

Tripartite Sequential classification Sampling Plans to monitor *Tetranychus urticae* Pest mite Population through time

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Abstract— *The objective of this study was to develop and evaluate a tripartite sequential classification sampling plans to monitor pest mite *Tetranychus urticae* (Koch, 1836) through time. Three tripartite plans using Wald's Sequential Probability Ratio Test based on tally 0 and 5 binomial counts were developed for use at different times. For each Wald's plan, three hypotheses were tested and three probabilities (P_{dec} ; $i=1; 2; 3$) for making decision were simulated. Tripartite sequential classification sampling plans with tally 0 binomial counts was compared to dichotomous plans repeated every Δt and after $2\Delta t$. Performance of monitoring protocols were studied by monitoring height *T. urticae* populations with logistic growth. The results showed that tripartite classification reduced from 30 to 40% of the expected bouts than dichotomous sampling plans after Δt and $2\Delta t$ days and reduce sampling costs. Monitoring protocol B reduced the probability of intervening and produced more sample bouts and more samples, which resulted in lower expected and 95th percentiles for density at intervention and expected loss compared to protocol A. The use of tripartite classification plan required adjustment of the cd_2 and cd_1 values to accomplish an efficient integrated pest management during growth season.*

Keywords— *Sampling, *Tetranychus urticae*, monitoring protocol, Binomial count, tripartite plan, intervention threshold.*

I. INTRODUCTION

In agro-ecology, ecologists are more confronted with the need to do their investigation in the most efficient manner (Krebs, 2014). Management requires a reliable method to monitor the pest populations. Therefore, many sampling plans have been developed and assessed for a wide variety of arthropods and insects of ecologic and economic importance. Sampling is a fundamental component of any experimentally based research program in the discipline of entomology, whether conducted in the laboratory, greenhouse or field (Naranjo, 2008). Sequential

sampling has been developed during thesecond war world (Wald, 1945a; Wald 1945b). Due of its great efficiency in control of the military equipment quality, this subject was classified as a "military secret" in the United States until 1945, when it was made public. It was applied first in forest ecology (Wald, 1947; Water, 1955) and later in agro ecology (Sylvester and Cox, 1961; Harcourt, 1966). Since then, sequential sampling has been used to estimate organism population levels on several agro ecosystems (Fowler and Lynch, 1987).

Most sampling procedures used in agro ecology have only been concerned with classifying or estimating animal density at a single point in time. This reflects the primary purpose of these procedures; to determine whether an intervention 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 treatment is substituted for 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 finding of a natural enemy - prey interaction based on the ratio of prey to predator and thereby obviate the need for monitoring (Nyrop, 1988). However, a number of factors such as uncertainty in the understanding of natural enemy -prey dynamics, errors in initial population estimates, and the influence of biotic and abiotic factors can obviate such predictions.

This work resumes Binns and Nyrop studies and recalled how to construct the SPRT of Wald when the distribution of insect pests corresponds to negative binomial probability law. The performance of tripartite sequential classification sampling plan parameters cascading through time was simulated by using readapted computer programs. We describe a methods that can be used to efficiently monitoring *T. urticae* to determine whether density remains or not below a critical threshold. The results are presented and sufficiently discussed in this document.

II. MATERIAL AND METHODS

Description of model:

Tripartite sequential sampling plan is a dynamic plan that takes into account the evolution of pest mite *T. urticae* population within a logistic grow ($r_m=0.078d^{-1}$). To classify population density (d) into one of three categories, two critical densities cd_1 and cd_2 were chosen accordingly to the population dynamic changes during season with: $cd_2 = cd_1 \times e^{(r_m \times 2\Delta t)}$. Based on the two critical densities, two dichotomous sequential classification sampling plans can be used to classifying population density into one of three regions that are defined by two lower and upper boundaries of each sampling plan number.

For each plan, three hypotheses were tested:

- Hypotheses A : $d \leq dc_1$: resampling after 2 weeks ($2\Delta t$) (decision 1)
- Hypotheses B : $dc_1 < d \leq dc_2$: resampling after one week (Δt) (decision 2)
- Hypotheses C : $d > dc_2$: density (d) is above the upper threshold and a treatment decision is considered (decision 3)

Model construction:

Model described here is inspired from studies of (Nyrop *et al.*, 1994; Binns *et al.*, 1996). The monitoring protocol is based on overlaying through time tripartite sequential classification sampling plans that use binomial counts, because counting spider mites in the field is difficult and often not even possible, binomial sampling plans based on tally number of 0 and 5 were constructed. The construction of each plan was essentially based on the critical value of second critical density cd_2 , which reflects a threshold where the intervention is necessary. These values have been chosen to set up the protocols, 3.0 mites of *Tetranychus urticae* per sample unit for the period from 1 June to 30 June, 6.0 mites for 1 July to 30 July and 8.0 mites thereafter. These thresholds vary according to the climatic conditions and the expected number of pest generations. The primary objective in managing this pest mite is to prevent cumulative density from exceeding 500 mite-days per sample unit over the 16 weeks when the pest is active. A complementary objective is to keep pest density at any particular point in time below about 15 per sample unit. The critical densities cd_1 defining the lower set of SPRT plans were chosen in such a way that, after $2\Delta t$ days with an exponential growth rate of $r_m = 0.078 d^{-1}$, densities cd_1 would result in cd_2 (a density that triggers an intervention). Value of intrinsic rate of increase (r_m) was obtained by averaging the fits to exponential growth models of 8 data sets on *T. urticae* population dynamics. For overcoming the difficulties related to counting mites in field, binomial sampling plans were used. These are based on a relationship between the proportion of sample

classification sampling plans based on tally 0 and 5 binomial counts were constructed. The dichotomous plans could be based on one of several different sequential classification schemes (Binns and Nyrop 1992). We used three hypotheses test of Wald's sequential probability ratio test (SPRT) resulted in three decisions. The first decision (dec1) to resample after a time interval $2\Delta t$ (region 1), the second decision (dec2) to resample after a time interval Δt (region 2) and the third decision (dec3) that dictates an intervention (region 3) (units with more than T mites (P_T), with $T = 0, 1, 2, 3, 4, \dots$, and the density (d) per sample unit. The parameter T is called a tally number. We constructed binomial count sampling plans based only on $T = 0$ and $T = 5$, because the field observations indicate that mostly population abundance levels correspond to the presence of more than 5 pest mites per sample unit and binomial sequential classification sampling plans for pest mites having a higher tally number were significantly more robust than plans with a tally number of 0 (Nyrop and Binns 1992). The negative binomial probability is defined by a common k , parameter of dispersion, which vary with increasing densities. The parameter k for the negative binomial distribution was estimated via Taylor's power law (Taylor 1961), $s^2 = am^b$ and the relationship $k = \frac{m^2}{s^2 - m}$ (Nyrop and Binns, 1992). A value for stabilised k was specified in order to compute P_T for a particular critical density, because this parameter is a function of the mean, which in turn affects the performance of sampling procedures that classify density based on a classification of P_T . 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 (Nyrop and Binns, 1992).

Simulation tests consist on setting a maximum sample size of 100, because the stop lines do not guarantee a decision will be reached within any given sample size. The parameters α and β are selected so that average sample number (ASN) remained below 100. When 100 samples are taken without making decision, the estimated proportion of occupied sample units is compared with the two converted threshold proportions (cd_1 and cd_2) and density classified accordingly. The parameters of SPRT (cd_1 , cd_2 , α and β) can be adjusted until a suitable sampling plan is found (**Error! Reference source not found.**)

To simulate the parameters of Wald's sequential probability ratio test (Taylor, 1961), we used the algorithms proposed by Jan Nyrop, Department of Entomology, Cornell University, USA. the programs have been written in Fortran 77 IBM version compiled using Microsoft FORTRAN compiler v5.1, we succeeded the correction and recodification of all instructions for a new use under Fortran 95 compiler.

Effect of cd_1 and cd_2 change on performance of tripartite sequential classification sampling plans:

To perfectionne Tripartite classification sampling plans, monitoring scheme must be balanced between different fluctuaying situations occuring during survey season. Two additional simulation experiments were conducted with monitoring protocols based on tally 0 tripartite sampling plans. In the first of these, we reduced the values for cd_1 (Plan A) (

Table 2).

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 (Plan B) (Table 3). This situation could occur when *T. urticae* population growth was being limited by natural enemies. Biological control against Tetranychidae species was conducted by using different species of predatory mites included among the Phytoseiidae family (Chant, 1959).

Validation of tripartite classification:

Binomial sampling plan based on tally threshold of 0 was used to monitoring 8 *Tetranychus urticae* populations from 8 apple plots located at Arbor orchard (33 ° 26'19.6 "N, 5 ° 58'35.7" O) in Morocco. The study was conducted during the summer of 2018 between 1 June and 31 August. Two leaves were observed on fifty trees. *T. urticae* density was estimated by counting the mites with a microscope. Based on the findings of the classification procedure, each population was either sampled again after one or two weeks or treated. Box plot was constructed of mite density that corresponded to the final decisions.

Performance of the monitoring procedures based on tally 0 and tally 5 sampling plans was studied using simulation by applying the monitoring protocols to a set of 8 populations described by logistic growth (r_m ranged from 0.18 to 0.21 d^{-1} and the maximum density was set to 500 mites). The height population trajectories were all influenced by predaceous mites. Sampling plans with intervention thresholds of 3.0, 6.0 and 8.0 were used respectively from day 1-30, 31-60 and 60 to the last sample time.

Comparative performance between tripartite sequential classification and dichotomous sampling plans:

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 two weeks to making a suitable decision. When sampling was carried out every two weeks, it was recommended to broaden the sampling period to time 96. We considered that the simulated densities at this limit were similar to those obtained at time 89. Criteria performance of sampling bouts and loss

values at 95th percentile were compared by applying honestly significant difference test of Tukey to reveal which of the plans used is more efficient.

III. RESULTS**Performance of Tripartite classification sampling plans:**

Probability of classification (P_{dec_i}) and average sample number (ASN) functions for the tally 0 and tally 5 tripartite classification plans are shown in Fig.2-Fig.3 respectively. For dynamically classifying the observed density through time with an average sample number amply sufficient to reach a suitable decision, probability values of each classification were simulated and graphically expressed for easing legibility of results. Probability of classification curves for the tally 5 sampling plans are steeper than those for the tally 0 sampling plans. A greatest precision was observed when the tally 5 procedure was applied. This can be seen by referring to the P_{dec_1} curve, which is the probability of resample after 2 weeks. The tally 5 sampling plans produced ASN functions slightly less than those for the tally 0 plan. Based on the P_{dec_i} and ASN functions for each plan, the tally 5 sampling plans are clearly better classifications with significant precision.

Validation of tripartite sequential classification sampling plans:

At an action threshold of 3.00 mites per sample unit, all density classifications made led in a decision (1) which stipulates resampling the population after two weeks. The median *T. urticae* density for which this decision was reached was 0.98 mites per sample unit. The simulated probabilities of making a decision to resample in two weeks for such densities were greater than 0.90 (Fig.2 Fig.3). A significant overlay was observed between field data and parameters simulated by computer. When the action threshold of 6.0 mites per sample unit was applied the probabilities obtained by simulation correspond to the three classifications of the densities observed. *T. urticae* mite populations for which a decision was made to resample in two weeks had a median density of 0.84 and 75 percent of the densities were less than 1.56 (Error! Reference source not found.). However, for both tally numbers, probabilities recommend resampling after two weeks show that these results were also in agreement with computer simulation.

For decision 2, the median density was 3.42 mites per sample unit and 75 percent of the densities were less than 4.02. 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 12. This result is also concordant with the simulated performance illustrated in Fig.2-Fig.3. For densities between five and twelve mites per sample unit, approximately 90 % of the

decisions are expected to be intervene, 9 % to resample in one week, and 1 % to resample in two weeks.

Cumulative density, expected sample bouts, operating characteristic (OC), average sample number (ASN) as well as expected loss values obtained with the cascaded tripartite plans, in which constituent sampling plans used binomial counts with a tally number of 0 and 5 were compared using simulation (

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 probabilities of intervening were nearly identical for the three monitoring protocols(

Table 4). Use of tripartite classification in the monitoring protocol resulted in 30 to 40% fewer sampling bouts compared with dichotomous classification each week. Dichotomous classification every second week did not result in appreciable savings in the number of sample bouts (Nyrop *et al.*, 1994). The expected sample size was less with the monitoring schemes based on dichotomous classification. 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.

). Densities of height *T. urticae* populations with exponential growth are graphically expressed in Fig.5. The OC and ASN curves are very steeper when densities exceed the intervention threshold. In fact, the OC is steeper than might be predicted based on the $Pdec_3$ values for each tripartite sampling plan. In addition to expected loss, losses that would occur with probability 0.2; 0.5 and 0.05 are also shown at 95th percentile (

Table 4). Tripartite sequential classification sampling plans based on higher tally number binomial count reduce overall sampling costs even if the loss related to both applied tally numbers were nearly identical (Nyrop *et al.*, 1994).

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Monitoring protocols based on dichotomous classification each week may also too hastily conclude that intervention is necessary. If the dichotomous classification each Δt was used to monitor the populations shown in (Fig.6), the probability of intervention with population 1 is 0.33 and with population 8 is 0.19(

Table 4). For both cases biological control was successful and the monitoring protocol based on tripartite classification produced probabilities of intervention of only 0.12 and 0.05. 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 4 from 241.52 for the tripartite classification (

Table 4). However, 241.52 is well within the range of acceptable loss so we do not feel this benefit outweighs the costs of using the dichotomous-based protocol.

Effect of cd_1 and cd_2 changes on the performance of tripartite sequential classification sampling plans:

Tripartite sequential classification sampling by cascading tally 0 binomial counts through time was readapted to different rapid change in population dynamics of *T. urticae*. Two simulations are necessary to achieve reasonable control of this pest mite. Presence of natural enemies constitutes a disturbance element of densities during the season; however, densities of *T. urticae* are influenced by predation and the number of Phytoseiidae species in the field. In some situations, prey densities observed appear to be higher so that a decision to intervene is frequently made. In reality, this error occurs when cd_2 values were considered as action thresholds or were close to but less than the intervention thresholds. That is why the monitoring protocol based on tally 0 sampling plans was applied to a population with an intervention threshold equal to (cd_2) and to a set of population trajectories that were 10, 20, 30, 40, and 50 percent less than intervention threshold.

Two sampling plans (plan A and plan B) based both on $cd_2 = 6.0$ mites as intervention threshold were simulated. Plan A was adapted so that cd_1 values were less than the previously thresholds tested(

Table 2), while plan B consists in raising the cd_1 values to simulate any unexpected increase in *T. urticae* numbers in the short term (Table 3).

Tripartite sequential classification sampling plans based on tally 0 binomial counts cascading through time according to an action threshold of cd_2 values, supports the decisions 1 or 3 resulted in either resample after $2\Delta t$ or intervene. A smaller region allowing to make decision 2 (sample after 7 days) was observed when the tally 0 binomial count was applied (Fig.2). For both plans A and B, probabilities and stop lines obtained for an intervention threshold of 6.0 mites are given in (Fig.7). This cd_2 value kept constant generate very similar probabilities for making decision of applying acaricide treatment and classification curves ($Pdec_3$) are almost identical, because the upper SPRT is unchanged. Plan B produces a greater chance for *T. urticae* population to be early resampled.

The performance for both plans A and B was studied. When density equaled the threshold of 500 mite.day⁻¹, intervention was practically assured. In fact, intervention occurred 98 % of the time when density was only 70 % of the original thresholds, this was the case for the population 4 (Table 5). Monitoring protocol based on current intervention threshold would too frequently result in a decision to intervene when densities remained close to the threshold. This situation is justified when population trajectories were that 10; 20; 30; 40 and 50 % less than the intervention thresholds.

Monitoring protocol of plan A produced a slightly greater probability of intervening compared with monitoring protocol B (Error! Not a valid bookmark self-reference.). 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 B was 0.33 compared with 0.98 for protocol A. Protocol B resulted in an increased number of sample bouts and increased expected total sample size, effective consequence due to lower expected loss at 95th percentiles compared with protocol A (Error! Not a valid bookmark self-reference.).

IV. DISCUSSION

The development of sampling schemes for arthropod pests is an extensive area of agroecosystemic researches (Morris, 1954; 1960; Coulson and Witter, 1984; -Fig.2 respectively were distinctly different. The OC for the tally 0 plans was not steep (Fig.2) as that for the tally 5 plan (Fig.3). Intervention thresholds for *T. urticae* are designed to prevent a cumulative density of 500, which was achieved by the tally 0 plans with probability 0.95 (Table 4). This is an important result because it previously was suggested that tally 0 plans be avoided because of their poor precision. In contrast to tally 0 binomial counts, probability of classification functions for the tally 5 sampling plans are steeper, this result indicates that the tally 5 procedures produce classifications with higher precision. Instead to plans using tally number 0, which the

Kuno, 1991). Sampling design consists of two distinct axis: the monitoring protocol and sampling theory married to the computer tools (Groves and Heeringa, 2006).

An effective sampling technique must first be developed to facilitate collection of data during each sample. The sampling program describes protocols for deploying the sampling technique temporally and spatially. These protocols, which we refer to as control decision rules, consist of at least two components and may include a third: a procedure for assessing the density of the pest population, an economic threshold and a phenological forecast, which is often necessary to determine the appropriate time to assess population densities (Binns and Nyrop, 1992). For example, a typical sampling program will define the sample unit, the appropriate insect stage to sample and the number of samples to be collected, the timing of each sample and the pattern of sampling (Southwood, 1978).

For monitoring a population through time, 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. Tripartite sequential classification sampling plans can be used for these purposes by cascading 16 plans of Wald's sequential probability ratio test (SPRT) through time, which is considered the performing dichotomous sequential classification plan scheme among several different sequential classification schemes (Binns and Nyrop, 1992).

Performance of the monitoring schemes based on tally 0 and tally 5 sampling plans was studied using simulation by applying the monitoring protocols to a set of 8 *T. urticae* populations described by logistic growth (r_m from 0.18 to 0.21 d⁻¹). The comparison between tally 0 and tally 5 sampling plans cascaded through time at different cd_i (Error! Reference source not found.) showed that tripartite sequential classification sampling plans used tally 5 binomial counts are practically the performing plans. Probability of classification ($Pdec_i$) and average sample number (ASN) for the tally 0 and tally 5 tripartite classification plans shown in function curve of ASN contains one peak, tripartite sequential classification sampling plans based on tally 5 produce an ASN within two peaks corresponding to the maximum samples in surroundings of each intervention threshold.

Furthermore, the performance of the monitoring protocol based on tripartite classification sampling plans was compared to a monitoring protocol in which height populations were sampled (dichotomous classification) every Δt and every $2\Delta t$ and a decision was made to either resample or to intervene. The results showed that the use of tripartite classification sequential sampling plans in the

monitoring protocol resulted in 30 to 40 % fewer sampling bouts compared with dichotomous classification each week and approximately 20% of expected loss at 95th percentiles than dichotomous sampling plans after 7 and 14 days ($P < 0.05$) (

Table 4). Probabilities of intervention were higher when tally 5 binomial counts and dichotomous sampling plan after 14 days were applied for monitoring height *T. urticae* populations with logistic growth.

However, our results are similar to those obtained by using tripartite classification to monitor *Tetranychus urticae* densities. Dichotomous plan every week generates more than of sampling bouts that other procedures (Nyrop *et al.*, 1994). Therefore, tripartite classification follows closely the dynamics of insect pest populations in time and usually prevent the high sampling costs 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.

The monitoring protocol based on dichotomous classification every 14 days and the protocol based on tally 0 tripartite classification had a comparable performance when used to monitor the height *T. urticae* populations (

Table 4). Average sample sizes were lower with the dichotomous plans but the 95th percentiles for expected loss were higher. When population growth rates are low, dichotomous classification every $2\Delta t$ is the best strategy and with higher growth rates, dichotomous classification every Δt is the best strategy comparing to tally 0 binomial count. 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.

Pest populations do have the ability to change rapidly by natural growth or immigration and correlations between sampling occasions may not be high, so continual sampling is required. However, with increased reliance on biological control, cultural management and host plant resistance, pest control decision rules and especially monitoring, will become even more important (Binns *et al.*, 1996). By using the higher intervention thresholds (protocol B), a reasonable management was established between correctly scheduling intervention when population density was growing rapidly and not intervening unnecessarily when densities remained below the nominal intervention thresholds. Monitoring protocol B should therefore be preferred to A to evaluate *T. urticae* density through time during a growing season.

V. CONCLUSION

Tripartite sequential classification sampling plans should be developed from observations that include seasonal change of climatic conditions and management programs that future users of the sampling plan are likely to encounter. In reality, however, tripartite classification sampling scheme can be developed by cascading binomial or sequential plans through time from a more restricted range of observations and then applied to similar or novel situations. In addition, regardless of the extent of data collection, tripartite classification plan is based on observations that are measured with some amount of error. Thus, it is important that the performance of a tripartite sequential classification sampling plan be evaluated so that its limitations and strengths can be better defined.

The validation of tripartite classification must be realised by use of the Monte Carlo simulation, according to probability law that reflects the sampling distribution of the pest mite in question. This procedure is repeated a large number of times (5000 iterations here) to represent a large number of possible sampling findings, probabilities of classification (P_{dec1} ; P_{dec2} and P_{dec3}) and total sample number are calculated.

Monitoring protocol B reduced the probability of intervening and produced more sample bouts and more samples, which resulted in lower expected and 95th percentiles for density at intervention and expected loss compared to protocol A.

Monitoring schemes based on tripartite classification are best suited to situations where information about the growth rate of the population being monitored cannot be obtained. Adjusting the cd_2 and cd_1 values appears to be the best way to accomplish an efficient integrated pest management.

CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

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REFERENCES

- [1] Binns, M. R., and Nyrop, J. P. (1992) Sampling Insect Populations for the Purpose of IPM Decision Making. *Annual Review of Entomology* **37**, 427–453.
- [2] Binns, M. R., Nyrop, J. P., and Van Der Werf, W. (1996) Monitoring Pest Abundance by Cascading Density Classification. *American Entomologist* **42**, 113–121.

- [3] Chant, D. A. (1959) Observations on Phytoseiidae family. *Acarologia***1**, 11–23.
- [4] Coulson, N. R., and Witter, J. A. (1984) ‘Forest Entomology: Ecology and Management’. John Wiley and Sons, New York.
- [5] Fowler, G., and Lynch, A. (1987) Bibliography of Sequential Sampling Plans in Insect Pest Management Based on Wald’s Sequential Probability Ratio Test. *The Great Lakes Entomologist***20**.
- [6] Groves, R. M., and Heeringa, S. G. (2006) Responsive design for household surveys: tools for actively controlling survey errors and costs. *Journal of the Royal Statistical Society: Series A (Statistics in Society)***169**, 439–457.
- [7] Harcourt, D. G. (1966) Sequential Sampling for the Imported Cabbageworm, *Pieris rapae* (L.). *The Canadian Entomologist***98**, 741–746.
- [8] Krebs, C. J. (2014) Sampling Designs - Random Sampling, Adaptive and Systematic Sampling. In ‘Ecological Methodology’. pp. 262–301. (Benjamin/Cummings.)
- [9] Kuno, E. (1991) Sampling and Analysis of Insect Populations. *Annual Review of Entomology***36**, 285–304.
- [10] Morris, R. F. (1954) A Sequential Sampling Technique for Spruce Budworm Egg Surveys. *Canadian Journal of Zoology***32**, 302–313.
- [11] Morris, R. F. (1960) Sampling Insect Populations. *Annual Review of Entomology***5**, 243–264.
- [12] Naranjo, S. E. (2008) Sampling arthropods. In ‘Encyclopedia of Entomology’. pp. 3593–3593. (Capinera, John L.: Arizona. USA.)
- [13] Nyrop, J. P. (1988) Spatial Dynamics of an Acarine Predator–Prey System: *Typhlodromus pyri* (Acari: Phytoseiidae) Preying on *Tetranychus urticae* (Acari: Tetranychidae). *Environmental Entomology***17**, 1019–1031.
- [14] Nyrop, J. P., and Binns, M. R. (1992) Algorithms for Computing Operating Characteristic and Average Sample Number Functions for Sequential Sampling Plans Based on Binomial Count Models and Revised Plans for European Red Mite (Acari: Tetranychidae) on Apple. *Journal of Economic Entomology***85**, 1253–1273.
- [15] Nyrop, J. P., Binns, M. R., van der Werf, W., and Kovach, J. (1994) 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. *Experimental and Applied Acarology***18**, 123–153.
- [16] Southwood, T. R. E. (1978) ‘Ecological methods: with particular reference to the study of insect populations’ 2., rev. ed. (Chapman and Hall [u.a.]: London.)
- [17] Sylvester, E. S., and Cox, E. L. (1961) Sequential Plans for Sampling Aphids on Sugar Beets in Kern County, California. *Journal of Economic Entomology***54**, 1080–1085.
- [18] Taylor, L. R. (1961) Aggregation, variance and the mean. *Nature***189**, 732–735.
- [19] Wald, A. (1947) A Note on Regression Analysis. *The Annals of Mathematical Statistics***18**, 586–589.
- [20] Wald, A. (1945a) Sequential Tests of Statistical Hypotheses. *The Annals of Mathematical Statistics***16**, 117–186.
- [21] Wald, A. (1945b) Statistical Decision Functions Which Minimize the Maximum Risk. *Annals of Mathematics***46**, 265–280.
- [22] Water, W. E. (1955) Sequential Sampling in Forest Insect Surveys. *Forest. Sci.***1**, 68–79.

Table 1: Parameters used to develop tripartite classification sampling plans and results of k_c for negative binomial distribution based on Taylor power law for use with *T. urticae*

plans for each hypotheses	critical densities			SPRT parameters			
	cdi	Prop infest	NgBK	H0	H1	α	β
tally0							
A1	1	0,358	0,183	0,308	0,408	0,28	0,28
A2	3	0,477	0,209	0,427	0,527	0,31	0,31
B1	2	0,531	0,221	0,481	0,581	0,33	0,33
B2	6	0,701	0,253	0,651	0,751	0,35	0,35
C1	3	0,645	0,243	0,595	0,695	0,35	0,35
C2	9	0,908	0,290	0,858	0,958	0,38	0,38
tally5							
A1	1	0,042	0,114	0,012	0,072	0,075	0,075
A2	3	0,183	0,138	0,133	0,233	0,18	0,18
B1	2	0,111	0,118	0,061	0,161	0,1	0,1
B2	6	0,382	0,188	0,332	0,432	0,29	0,29
C1	3	0,183	0,138	0,133	0,233	0,18	0,18
C2	9	0,540	0,222	0,490	0,590	0,33	0,33

There are three hypotheses for each dichotomous plan, the number following the letter in upper case indicates signifies whether it is plan 1 or 2 of the tripartite scheme.

K parameter for negative binomial distribution computed using moments and based on a predicted variance calculated using the Taylor power law model.

H0 and H1 are two hypothetical true proportions of occupied sample units an arbitrary distance at both sides of the threshold proportion.

α is probability of erroneously classifying proportion = H1 when H0 is true.

β is probability of erroneously classifying proportion = H0 when H1 is true.

Alpha and beta are chosen in such a way as to maintain ASN under 100.

Table 2: Parameters for tripartite classification plans with lower values of cdi and increased probability of decision 2

Plan	critical density			SPRT parameters			
	cdi	Nbgk	Propor. infes	H0	H1	α	β
A1	0.5	0.150	0.227	0.177	0.277	0.21	0.21
A2	3.0	0.209	0.477	0.427	0.527	0.31	0.31
B1	1.5	0.205	0.455	0.405	0.505	0.31	0.31
B2	6.0	0.253	0.701	0.651	0.751	0.35	0.35
C1	2.5	0.233	0.593	0.543	0.643	0.34	0.34
C2	9.0	0.290	0.908	0.858	0.958	0.38	0.38

Table 3: Parameters for tripartite classification plans with higher values of cdi and cd2.

Plan	critical density			SPRT parameters			
	cdi	Nbgk	proportion	H0	H1	α	β
A1	2.0	0.221	0.531	0.481	0.581	0.33	0.33
A2	4.0	0.258	0.725	0.675	0.775	0.36	0.36
B1	3.0	0.243	0.645	0.595	0.695	0.35	0.35
B2	8.0	0.285	0.880	0.830	0.930	0.38	0.38
C1	4.0	0.258	0.725	0.675	0.775	0.36	0.36
C2	12.0	0.297	0.949	0.899	0.999	0.38	0.38

Table 4 : Results of Tripartite sequential classification sampling plan to sample height populations of T. urticae.

Pop.	Cum.den.	Pdec ₃	ASN	Bouts	Exp.loss	P(0.5)loss	P(0.2)loss	P(0.05)loss
Start Interval Last sample at Possible bouts								
12.0	7.0	89.0	12.0					
Population scale factor 1.000								
Tripartite classification sequential sampling plans								
Tally 0								
1	157.15	0.12	102.27	6.60bc	79.45	24.19	41.55	53.11bc
2	467.81	1.00	147.79	6.61bc	124.31	89.46	102.78	117.34b
3	55.23	0.01	111.54	5.7c	55.54	55.54	55.54	55.54b
4	509.46	1.00	79.71	5.28bc	147.45	98.66	123.74	241.52a
5	33.67	0.00	231.24	7.3bc	33.24	33.24	33.24	33.24a
6	368.55	1.00	156.57	4.9b	123.11	113.16	134.11	145.61ab
7	321.51	1.00	136.28	4.5b	101.36	101.24	115.04	98.54b
8	101.22	0.05	58.12	1.87b	168.68	51.22	51.22	142.72b
Tally 5								
1	157.15	0.00	119.31	6.24d	58.32	55.4	50.04	43.22d
2	467.81	1.00	168.18	6.01d	113.63	104.35	97.66	110.48bcd
3	55.23	0.00	176.44	4.41d	55.54	55.14	55.03	28.7c
4	509.46	1.00	53.35	5.35b	122.36	117.26	111.34	115.64d
5	33.67	0.00	224.15	5.54d	33.24	33.24	33.24	N.C
6	368.55	1.00	177.12	4.07d	106.72	106.34	106.21	102.53c
7	321.51	0.35	154.26	4.02bc	88.46	87.6	83.71	81.64cd

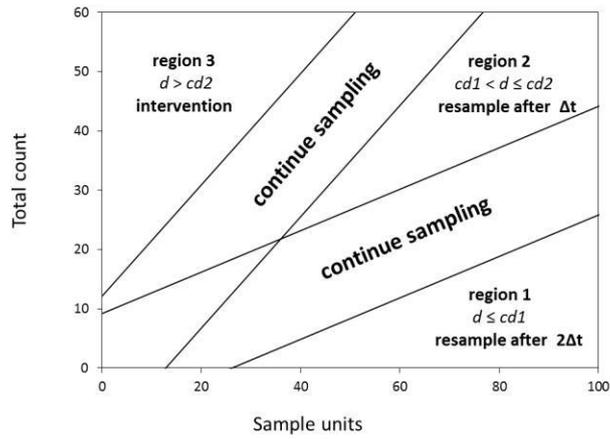


Fig.1: Stop lines for a tripartite sequential classification sampling scheme and three regions for making a suitable decision

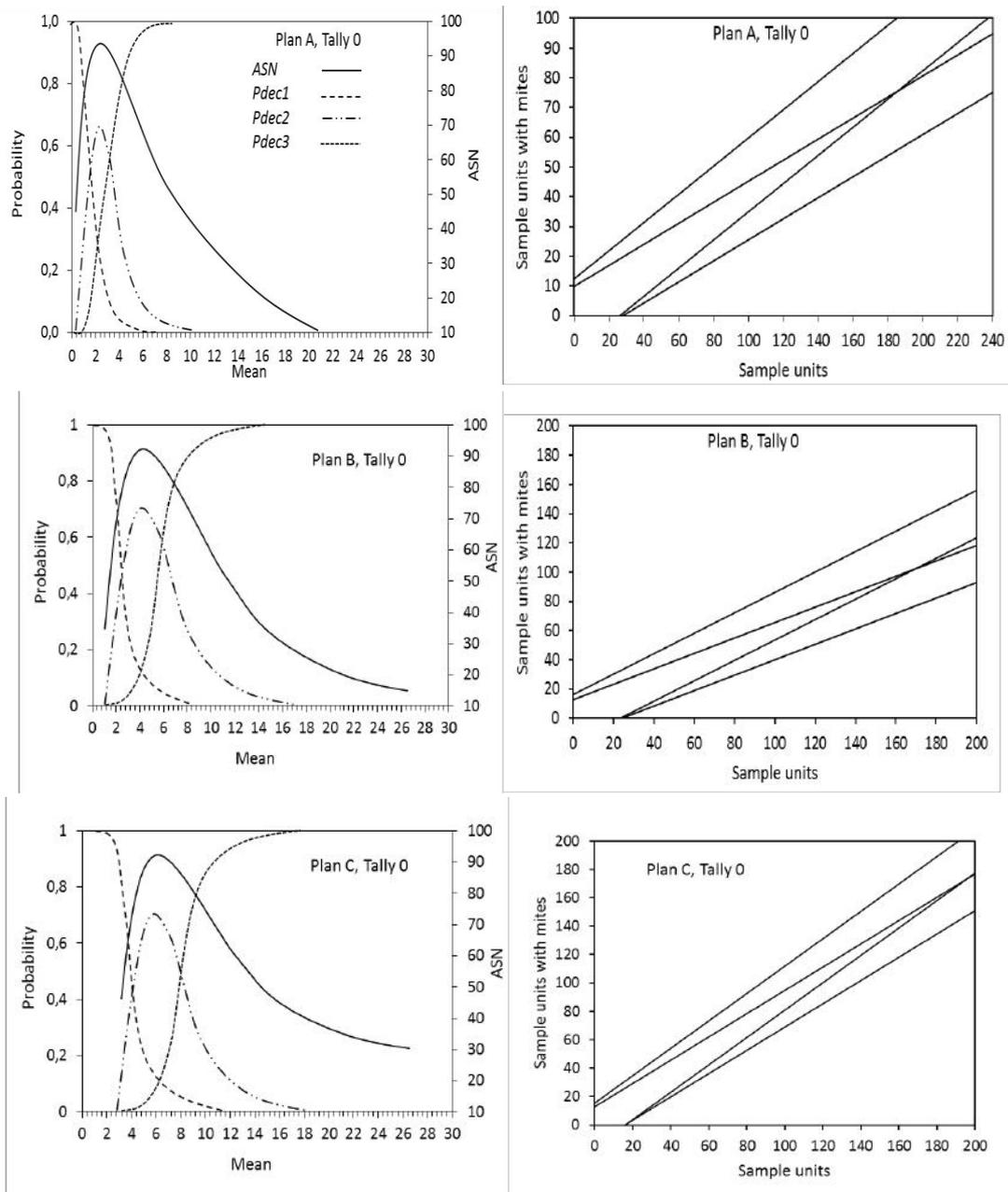


Fig.2: Stop lines, probability of classification (P_{dec_i}) and average sample number (ASN) obtained by simulation for tripartite sampling plans at each threshold with a fixed tally number $T=0$

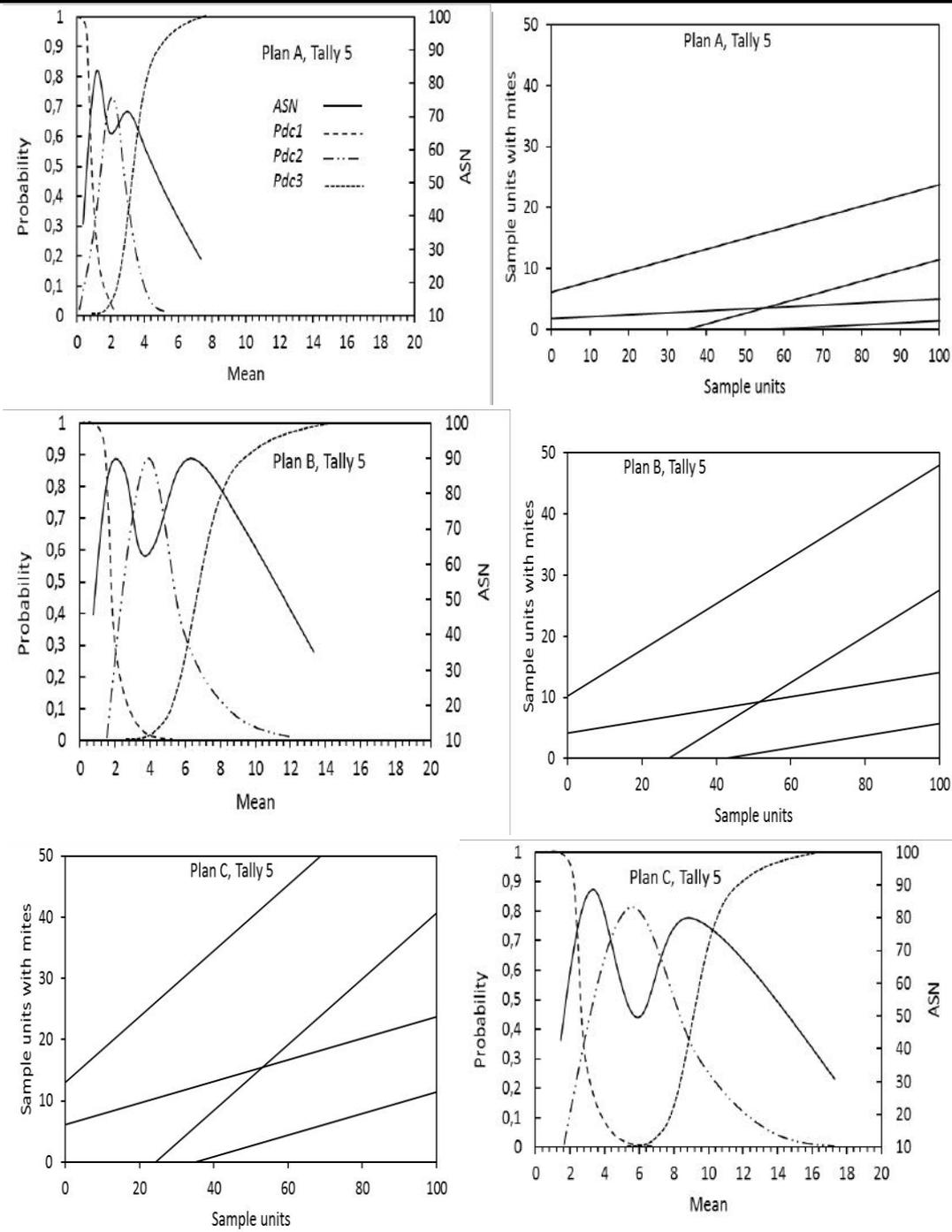


Fig.3:Expected probability of classification (P_{dc}) and average sample size (ASN) curves for tripartite classification binomial sampling plans, obtained by simulation with tally number $T=5$

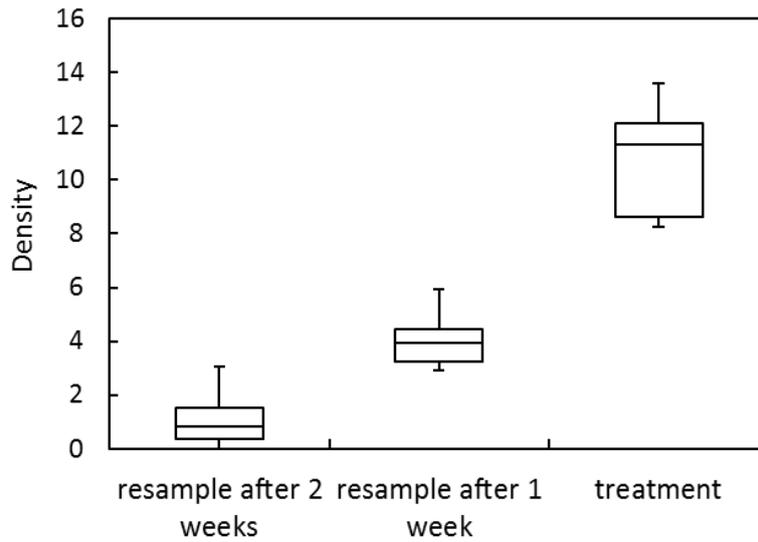


Fig.4 : Distribution of estimated mean densities corresponding to monitoring decisions using tripartite classification binomial sampling plans with tally number $T=0$.

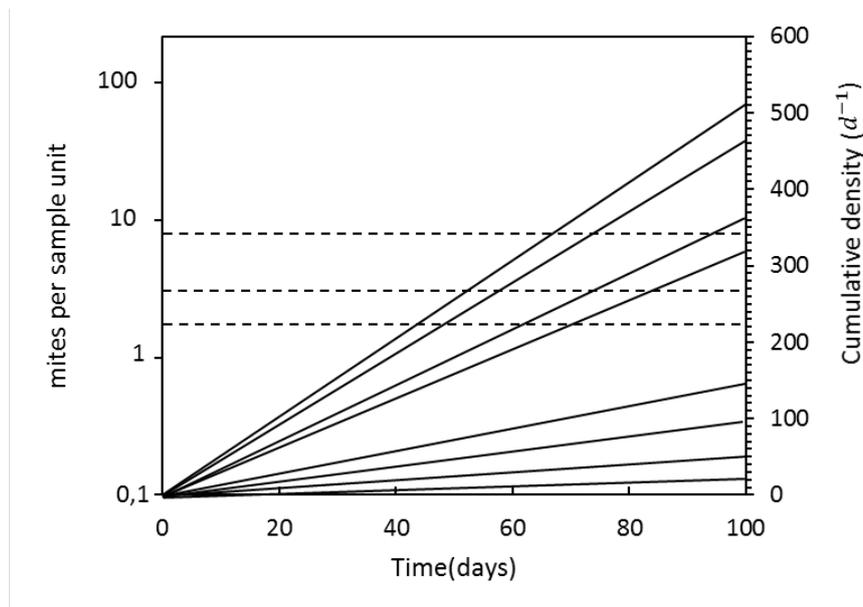
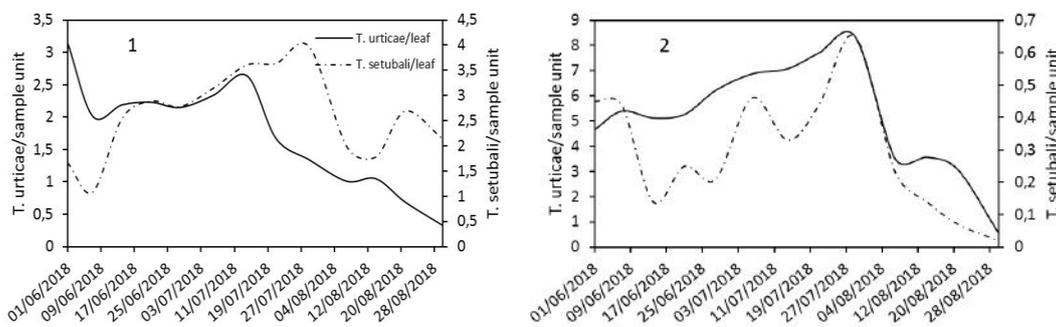


Fig.5:Tripartite sequential classification sampling plans applied to height population trajectories. Cumulative densities of *T. urticae* populations with exponential growth. Short horizontal dashed lines are action thresholds.



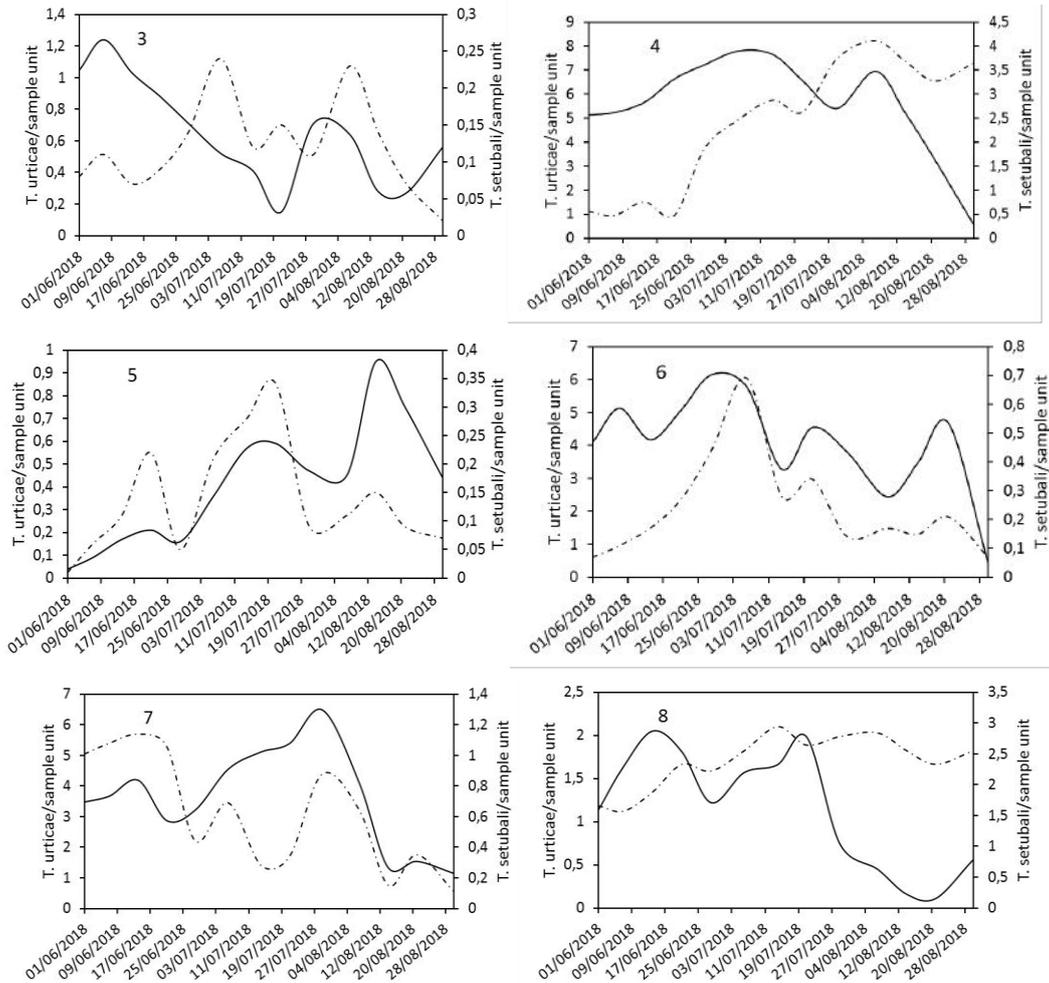


Fig.6:Population dynamic of height density trajectories of *Tetranychus urticae* and predatory mite *Typhlodromus setubali*.

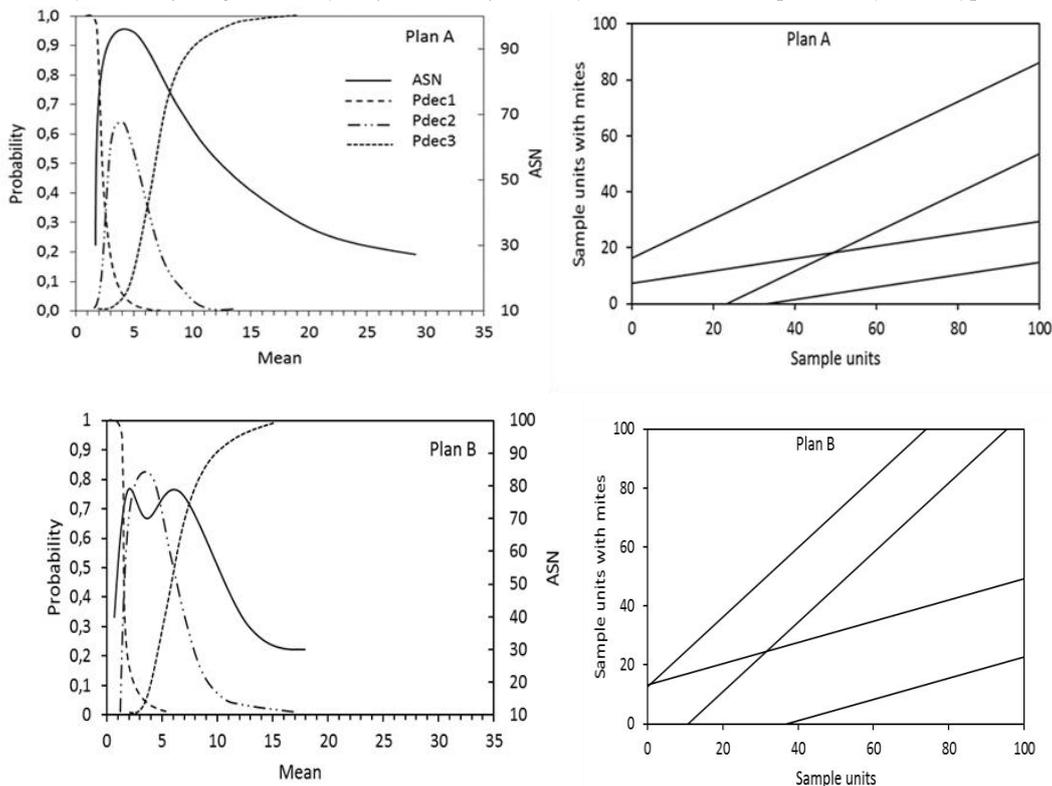


Fig.7: Stop lines, probability of classification (P_{deci}) and average sample number (ASN) for two tripartite classification sampling plans. Both plans are based on $cd_2=6.0$. Plan A is based on $cd_1=3.0$ and plan B on $cd_1=0.5$.