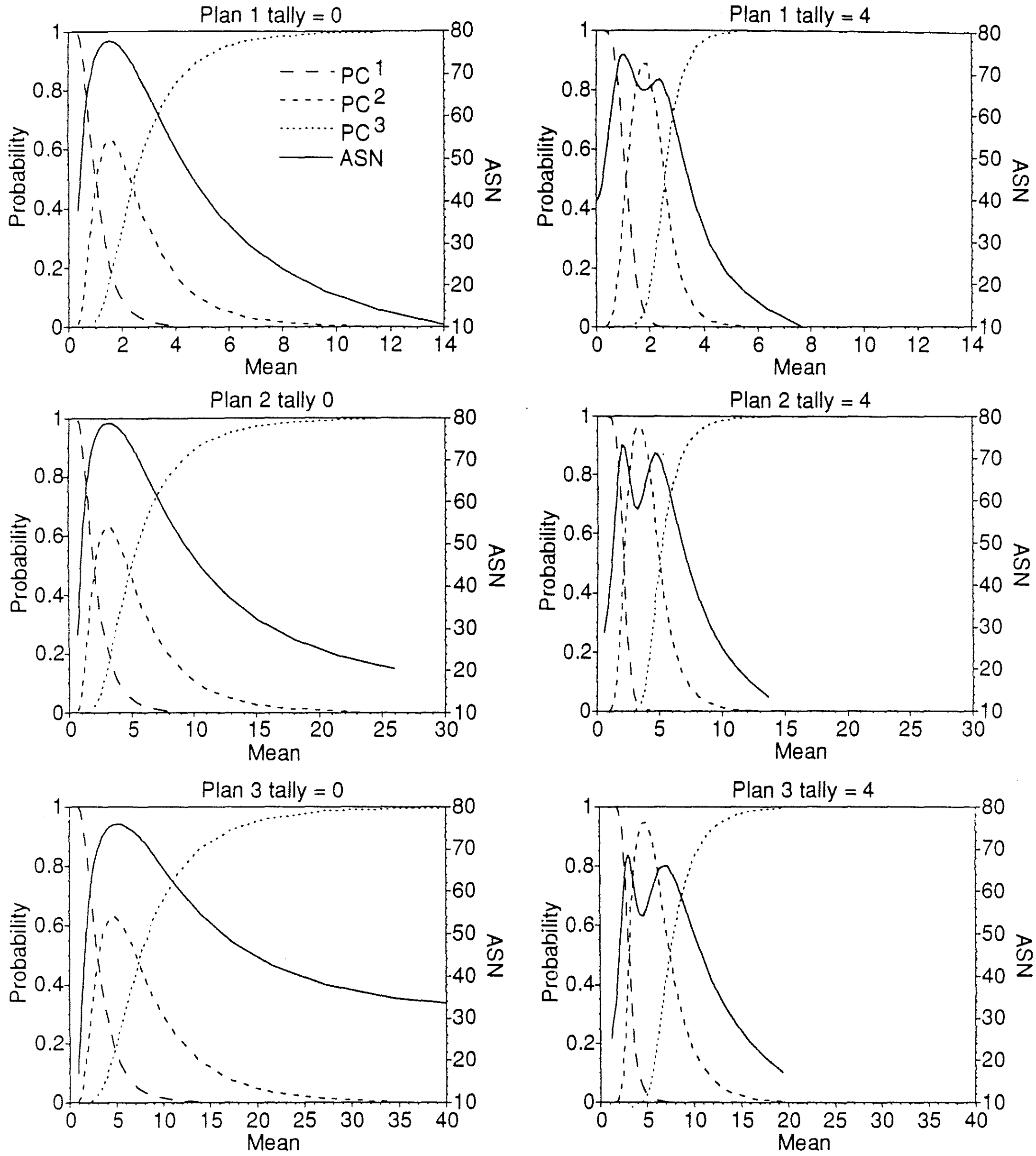

Fig. 3. Expected probability of classification (PC) and average sample size (ASN) functions for "standard" tripartite classification binomial sampling plans, obtained by simulation.

classifications with greater precision. This can be seen by referring to the PC^3 function which is the probability of intervening. Ideally this function should resemble a step with a value of 0.0 when the density is less than the intervention threshold and 1.0 when the density exceeds this threshold. This ideal is better met by the tally 4 schemes. The tally 4 sampling plans produced ASN functions equivalent to or always slightly less than those for the tally 0 plans. Based on the PC and ASN functions for each plan, the tally 4 sampling plans are clearly superior.

Field evaluation of the monitoring protocol

All density classifications made while an intervention threshold of 2.5 was applicable resulted in a decision to resample the population after two weeks. The median *P. ulmi* density for which this decision was reached was 0.19 mites per leaf and all but three were less than 0.5 per leaf. The expected probability of making a decision to resample in two weeks for such densities is greater than 0.95 (Fig. 3), so the field results were congruous with the simulated performance of the sampling plan.

While the intervention threshold of 5.0 was applicable, the tripartite sampling plan produced density classifications that resulted in all of the three possible decisions (Fig. 4). European red mite populations for which a decision was made to resample in two weeks had a median density of 0.94 and 93 percent of the densities were less than 2.5. Examination of the PC[1] function for this sampling plan (Fig. 3) shows that these results are also in accord with the computer simulation. When a decision was made to resample after one week, the median density was 3.64 and all densities were less than 7.0. This is the range of densities that the simulation indicated decisions to resample in one week are most likely. When a decision was made to intervene, all but two densities were in the range of 5.0 to 7.0. This result is also concordant with the simulated performance illustrated in

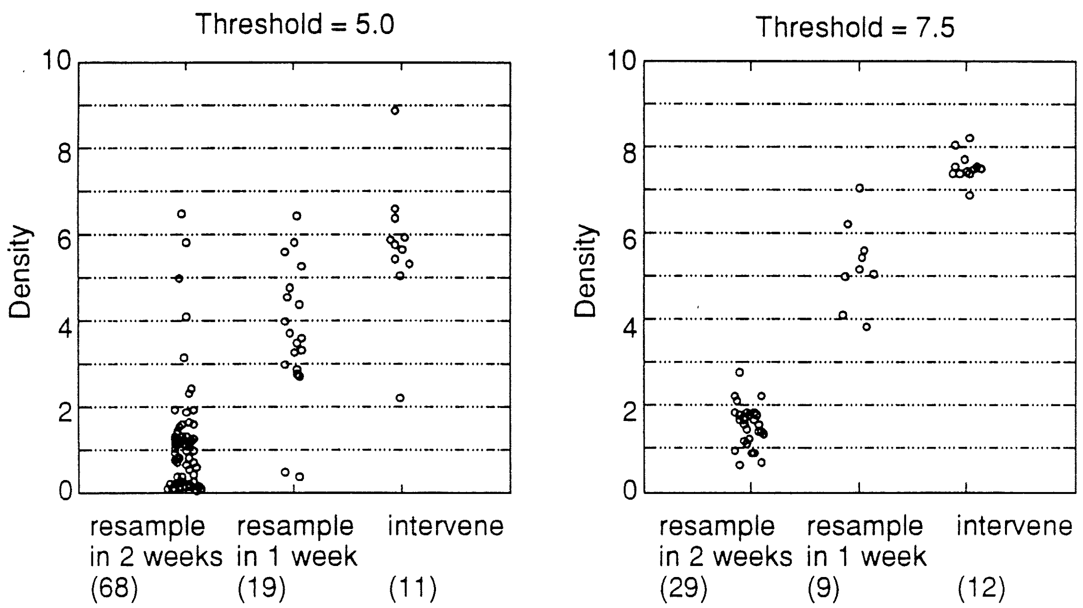

Figure 4. Distribution of estimated mean densities corresponding to monitoring decisions using "standard" binomial tripartite classification sampling with T = 0. Numbers in parentheses are data points in each group.

Fig. 3. For densities between five and seven mites per leaf, approximately 60 percent of the decisions are expected to be intervene, 35 percent to resample in one week, and 5 percent to resample in two weeks. There were 15 sampled field populations with densities between five and seven. Of these, nine (60 percent) produced a decision to intervene, four (27 percent) a decision to resample in one week, and two (13 percent) a decision to resample in two weeks.

Concordance between the field results and simulated performance of the sampling plan based on an intervention threshold of 7.5 was not as good as for the sampling plan based on a threshold of 5.0. However, the discrepancy was that the sampling plan performed better than expected. Populations with densities less than approximately three mites per leaf all resulted in decisions to resample after two weeks (Fig. 4), whereas 10 to 20 percent of these decisions should have been to resample in one week. All populations with densities in the range 4.0 to 6.5 (9) produced a decision to resample in one week, whereas only about 60 percent of these decisions should have been to resample in one week and the remaining decisions should have been to resample in two weeks (20%) or intervene (20%). All of the populations (12) with densities in the range of 7.0 to 8.0 resulted in a decision to intervene, whereas decisions for this range of densities should have been approximately evenly distributed between decisions to intervene and resample after one week.

One factor that may have contributed to divergence between the simulated and field results is that the simulated PC^i functions are expected values based on modelled variation in the parameter k of the negative binomial distribution. The sampled populations may not have had k values corresponding to the k values used in the simulation. If the k values for the field populations were concentrated in the upper part of the range of k values used in the simulation, sampling in the field would have resulted in more decisions to intervene than predicted from the simulations. Unfortunately, this could not be tested because k could not be estimated from the field data because mite counts were not recorded on a leaf by leaf basis but were pooled when mites were brushed from leaves onto the glass plates.

The overall performance of the monitoring protocol used in the field study is portrayed by the box plots shown in Fig. 5. In this figure, box plots of cumulative mite density are plotted with respect to the three final decisions; not to intervene, to intervene when the threshold was 5.0, and to intervene when the threshold was 7.5. Cumulative mite density never exceeded 250 which is only half of the threshold (500). Based on these results it can be concluded that the monitoring protocol based on tally 0 binomial count sampling plans functioned adequately and in good agreement with the simulated performance shown in Fig. 3.

Evaluation based on simulation and known population trajectories

Performance of the monitoring schemes based on tally 0 and tally 4 sampling plans was studied by applying the plans to a set of populations described by logistic growth and to a set of trajectories estimated from field populations. One specific

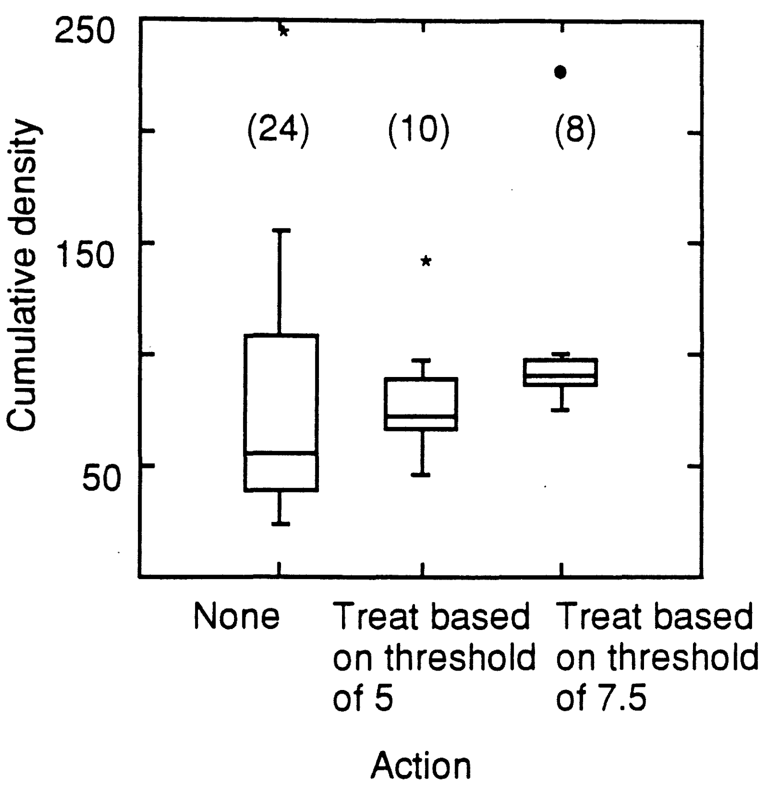

Fig. 5. Box plots of mite-days versus treatment decision for a monitoring protocol based on cascaded binomial tripartite classification sampling plans. Each box encloses 50% of the data and the horizontal line within the box is the median. Lines extending from either end of the box mark minimum and maximum values that fall within an acceptable range. Points outside this range are outliers. Numbers in parentheses are data points in each group.

question that we wanted to address with this comparison was whether the rather high probability of erroneously not intervening of tally 0 plans could be corrected in the framework of the monitoring protocol by sampling and intervening at subsequent bouts.

The populations described by logistic growth and the performance criteria for the two monitoring protocols used to monitor these populations are shown in Fig. 6. In all of these plots the performance criteria are graphed with respect to cumulative density (*i.e.*; total mite-days at season end). This is possible because each population had the same initial density and the shape of the populations trajectories were similar. Therefore, cumulative density is a concise and intuitive summary of each curve. The monitoring period for these populations was from time 0 to 98. Thus, 15 sample bouts could potentially occur. The endpoint of 98 was used to facilitate comparisons among different monitoring protocols.

The overall probabilities of intervening for tally 4 and tally 0 were both both centered around 200 mite-days, but the curve for tally 4 was steeper (Fig. 6). This is expected based on the PC^3 functions for each of the respective plans. Expected

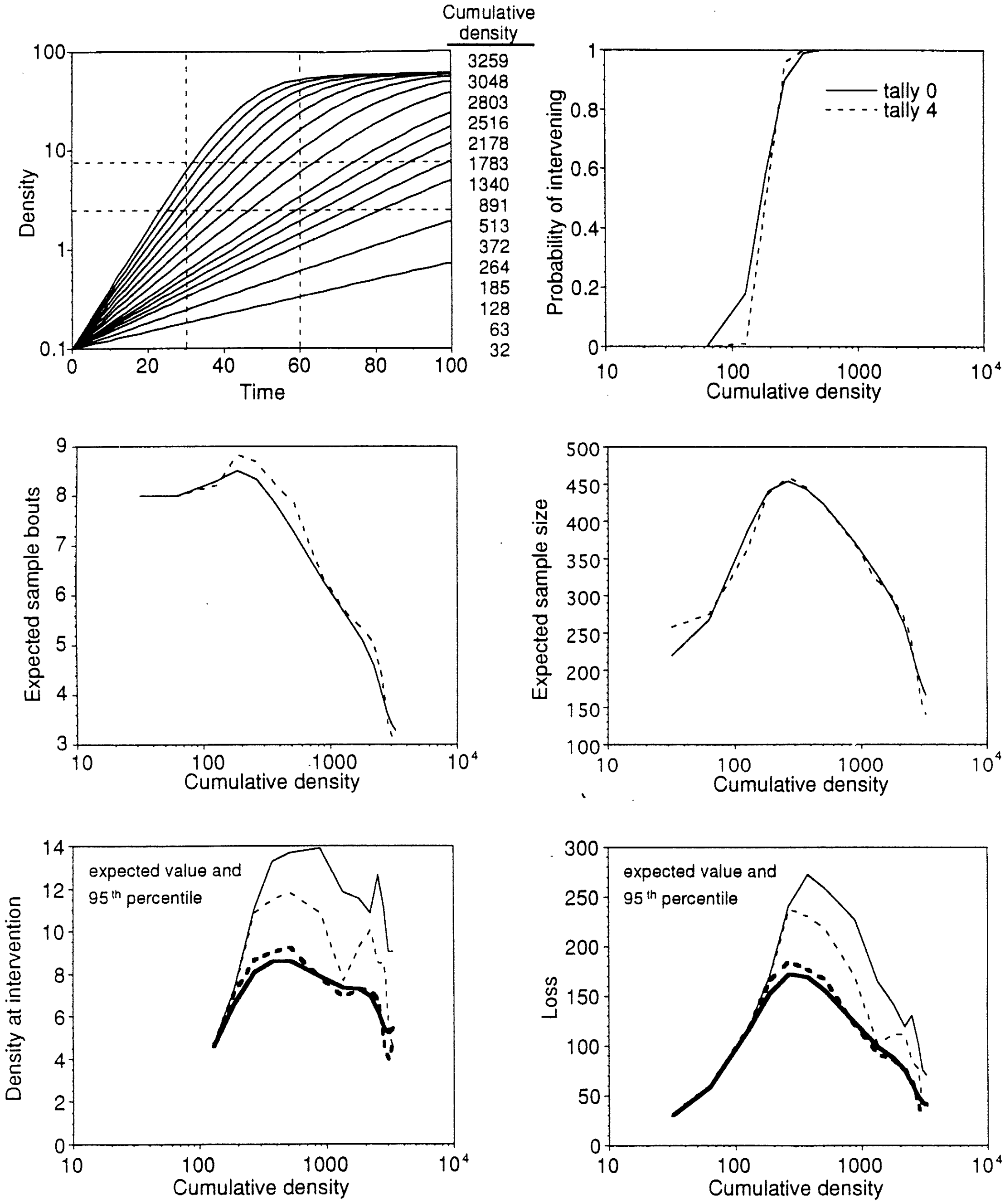

Fig. 6. Performance of protocols used to monitor 15 populations with logistic growth. Numbers to the right of the first figure are cumulative density for each of the 15 populations. Monitoring protocols were based on tripartite classification sampling plans that used either tally 0 or tally 4 binomial counts. Density at intervention not applicable for populations with cumulative density < 128 because the probability of intervention was zero. Maximum number of sample bouts was 15.

number of sample bouts and expected sample sizes for the two monitoring protocols were similar.

Expected densities at intervention were similar for monitoring protocols based on tally 0 and tally 4 sampling plans. These expected densities increased to a maximum of about nine when cumulative density approximated the threshold value of 500. Populations with cumulative density close to the threshold value of 500 had dynamics such that intervention density thresholds were not exceeded until late in the sampling period. For populations with faster growth and dynamics such that intervention density thresholds were reached during the first half of the sampling period, expected density at intervention declined as the growth rate increased. This pattern was not unique to the logistic populations shown in Fig. 6. We conducted simulations with other sets of populations described by logistic and purely exponential growth and obtained similar results (data not presented). Note that the expected density at intervention is independent of the the probability of intervening. Therefore, when the final density of a monitored population is low, the expected density at "intervention" is often equal to this final density.

The 95th percentiles for expected density at intervention were greater for the monitoring protocol based on tally 0 plans compared with tally 4 plans. However, these percentiles were always less than 14 and deemed to be acceptable. The pattern for these percentiles with increasing cumulative density was similar to that for the expected values but more jagged. This jaggedness occurred for two reasons: First, the shown percentiles are linear interpolations of functions that are curvilinear. Second, when growth rates were high, small changes in the time of intervention resulted in large changes in the density at intervention.

Expected losses were approximately equal; however, the 95th percentiles for loss were greater for the monitoring protocol based on tally 0 plans than for the protocol based on tally 4 plans when cumulative density exceeded approximately 250. This occurred because for populations with cumulative density greater than 250, the monitoring protocol based on tally 0 sampling plans was less likely to result in a decision to intervene than the protocol based on tally 4 sampling plans. However, losses for the monitoring protocol based on the tally 0 plans were less than 300, 95 percent of the time. This is an important result because it has previously been suggested (Nyrop and Binns, 1992) that binomial sampling plans based on tally 0 should be avoided because of their poor precision. Monitoring protocols based on cascaded tally 0 sampling plans are, in this case, acceptable. These monitoring schemes will almost always result in a decision to intervene before cumulative mite density exceeds a threshold of 500. This is despite the fact that the results from individual sample bouts will be to resample even when density exceeds the intervention threshold.

Sampling plans based on tally 0 were less precise than plans based on tally 4. Although in the long run average performance of monitoring protocols with constituent tally 0 and tally 4 sampling plans were similar, the variances were different: Tally 4 plans will make the right decision at the right time but tally 0 relies on "having a second chance" to reach the right decision[1]. Erroneous decisions to not intervene are corrected at later sampling bouts. Such corrections can, however, not occur for erroneous intervene decisions. Therefore, when the PC^3 function is flat (as with tally 0 plans), errors of such sort should be avoided by raising the intervention threshold. Otherwise the protocol becomes overly intervention-prone. This will be discussed further later in the paper.

Simulated sampling of the estimated population trajectories (Fig. 7) was started at time 12 and the last sample was taken at time 89. Performance of the monitoring protocols based on tally 0 and tally 4 sampling plans did not differ greatly except for the 95th percentiles for density at intervention and for loss (Table 4). These values were higher for the monitoring protocol based on tally 0 plans. Except for population two, the 95th percentiles for density at intervention were less than 15. All of the percentiles for loss were less than the threshold of 500. With populations 1 2, 4, and 6 intervention was assured. These populations all had densities in excess of the intervention thresholds and cumulative densities at or near the level for which damage occurs (500). For populations 3, 5, and 7 biological control was successful and there was very low or no probability of intervention.

The results presented thus far clearly show that the "standard" monitoring protocol of table 1 based on tally 0 sampling plans has acceptable performance. Therefore, all additional simulations were conducted using only binomial count sampling plans with a tally number of 0 because these plans are favored over plans with higher tally numbers by practitioners.

The performance of the monitoring protocol based on tripartite classification sampling plans was compared to a monitoring protocol in which populations were sampled each week or every second week and a decision was made to either sample again or to intervene (dichotomous classification). The comparison was made using the set of populations described by logistic growth and using the historical populations. When sampling was conducted every second week to monitor the historical populations it was necessary to extend the sampling period to time 96 so that the end of the population trajectories could be reached. In the simulations densities at time 96 were set equal to densities at time 89.

The probabilities of intervening were nearly identical for the three monitoring protocols (Fig. 8). Use of tripartite classification in the monitoring protocol resulted in 30 to 45 percent fewer sampling bouts compared with dichotomous classification each week. Dichotomous classification every second week did not result in

[1]Suppose a monitoring scheme consists of three sample bouts where the probabilities of classifying a given population trajectory, which is above threshold, at each bout are: $PC_1^1 = 0.2$, $PC_1^2 = 0.4$, $PC_1^3 = 0.4$; $PC_2^1 = 0.0$, $PC_2^2 = 0.5$, $PC_2^3 = 0.5$; $PC_3^1 = 0.0$, $PC_3^2 = 0.4$, $PC_3^3 = 0.6$. Note that the probability of intervening at each bout is maximally 0.6. For a damaging population trajectory, an overall probability of intervention of only 0.6 would be unacceptable. But the overall probability of intervention is 0.84. This is calculated as follows. The probability of sampling on the second occasion is $ps_2 = PC_1^2 = 0.4$ and the probability of sampling on the third bout is $ps_3 = PC_1^1 + ps_2 \bullet PC_2^2 = 0.2 + (0.4*0.5) = 0.4$. Therefore, the overall probability of intervention is $pi = PC_1^3 + ps_2 \bullet PC_2^3 + ps_3 \bullet PC_3^3 = 0.4 + (0.4*0.5) + (0.4*0.6) = 0.84$.

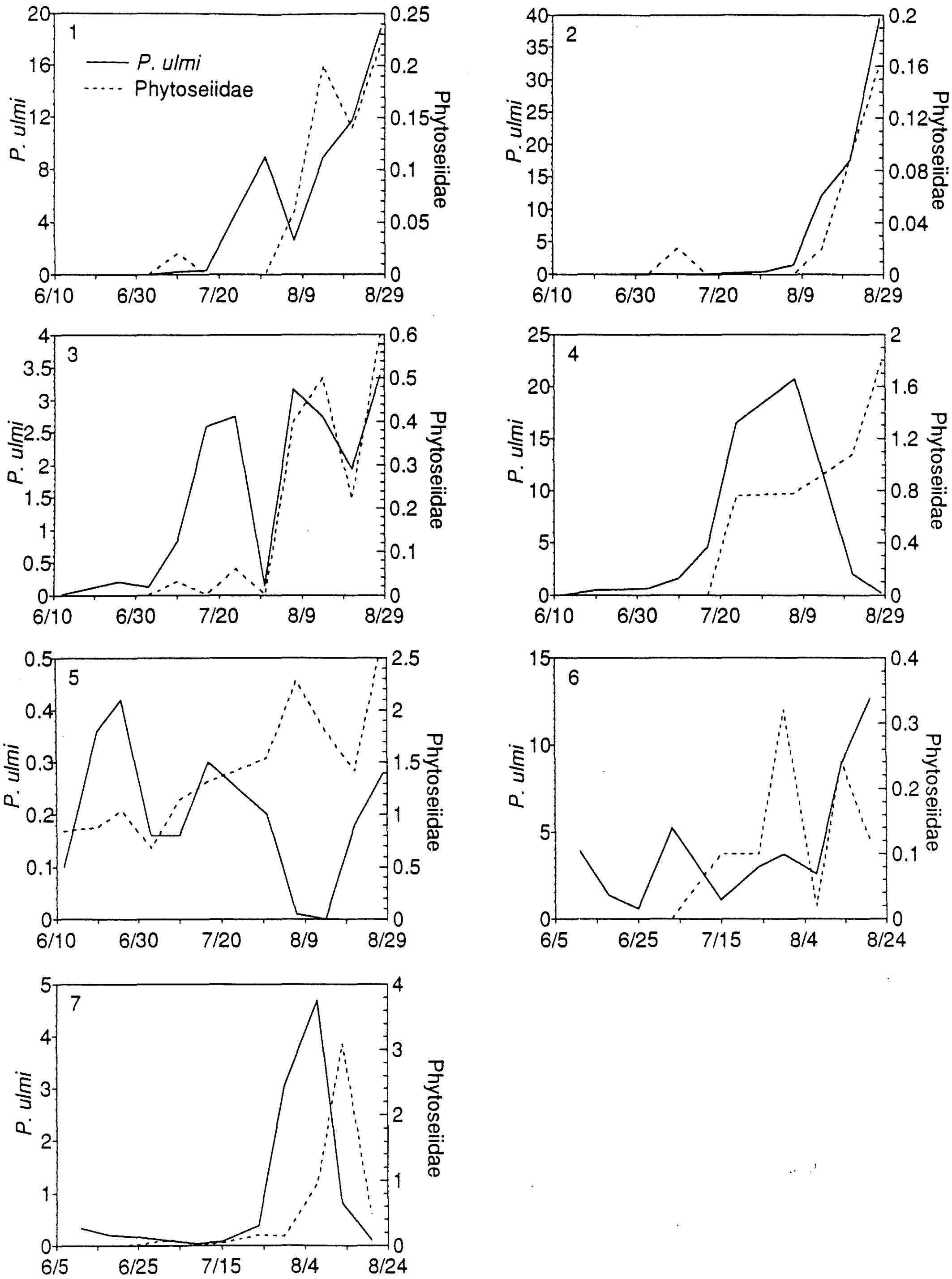

Fig. 7. Seven estimated density trajectories for *P. ulmi* populations preyed upon by phytoseiid mites.

appreciable savings in the number of sample bouts. The expected sample size was less with the monitoring schemes based on dichotomous classification because the dichotomous classification sampling plans had lower ASN functions. This is

TABLE 4

Results from applying tally 0 and tally 4 "standard" cascaded tripartite sequential classification sampling plans to seven population trajectories (Fig. 7).

Pop.[a]	Cumulated density	Probability of intervention	Expected sample size	Expected number of bouts[b]	Density at intervention Expectation	Density at intervention 95 per.[c]	Loss (mite-days per leaf) Expectation	Loss (mite-days per leaf) 95 per.
Tally 0								
1	329.67	1.00	247.71	5.06	7.92	11.62	91.41	217.15
2	363.08	1.00	221.63	6.08	18.89	23.85	171.49	219.71
3	103.85	0.06	340.20	6.70	3.37	3.38	101.77	103.85
4	462.20	1.00	222.45	4.29	10.26	13.96	109.08	153.86
5	15.45	0.00	171.41	6.03	n.a.d	n.a.	15.45	15.45
6	363.41	1.00	118.95	1.96	4.77	10.53	31.58	210.69
7	69.53	0.11	254.02	6.38	0.57	n.c.e	66.22	69.53
Tally 4								
1	329.67	1.00	231.27	4.95	7.82	10.94	79.47	199.74
2	363.08	1.00	186.96	6.01	17.84	17.45	164.53	158.60
3	103.85	0.00	327.69	6.58	n.a.	n.a.	103.85	103.85
4	462.20	1.00	193.49	4.10	10.32	10.29	108.87	108.54
5	15.45	0.00	202.29	6.01	n.a.	n.a.	15.45	15.45
6	363.41	1.00	51.50	1.27	4.19	3.88	9.38	n.c.
7	69.53	0.00	267.96	6.47	n.a.	n.a.	69.44	69.53
Dichotomous every 7 days[f]								
1	329.67	1.00	158.22	8.07	7.43	10.27	78.06	182.52
2	363.08	1.00	134.79	10.21	13.61	16.61	81.94	142.67
3	103.85	0.18	177.87	11.35	3.29	3.38	93.97	103.85
4	462.20	1.00	143.34	6.63	8.32	11.06	84.71	118.02
5	15.45	0.00	105.03	12.00	n.a.	n.a.	15.45	15.45
6	363.41	1.00	103.86	1.97	4.33	4.81	19.64	152.24
7	69.53	0.20	148.76	11.57	0.96	0.10	64.23	69.53
Dichotomous every 14 days[g]								
1	329.67	1.00	129.40	5.73	9.44	16.13	151.87	288.21
2	363.08	1.00	86.90	6.07	19.26	24.47	177.59	225.41
3	103.85	0.10	103.10	6.92	3.37	3.38	101.54	103.85
4	462.20	1.00	86.83	4.10	11.37	15.54	130.98	211.84
5	15.45	0.00	62.50	7.00	n.a.	n.a.	15.45	15.45
6	363.41	1.00	93.88	1.98	5.63	11.49	50.95	239.96
7	69.53	0.03	75.61	6.94	0.19	n.c.	67.98	69.53

[a] population.
[b] maximum 12 bouts.
[c] 95th percentile.
[d] not applicable; the probability of intervention was 0.0.
[e] not calculable; percentile could not be calculated because probability of intervening at the first sample bout was > 0.95.
[f] SPRT using upper arm of "standard" plans; potential number of sample bouts = 12.
[g] SPRT using upper arm of "standard" plans; potential number of sample bouts = 7.

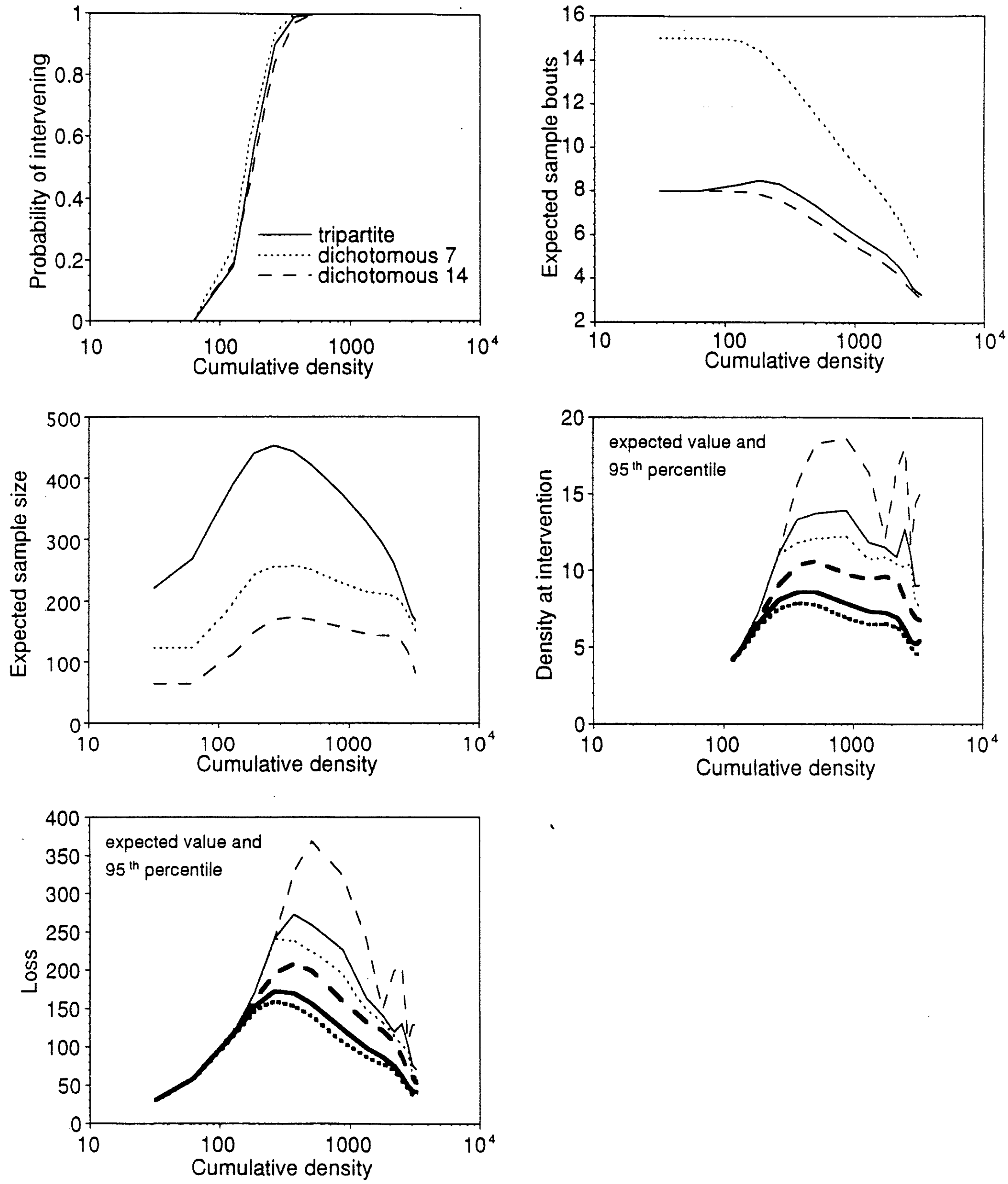

Fig. 8. Performance of monitoring protocols based either on tripartite or dichotomous classification of density. The dichotomous protocol sampled populations either every 7 or 14 days. Population trajectories were described by logistic growth. Maximum possible number of sample bouts was 15.

because tripartite plans have an extra set of stop lines, in addition to the set already present in the dichotomous plans. This extra set of stop lines expands the set of possible sampling sequences that make short or long excursions in the indecision region, before crossing one of the stop lines. Expected values and 95th percentiles for density at intervention and loss were lowest for the monitoring protocol based on dichotomous classification each week, intermediate for the protocol based on tripartite classification, and highest for the protocol based on dichotomous classification every second week.

These results show that dichotomous classification every second week would too frequently allow high density populations to develop before scheduling intervention. Tripartite classification usually prevented this from occurring by scheduling a shorter time to the next sample bout when densities were close to the intervention threshold. Monitoring protocols based on tripartite classification can also provide considerable savings in sampling costs compared with monitoring protocols based on dichotomous classification every week. To make a three-way classification of density, more samples must be taken than to make a two-way classification. However, because trips to a field to collect samples will usually be more time consuming and costly than processing additional samples once at the field site, the savings in sample bouts will greatly outweigh the costs of additional sample observations at each bout.

Monitoring protocols based on dichotomous classification each week may also too hastily conclude that intervention is necessary. For example, if the monitoring protocol based on weekly dichotomous classification was used to monitor the populations shown in Fig. 7, the probability of intervention with population 3 is 0.18 and with population 7 is 0.20 (Table 4). In both cases biological control was successful and the monitoring protocol based on tripartite classification produced probabilities of intervention of only 0.06 and 0.11. Furthermore, the monitoring protocol based on the tripartite plans required only two thirds as many sample bouts as the monitoring protocol based on the dichotomous plans. Dichotomous classification each week did reduce the 95th percentile for density at intervention for population 2 from 219.7 for the tripartite classification (Table 4). However, 219.7 is well within the range of acceptable loss so we do not feel this benefit outweighs the costs of using the dichotomous-based protocol.

The monitoring protocol based on dichotomous classification every second week and the protocol based on tally 0 tripartite classification had, with the exception of average sample size and 95th percentiles for density at intervention, comparable performance when used to monitor the seven historical populations (Table 4). Average sample sizes were lower with the dichotomous plans but the 95th percentiles for density at intervention were higher. These results show that when population growth rates are low, dichotomous classification every two weeks is the best strategy and when growth rates are high, dichotomous classification every week is the best strategy. However, when a priori knowledge of growth rates is lacking, tripartite classification is the best compromise between sampling very frequently or with a longer time interval between sample bouts.

The influence of cd_I *on the performance of the monitoring protocol*

We observed that stop lines for the constituent tripartite classification sampling plans of the monitoring protocol produced very small regions where a decision to resample after one week would be made. We therefore constructed a new set of sampling plans (table 2) with the same cd_2 values but lower cd_1 values to produce stop lines that had wider regions in which a decision to resample in one week would be made. Differences in the stop lines and resulting probabilities of classification are illustrated for an intervention threshold of 5.0 in Fig. 9. It is worth noting that, because the upper SPRT is unchanged, the PC^3 curves for plans A and B are almost identical. The difference between the plans is that, under B, there is generally a greater chance of early resampling.

Monitoring protocols based on these two sets of tripartite sampling plans were used to simulate monitoring the populations described by logistic growth. We will refer to the original monitoring protocol as protocol A. The protocol based on the sampling plans with reduced cd_1 values will be referred to as protocol B. Monitoring protocol B produced a slightly greater probability of intervening, required more sample bouts and more samples, and resulted in lower expected and 95th percentiles for density at intervention and loss compared to protocol A (Fig. 10). This resulted mainly because of the greater chance of early resampling with protocol B, which, in turn increased the overall probability of intervening.

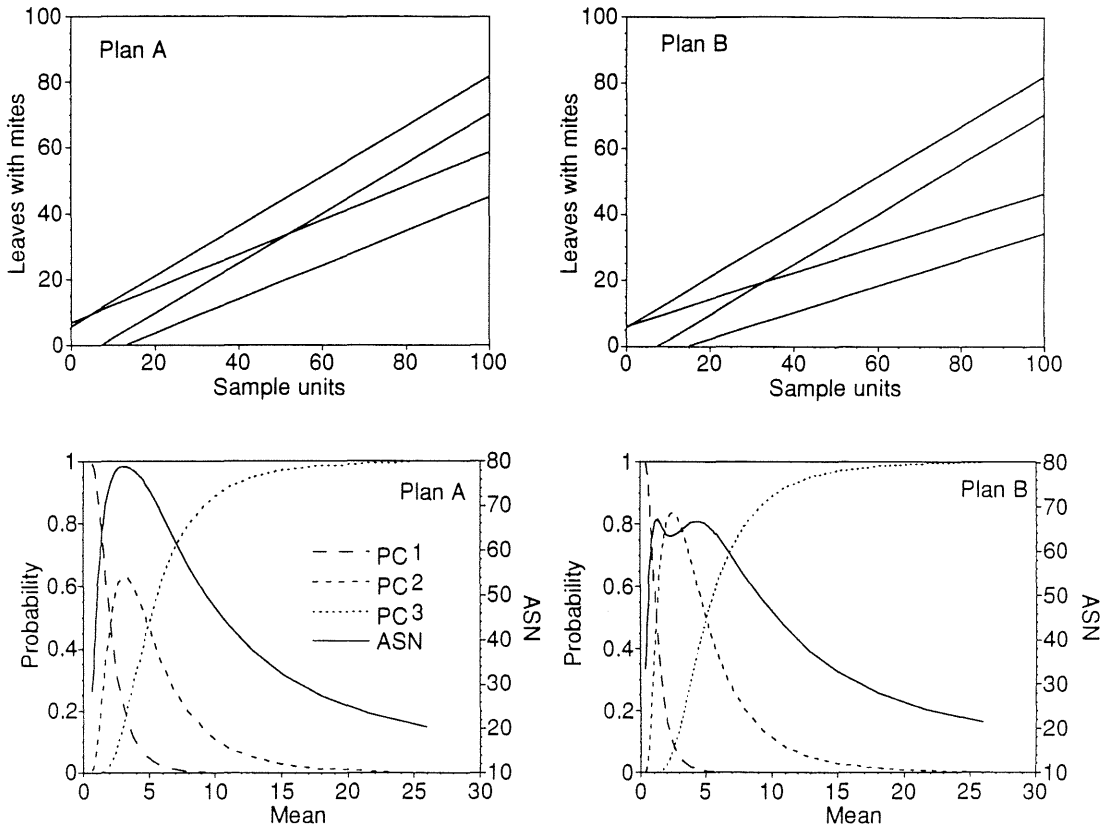

Fig. 9. Stop lines, probability of classification functions (PC) and average sample size functions (ASN) for two tripartite classification sampling plans. Both plans are based on $cd_2 = 5.0$. Plan A is based on $cd_1 = 2.0$ and plan B on $cd_1 = 0.5$.

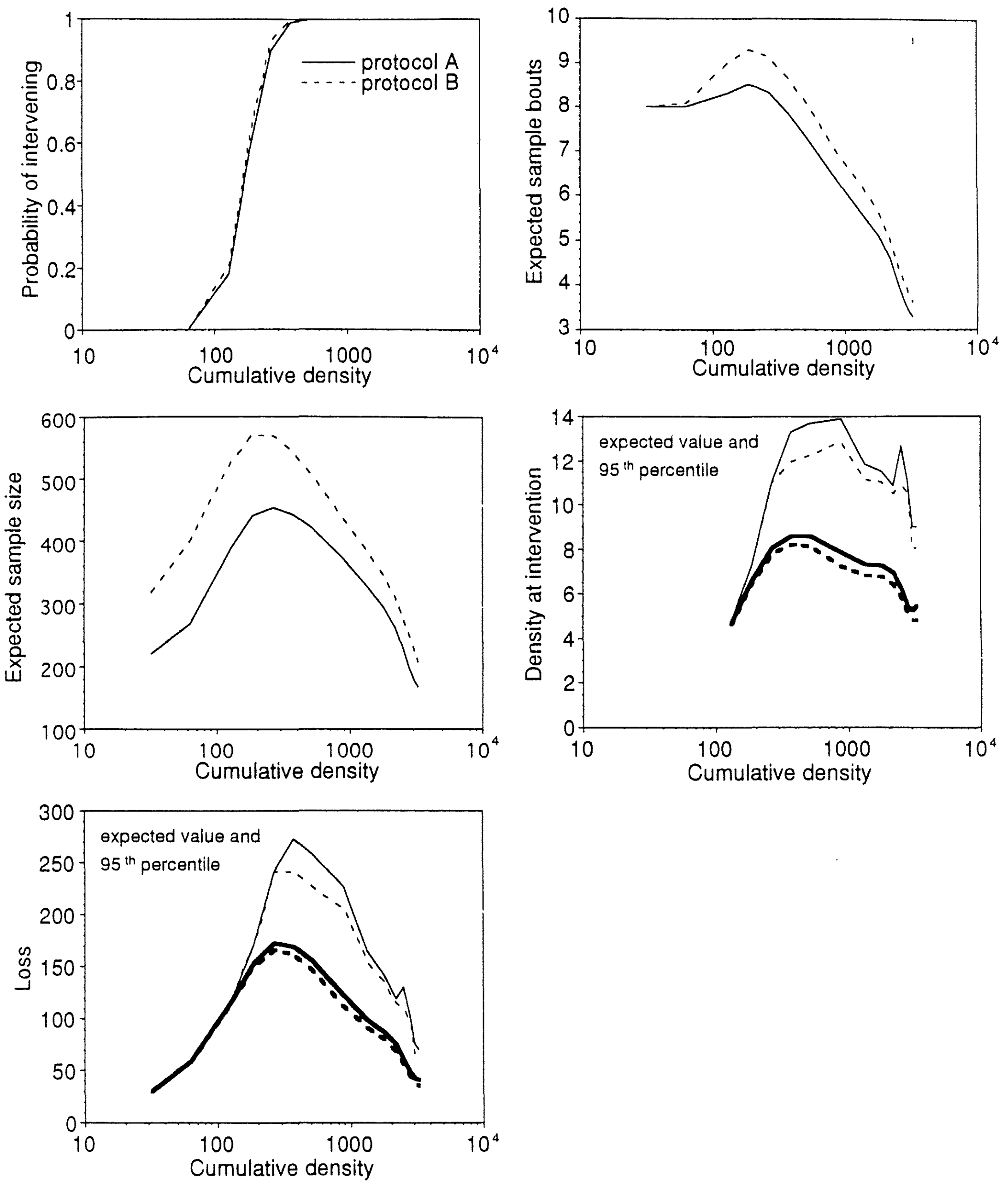

Fig. 10. Performance of two monitoring protocols based on tripartite classification sampling. Constituent sampling plans have identical cd_2 values; however, cd_1 values for protocol B were less than those for protocol A. Maximum possible number of sample bouts was 15.

Based on these results we conclude that when monitoring European red mite, a protocol based on sampling plans that produce higher probabilities of resampling in one week is inferior to the original monitoring protocol based on sampling plans that produce a lower probability of resampling in one week.

The influence of cd_2 *on the performance of the monitoring protocol*

As shown previously, the overall probability of intervening when using a monitoring protocol with constituent tripartite classification sampling plans is often greater than might be expected based on the performance of the individual tripartite plans. As a result, we hypothesized that a monitoring scheme in which constituent sampling plans had cd_2 values equal to the intervention threshold(s) might call for intervention too frequently when densities were close to but less than the intervention thresholds. This situation might arise when natural enemies are effectively regulating *P. ulmi* densities. To examine this question further, the monitoring protocol based on tally 0 sampling plans was applied to a population trajectory that exactly followed the intervention thresholds (cd_2) and to a set of population trajectories that were 10, 20, 30, 40, and 50 percent less than the intervention thresholds

When density equalled the threshold, intervention was practically assured (Table 5). In fact, intervention occurred 97 percent of the time when density was only 70 percent of the original thresholds (population 4 in Table 5). These results substantiated our concern that a monitoring protocol based on current intervention thresholds would too frequently result in a decision to intervene when densities remained close to the threshold. We further hypothesized that this situation could be remedied by increasing the cd_2 and associated cd_1 values. Therefore, we developed sampling plans based on cd_2 values of 5.0, 7.5, and 10.0 (Table 3) and used these sampling plans in a monitoring scheme. We will refer to the monitoring protocol based on these higher cd_2 values as monitoring scheme C and the original monitoring protocol as scheme A.

When monitoring protocol C was used to monitor the populations whose

TABLE 5

Results of applying the "standard" monitoring protocol based on tally 0 sampling plans to populations with density equal or close to the intervention thresholds.

Pop.[a]	Cumulated density	Probability of intervention	Expected sample size	Expected number of bouts	Density at intervention Expectation	Density at intervention 95 per.[b]	Loss (mite-days per leaf) Expectation	Loss (mite-days per leaf) 95 per.
1	527.50	1.00	139.15	1.95	2.60	2.50	19.53	63.46
2	474.75	1.00	173.94	2.35	2.47	4.50	27.26	92.27
3	422.00	0.99	227.73	3.00	2.42	4.00	41.03	155.66
4	369.25	0.97	313.89	4.06	2.52	5.25	65.91	295.49
5	316.50	0.86	446.00	5.74	2.74	4.50	107.23	307.50
6	263.75	0.59	590.77	7.74	2.91	3.75	154.17	256.25

[a] Population 1: 2.5 for time 1 to 30, 5.0 for time 31 to 60, 7.5 for time 61 to 98. Populations 2 through 6: 90, 80, 70, 60, and 50 percent of population 1.

[b] 95th percentile.

densities remained close to the original intervention thresholds, the probability of intervening was reduced compared with monitoring protocol A (Table 6). For example, when the population with density equal to 70 percent of the intervention thresholds (population 4) was monitored, the probability of intervening when using protocol C was 0.49 compared with 0.97 for protocol A. Protocol C resulted in an increased number of sample bouts and increased expected total sample size compared with protocol A. This is because there was a reduced probability of intervening with protocol C and hence there were more sample bouts. Note that in this case an increased number of sample bouts did not lead to an increased overall probability of intervening.

Monitoring protocol C was also applied to the logistic populations and the results compared to those obtained using protocol A . With the logistic populations protocol C resulted in reduced probabilities of intervening, slightly more sample bouts, lower sample sizes, and increased densities at intervention and increased loss (Fig. 11). Some 95th percentiles for density at intervention exceeded the target value of 15 when protocol C was used. However, 90th percentiles for density at intervention were always less than 16 (data not shown).

By using the higher intervention thresholds (protocol C) a better balance was obtained between correctly scheduling intervention when population density was growing rapidly and not intervening unnecessarily when densities remained just below the nominal intervention thresholds. Monitoring protocol C should therefore be preferred to A to assess *P. ulmi* density throughout a growing season.

TABLE 6

Results of applying a monitoring protocol with higher values of cd_1 and cd_2 (protocol C) to populations with density equal or close to the intervention thresholds.

Pop.[a]	Cumulated density	Probability of intervention	Expected sample size	Expected number of bouts	Density at intervention Expectation	Density at intervention 95 per.[b]	Loss (mite-days per leaf) Expectation	Loss (mite-days per leaf) 95 per.
1	527.50	0.94	485.85	6.35	5.28	7.50	198.36	512.50
2	474.75	0.85	548.26	7.26	5.30	6.75	232.14	461.25
3	422.00	0.71	604.36	8.17	5.20	6.00	262.51	410.00
4	369.25	0.49	636.51	8.88	4.89	5.25	280.15	358.75
5	316.50	0.27	621.83	9.14	4.38	4.50	275.34	307.50
6	263.75	0.10	554.45	8.94	3.73	3.75	247.46	56.25

[a] Population 1: 2.5 for time 1 to 30, 5.0 for time 31 to 60, 7.5 for time 61 to 98. Populations 2 through 6: 90, 80, 70, 60, and 50 percent of population 1

[b] 95th percentile

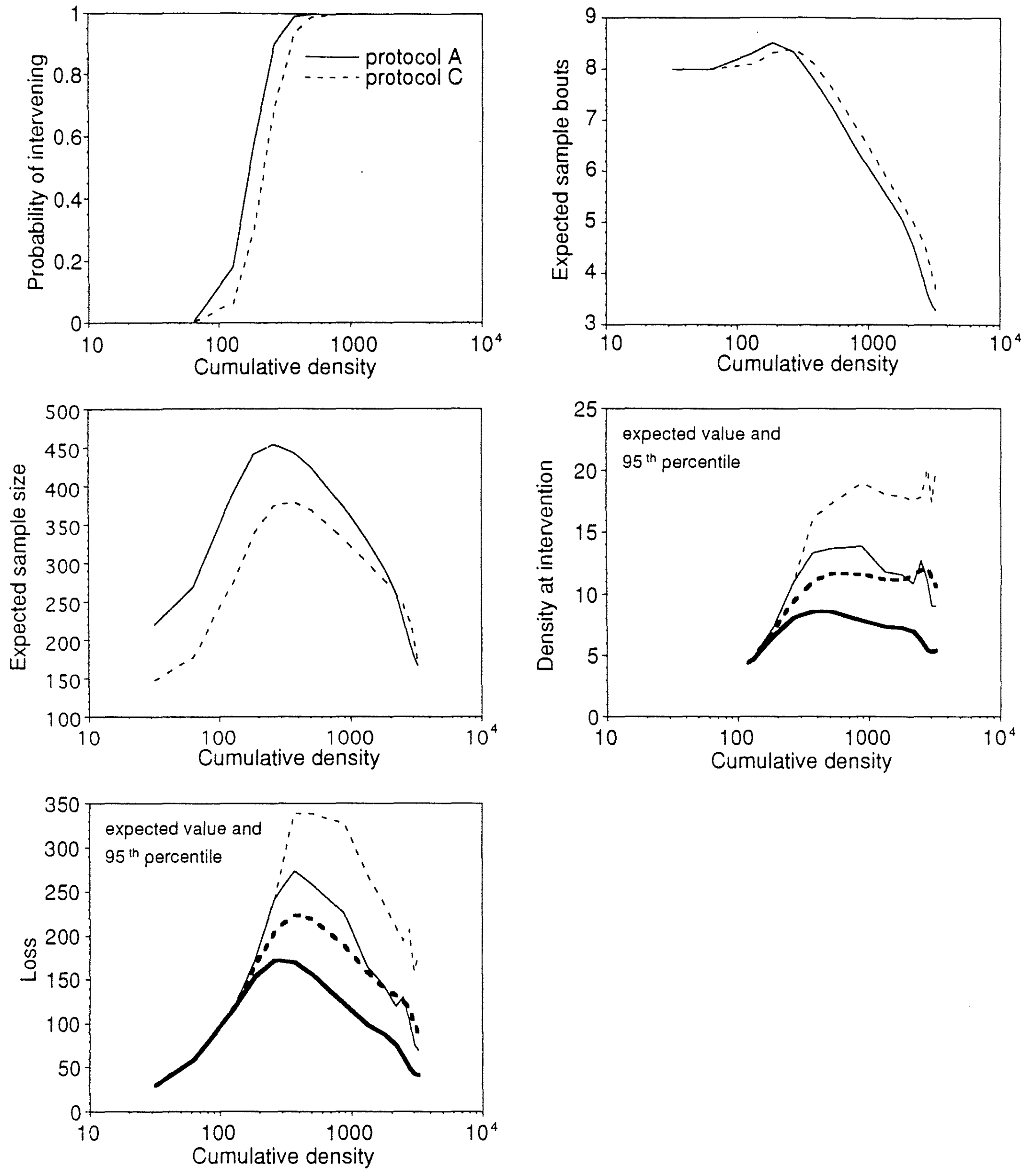

Fig. 11. Performance of two monitoring protocols based on tripartite classification when applied to populations with exponential growth. Protocol C was based on sampling plans with cd_1 and cd_2 values greater than those used for the constituent sampling plans of protocol A.

DISCUSSION

In pest management it is often necessary to monitor a population through time in order to ascertain that density does not exceed potentially damaging levels that require intervention. When doing this it is desirable to minimize the number of times the population is sampled during the growing season and to minimize the number of sample units examined during a single sample bout. Sequential sampling can be used to minimize sample size at each sample bout. To minimize the number of times the population is sampled, we developed a monitoring protocol that schedules sample bouts based on a classification of current population density and expected population growth. At each sampling bout density is classified into one of three categories with resultant decisions to intervene when the density is high, resample at the next sample occasion when the density is intermediate, and resample at the second sample occasion when density is low. The monitoring protocol is evaluated for a particular population trajectory by five criteria: (1) the overall probability of intervening, (2) the expected number of sample bouts, (3) the expected total sample size, (4) expected density at intervention, and (5) expected loss.

We parameterized this procedure for monitoring European red mite in apples and classified density at each sample bout using binomial count sampling plans. With binomial count plans records of the proportion of sample units with more than T organisms (p_T) are substituted for complete enumeration of the samples. The easiest binomial counts to make are when $T = 0$. However, due to the effect of variation in the model that relates mean density to p_T on the precision of binomial count sampling plans, it has been suggested that $T>0$ be used or that binomial counts be avoided entirely. This admonition may be less important when sampling plans are concatenated and used to assess population density repeatedly through time.

Sampling plans that classify *P. ulmi* density based on binomial counts with $T = 0$ are imprecise. However, when these plans were cascaded in a monitoring protocol, the performance of the monitoring scheme was acceptable. The principles that led to this result will apply to other binomial count plans; however, the overall effect of the concatenation will be system specific and will require individual examination.

When classification sampling plans are cascaded in the manner we have described, the overall probability of intervening will always be greater than the probability of intervening at any single sampling bout. This is an important point because concatenation can inadvertently lead to overall higher probabilities of intervention than desired.

To overcome the problem of overly high probabilities of intervention when using a monitoring protocol, constituent sampling plans can be modified in two ways. First, the expected number of sample bouts may be reduced by making the region of the sample path that results in an intermediate density classification smaller (increase cd_1 and keep cd_2 constant). The reverse of this was illustrated with the European red mite monitoring protocols when the values for cd_1 were reduced and values for cd_2 were kept constant. These changes led to an increased number of sample bouts and increased probability of intervention compared with the original monitoring protocol. Second, the probability of intervening at each sample bout can be decreased by increasing cd_2 and associated cd_1 values. This was also illustrated with the *P. ulmi* monitoring schemes.

Monitoring protocols based on tripartite classification will result in reduced number of sample bouts compared with a monitoring protocol based on dichotomous classification and sampling at each possible sample bout. For the procedure designed for monitoring European red mite, expected sample bouts were reduced 30 to 45 percent. When the sampling plan constructed about cd_2 is the same for the tripartite and dichotomous plans, the tripartite procedure will always require more sample units each time. We think a reduced number of sample bouts will usually compensate for this increase.

Monitoring schemes based on tripartite classification are best suited to situations where information about the growth rate of the population being monitored can not be obtained. If for example predaceous phytoseiid mites were abundant and *P. ulmi* densities were modest, the best monitoring strategy would be to make dichotomous classifications at two week intervals. However, when data that might be used to make inferences about population growth is lacking or confusing, tripartite classification is the best choice.

When designing tripartite classification sampling plans for use in a monitoring protocol a balance must be obtained between intervening unnecessarily when densities are low and allowing rapidly growing populations from becoming too numerous. Adjusting the cd_2 and cd_1 values appears to be the best way to accomplish this. At present a trial and error methodology must be used to obtain an acceptable monitoring protocol.

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APPENDIX

In this appendix we provide a mathematical description of performance criteria for a monitoring scheme based on tripartite classification of density. Lower case italics indicate variables associated with the overall monitoring scheme. Upper case denotes variables associated with constituent tripartite classification plans. We first introduce some notation.

- b: The index for sampling bouts (sessions) which takes on the range 1 through *last*. With a sampling period of 50 days and a minimum time between samples of 7 days, b would run from 1 to 8 if the first sample was taken on day 1.
- d_b: The density at sample bout b.
- PC_b^i: The probability of classification i at sample bout b when the density is d_b.
- ASN_b: The average sample size at bout b for density d_b.
- ps_b: The probability of sampling at sample bout b.
- l_b: The loss at sample bout b.

We further define some terminology in order to be able to clearly distinguish between the probability of decisions taken within the framework of the monitoring protocol and the probability of classifications in one of the constituent sampling plans. The probabilities of decisions taken within the framework of the monitoring protocol are unconditional. Within the framework of the monitoring protocol, the probabilities of classifications in a specific sampling bout are conditional on the fact that sampling at that bout occurs at all. The classification probabilities for a single bout add up to one for that bout. The probabilities of monitoring decisions add up to one for the whole of the monitoring protocol.

At the first sampling bout, the density is d_1, the probability of sampling is one ($ps_1 = 1$), the probability of each of the three density classifications is , and the loss is l_1. At the second sampling time the density is d_2, the probability of sampling at this time is $ps_2 = \mathrm{PC}_1^2 \times ps_1$, and the probability of each of the three density classifications is PC_2^i. The probability of each of the three monitoring decisions that are possible at bout 2 are given by $ps_2 \times \mathrm{PC}_2^i$. At the third sampling time the density is d_3 and the probability of sampling at this time is $ps_3 = (\mathrm{PC}_2^2 \times ps_2)+(\mathrm{PC}_1^1 \times ps_1)$. Sampling at time three can only occur if a decision was made to resample after one time interval during the second sample bout or if a decision was made to resample after two time intervals during the first sample bout. The probability of each of the three monitoring decisions made at the third sample bout is $ps_3 \times PC_3^i$.

The probability of sampling at periods 3 through *last* can be generalized as:

$$ps_b = (PC_{b-1}^2 \times ps_{b-1}) + (PC_{b-2}^1 \times ps_{b-2}) \qquad (1)$$

Note that this equation will apply to all sampling periods provided we define $ps_0 = 1$, $PC_0^2 = 1$, $ps_{-1} = 0$, and $PC_{-1}^1 = 0$.

The probability of intervention (*pi*), expected sample bouts (*eb*), and expected total sample size (*ess*) are now calculated as:

$$pi = \sum_{b=1}^{last} ps_b \times PC_b^3 \qquad (2)$$

$$eb = \sum_{b=1}^{last} ps_b \qquad (3)$$

$$ess = \sum_{b=1}^{last} ps_b \times ASN_b \qquad (4)$$

Expected density at intervention (*edi*) is the sum of the density at each sample bout multiplied by the product of the probability of sampling and the probability of intervening. Two end points must be considered. First, if the last sample period is reached, then the contribution to expected density at intervention at that time is simply the probability of sampling times the density. Second, at the next to last sampling period a decision to wait two time periods to sample again is equivalent to not intervening because sampling will not be repeated. Thus, the density that would occur at the last sampling time applies here as well. The following equation accounts for these endpoints:

$$edi = \sum_{b=1}^{last-1} \left[d_b \times ps_b \times PC_b^3 \right] + \left(d_{last} \times ps_{last-1} \times PC_{last-1}^1 \right) + \left(d_{last} \times ps_{last} \right) \qquad (5)$$

Expected loss is the sum of the cumulative density at each sample bout multiplied by the product of the probability of sampling and the probability of intervening. The two end points considered when computing the expected density at intervention must be incorporated here as well. The following equation does this:

$$el = \sum_{b=1}^{last-1} \left[l_b \times ps_b \times PC_b^3 \right] + \left(l_{last} \times ps_{last-1} \times PC_{last-1}^1 \right) + \left(l_{last} \times ps_{last} \right) \qquad (6)$$

Any loss occurring after the last sample bout is not taken into account.

It is important to understand that *pi*, *eb*, *ess*, *edi*, and *el* pertain to a specific population trajectory being monitored and there will be different values for these variables for each population trajectory considered.

Variability in density at intervention and loss is the result of variability in the timing of intervention which in turn is due to sampling uncertainty. The probability that intervention will have occurred at or before a sample bout is provided by the cumulative probability of intervention which is calculated as:

$$cpi_b = \sum_{i=1}^{b} ps_i \times PC_i^3 \tag{7}$$

This is also the probability of having the density at intervention be less than or equal to d_b and of incurring loss less than or equal to l_b. Percentage points of density at intervention and of loss can be approximated by selecting a desired cumulative probability and interpolating. Note that loss will usually be a continuously increasing function of time; however, density may rise or fall with time. Depending on the population dynamic being monitored, this can lead to percentiles of density at intervention being less than the expected value.