Binomial sampling plan for classifying population density of *Thrips palmi* (Thysanoptera: Thripidae) in potato

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Abstract

Binomial sequential classification sampling plans were developed for use in classifying populations of *Thrips palmi* Karny, below or above a mean intervention threshold density \((m_T)\) for management decision making on the fall potato on Cheju Island, Korea. The proportion of potato leaves with at least \(T\) (tally threshold) thrips \((P_T)\) was related to mean thrips density \((m)\) with an empirical model \(\ln(-\ln(1-P_T))=\gamma + \delta \ln(m)\). The \(P_T-m\) relationship fit the data well for \(T\) values of 1–10, with \(T=3\) having the best fit. Wald’s sequential probability ratio test was used to formulate sequential sampling stop lines relative to \(m_T\) values of 5 and 10 thrips per potato leaf with a series of \(T\). The sampling plans were evaluated using the operating characteristic and average sample number functions. Simulation analysis indicated that a binomial model with \(T=3\) was best, and less than 60 samples, on average, were needed to classify populations relative to either \(m_T\) value. The binomial sequential sampling plan was tested with sequential resampling simulation using 8 independent data sets for the validation. The binomial sequential classification sampling plans presented here should enhance the efficiency of pest management programs based on the prescriptive suppression of *T. palmi* on fall potato.

Key words: *Thrips palmi*, binomial sequential sampling, pest management, potato, decision-making

INTRODUCTION

A recently introduced thrips species, *Thrips palmi* Karny, has become a serious pest of vegetable and ornamental crops in the southern coastal areas of Korea, including Cheju Island (33°30′, 126°30′) (Lee, 1996). Of South Asia origin (Bournier, 1983), it was first collected from greenhouse-grown peppers on Cheju Island in Korea in 1993 (Ahn et al., 1994). Since that time it has dispersed rapidly from this source and is now distributed throughout the southern and central districts of Korea.

The fall potato, *Solanum tuberosum* L., has become a major agricultural commodity on Cheju Island with great economic returns. Fall potato production on Cheju Island accounted for >52% of the total Korea fall potato production in 1996 (Ministry of Agriculture and Fishery, Korea, 1997). *T. palmi* has become established as a key pest of the fall potato in Cheju Island and colonized potato fields from early-September through mid-November (Lee, 1996). In 1994, the widespread outbreak of *T. palmi* on fall potatoes on Cheju Island resulted in a yield loss of ≈30% (Lee, 1996). Large populations of *T. palmi* on potato cause bronzing of foliage and eventually total destruction of potato plants. Cause of outbreak on fall potatoes is not clearly understood, and little is known about the population dynamics and economic threshold of *T. palmi* on potato plants. Pesticides are currently relied on to control this pest because of a lack of alternative control measures. Consequently, thrips infestations on potato have resulted in the increased use of insecticides for suppression of this pest. Today most growers apply up to nine insecticidal sprays during each growing season, generally as a tank mix with several fungicides.

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Sampling plans for properly monitoring pest populations in the field and rules for pest management decision making are needed to implement integrated pest management programs (Feng et al., 1994). A number of sampling programs have been developed to estimate population densities of various thrips species in numerous crops based on a numerical (Shipp and Zariffa, 1991; Cho et al., 1998) or binomial sampling plan (Steiner, 1990; Salguero Navas et al., 1994). However, there has been relatively little effort to devise viable sampling strategies for *T. palmi* management applications.

Binomial approaches used to monitor the population of thrips can be more advantageous than numerical sampling that are often costly in time and effort (Salguero Navas et al., 1994). When sampling is used for decision making, it often suffices to classify population density sequentially relative to some action threshold or economic threshold (Nyrop et al., 1989). The use of binomial sampling to classify a density sequentially requires a smaller sample size than does the use of binomial sampling to obtain population parameter estimates (Nyrop et al., 1989). Binomial sampling plans are typically less precise than sampling plans based on complete enumeration. Thus, considerable effort is required in the development and testing of binomial sampling plans to ensure that they can accurately classify damaging populations.

Wald’s sequential probability ratio test (SPRT) (Wald, 1947) based on binomial counts is an efficient and widely used method for classifying population density. To use binomial counts to classify pest populations, an intervention threshold that usually corresponds to a mean population density (*m̄*) must be converted to the proportion of sample units infested. The following two methods can be used: (1) the empirical *P* = *m* relationship (Nyrop et al., 1989) and (2) a probability model based on the negative binomial distribution (Feng et al., 1994). The latter model requires the estimation of a nuisance parameter, *k*, that can change with mean density, whereas the former model is independent of the underlying distribution (Naranjo et al., 1996). Thus, it is possible to develop sampling plans on a more realistic and unbiased manner with the empirical model.

Four parameters are required to specify sequential sampling stop lines for Wald’s SPRT: the lower (*P*0) and the upper (*P*) boundaries of the decision area given as proportions, and δ and β error rates. Wald’s SPRT with varying activity thresholds can be evaluated by the operating characteristic (OC) curves and average number of sample (ASN) curves (Jones, 1994). The OC is the probability of taking no action relative to a damage threshold given the true mean density, and the ASN estimates the average number of samples needed to make a classification given any true population mean. Thus, the robustness and precision of the sampling plan is indicated by OC curves and the cost of sampling is implied by ASN curves.

Development of management-decision rules requires reliable economic threshold levels for the target pest. Action thresholds for *T. palmi* on fall potato have not been determined yet in Korea. However, the nominal action threshold for this species has been empirically set at 5 to 10 per potato leaf.

The objective of this study was to develop the binomial sequential sampling plans for classifying the populations of *T. palmi* relative to two nominal action thresholds based on the empirical binomial model. Robustness of the binomial sampling plan was evaluated by the resampling technique using independent data sets.

**MATERIALS AND METHODS**

**Sampling of thrips populations.** Commercial fields of fall potatoes on Cheju Island, Korea, were sampled during the growing seasons of 1995 (nine fields) and 1996 (four fields). *T. palmi* was the only adult thrips species collected from fall potato fields on Cheju Island during this study (Lee, 1996). Thus, immature thrips on potato leaves were assumed to be offspring from *T. palmi*.

The data sets of 64 population estimates were obtained by sampling potato leaves. Because *T. palmi* was more concentrated on the upper plant canopy (0.4–0.5 m above ground level) than the other canopies (Cho, unpublished data), the thrips were collected from the upper canopy throughout this study. The sample unit was a single leaf from the top plant canopy and sam-
sample size ranged from 55 to 65 leaves per field. Each leaf was ≈25 cm length with 11 to 13
leaflet. Adult *T. palmi* and immature thrips were counted *in situ* on the underside of a single
leaf from each randomly selected plant by carefully turning the leaf over by rotating the petiole.

**Development of the \( P_T - m \) relationship.** Each
estimate included information on mean thrips
density (\( m \)) (i.e., the number of thrips adults
and immatures per leaf), and proportion of
leaves infested with at least \( T \) thrips (\( P_T \)).
The empirical relationship between \( P_T \) and \( m \) at
each \( T \) was developed by linearly regressing
\[ \ln(-\ln(1-P_T)) = \gamma + \delta \ln(m) \] (1)
where \( \gamma \) and \( \delta \) are the intercept and slope pa-
rameters, respectively. This binominal model was
evaluated with different tally thresholds (\( T = 1, 2, 3, ..., \) and 10 thrips per leaf) for use in clas-
sification of population density. The empirical
relationship was generated with pooled data for
adult and immature thrips because both stages
have similar spatial distribution patterns on
potato plants (Cho, unpublished data).

The performance of this empirical model is
influenced by binomial variation in the sample
observations and by variability in the \( P_T \) values
predicted from a mean (Nyrop and Binns,
1992). The variance at \( P_T \) of normally distrib-
uted values \( S_{\ln(-\ln(1-P_T))}^2 \) is given (Snedecor
and Cochran, 1980) as,
\[ S_{\ln(-\ln(1-P_T))}^2 = \text{MSE}/N + (\ln(m) - \bar{m})^2s_\delta^2 + \text{MSE} \] (2)
where MSE is the mean square error from the
regression (Eq. 1), \( N \) is the size of the data set
used in the regression, \( \bar{m} \) is the mean of the
independent variables in the regression, \( s_\delta^2 \) is
the variance of the parameter \( \delta \), and \( m \) corre-
sponds to \( P_T \).

**Development of binomial classification sam-
ing plans.** Because the contribution of
\( \text{MSE}/N + (\ln(m) - \bar{m})^2s_\delta^2 \) in Eq. 2 to the total
variance is minimal (Jones, 1994), the variance
estimate from Eq. 2 is approximately constant
and equal to MSE. The result is that the confi-
dence limits for the best fit \( P_T - m \) line are ap-
proximately parallel lines rather than the standard
curving lines. This relationship can be used to
determine the effect of \( P_T - m \) model variabil-
ity on the OC and ASN functions.

For a population mean \( m \), an estimate of \( P_T \)
from Eq. 1 is the nominal \( P_T \), which incor-
porates only binomial classification (Nyrop and
Binns, 1992). However, because of variability in
the \( P_T - m \) relationship, \( P_T \) actually may lie
above and below the nominal \( P_T \). Thus, given
an intervention threshold density \( m_{IT}, \) the cor-
responding \( P_{IT} \) actually may be greater than the
nominal \( P_{IT} \). This \( P_{IT} \) corresponds to the density
\( m_{IT-} \) (denoted by \( P_0 \)), which can be expressed as
a function of original \( m_{IT} \) (Binns and Bostani-
an, 1990) as,
\[ m_{IT-} = m_{IT}/\exp(h/\delta) \] (3)
where \( \delta \) is the slope in Eq. 1 and \( h \) is the abso-
late value of the difference between the larger
\( P_{IT} \) and the nominal \( P_{IT} \). Assuming a normal
distribution, the variable \( h \) can be calculated as
\( z \cdot (S_{\ln(-\ln(1-P_0)))}^{0.5} \), where \( z \) is a standard normal deviate from the posi-
tive side of the distribution and \( S_{\ln(-\ln(1-P_0))} \) is the prediction variance at \( m_{IT} \).
Similarly, if the \( P_{IT} \) corresponding to
\( m_{IT} \) (denoted by \( P_1 \)) is smaller than the nominal
\( P_{IT} \), it corresponds to a density \( m_{IT+} \),
\[ m_{IT+} = m_{IT}/\exp(h/\delta) \] (4)

A family of OC and ASN curves in relation to
mean density can be computed by specifying the
displacement of the \( P_T - m \) relationship (i.e., the
value of \( h \)) away from the regression (Nyrop
and Binns, 1992). \( P_{IT}, P_0, \) and \( P_1 \) were
determined by Eqs. 1, 3, and 4, respectively, and
Wald’s (1947) SPRT was performed around the
\( P_{IT} \) under the null hypothesis \( H_0 : P_{IT} < P_0 \) and
the alternate hypothesis.

The simulation method of Nyrop and Binns
(1992) generated nominal, expected, and ex-
treme OC and ASN functions using the param-
ters from Eqs. 1–4. Nominal OC and ASN
functions assume that the sampling distribu-
tions of the population being sampled are iden-
tical to empirical \( P_T - m \) model. Expected OC
and ASN functions include variability in the
\( P_T - m \) model. Extreme OC and ASN functions
were set to include 74% of all expected values
corresponding to \( z = 1.125 \) in Eqs. 3 and 4.

Sampling stop lines for binomial sequential
classification sampling plans were developed
using the common slope
\[ \ln([1-P_0]/(1-P_1))/\ln(P_r/(1-P_0)/(P_r(1-P_0))] \]
and the intercepts.
\[ \pm \ln[(1-a)/\beta]/\ln[P_t(1-P_o)/(P_t(1-P_o))] \]

where \(a\) and \(\beta\) are error rates used in the Wald's SPRT and both were set at 0.01 throughout this study. These error rates are defined as the probability of accepting the alternative hypothesis (control needed) when the null hypothesis is correct (no control needed) and the probability of accepting the null hypothesis when the alternative is correct, respectively (Naranjo et al., 1996). If \(a\) and \(\beta\) are equal, the intercepts will be the same magnitude but opposite in sign. The decision zone can be increased as increasing the width of the intercepts.

Validation of sampling plans. The accuracy of our sampling plans was validated using eight independent data sets not used in developing sampling plans. For this purpose, two fields were surveyed on 4 different dates in 1996. On each sampling date, 60 potato leaves were selected in the same manner described above and counted the number of thrips (adults and larvae) on the underside of potato leaves was counted. Actual OC and ASN values obtained from the sequential sampling program were evaluated by a resampling technique using the Resampling Validation Sampling Program (RVSP) software (Naranjo and Hutchison, 1997). The RVSP simulation randomly selected successive samples without replacement from a given data set until the stop line criteria met. The number of times to resample each data set was set at 500. The OC and ASN functions were calculated after the sequential decision rule was satisfied. These were estimated directly as the proportion of iterations in which the proportion infested does not exceed the lower sequential stop line. Thus, the OC and ASN functions can be generated by plotting these probabilities against the true mean density. RVSP validation was applied to the 2 final sampling plans that were based on a tally threshold of 3 and action thresholds of 5 and 10 thrips per leaf. Naranjo and Hutchison (1997) described the basic assumptions and advantages of this approach in detail.

RESULTS AND DISCUSSION

Development of the \(P_T-m\) relationship

A total of 64 separate population density estimates were collected during 1995 and 1996. However, after elimination of the \(P_T\) values of 0 and 1, only 31 to 43 of these estimates were used for the development of the binomial sampling plan, depending on the tally thresholds (\(T\)) (Table 1). The empirical \(P_T-m\) model described each \(T\) well, as evidenced by the low mean square error (MSE), and high \(r^2\) values ranging from 0.87 to 0.95. The \(P_T-m\) relationship based on \(T=3\) had the smallest slope variance, lowest MSE and highest \(r^2\) values of the tally thresholds tested. A further increase of tally threshold had adverse effect on the \(P_T-m\) relationship. This results primarily from relative stability in MSE at \(T>3\) and the fact that MSE is the largest variance component (Jones, 1994). Therefore, tally thresholds from 1 through 4 were used to develop and evaluate binomial sequential sampling plans based on intervention thresholds (\(m_{IT}\)) of 5 and 10 thrips per leaf.

Sampling plan development

Parameters used to develop a binomial sequential classification sampling plan are listed in Table 2. Corresponding to the each \(m_{IT}\), the values of \(P_{IT}, P_0\), and \(P_t\) were determined using the empirical \(P_T-m\) model (Table 1). This model was evaluated with \(T=1, 2, 3\), and \(4\) for use in the classification of population density by analyzing the OC and ASN curves associated with sequential sampling stop lines derived from Wald's SPRT using the simulation method of Nyrop and Binns (1992). Increasing \(m_{IT}\) values from 5 to 10 reduced the width of the decision zone, as indicated by the sampling stop line intercepts, and increased the slope of the sampling stop lines (Table 2). Conversely, increasing \(T\) values from 1 to 3 increased the width of the decision zone and decreased the slope of the sampling stop lines.

Families of OC and ASN functions for \(m_{IT} = 5\) and 10 are shown in Fig. 1 and Fig. 2, respectively. The nominal OC and ASN functions for each \(T\) at each \(m_{IT}\) were determined with the assumption that the sampling distribution for the populations being sampled is identical. The steepness of the nominal OC curves was increased with increasing \(T\) values from 1 to 3, regardless of \(m_{IT}\) values. Because variability existed when estimating the populations, the
nominal OC and ASN functions represent only a specific situation and are incomplete for a binomial sequential classification sampling plan (Nyrop and Binns, 1992).

The most important step in developing a sequential sampling plan using binomial counts is determining the robustness and performance characteristics of the plan (Binns and Bostanian, 1990). The other OC and ASN functions portray the performance of the sampling plans when the populations being sampled do not conform to the nominal distribution. The closer the expected and extreme lines are to the nominal line for a given \( T \) and an action threshold \( (m_{IT}) \), the greater is the likelihood of correctly classifying the population (Boeve and Weiss, 1997). In this study, increasing \( T \) from 1 to 3 reduced the range between the extreme OC curves and increased the steepness of the slopes of the expected OC curves for both \( m_{IT} \) values. Steeper OC curves indicate lower error probabilities relative to \( m_{IT} \). Increasing \( T \) from 1 to 3 reduced the ranges between the extreme OC functions. Increasing the \( T \) values from 1 to 3 also reduced the ranges between the extreme ASN functions. However, the expected ASN

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### Table 1. Parameters estimated from the linear regression (Eq. 1) for \( T. palmi \) populations on potatoes in Cheju Island, Korea, during 1995 and 1996

<table>
<thead>
<tr>
<th>( T )</th>
<th>( \gamma )</th>
<th>( \delta )</th>
<th>( N )</th>
<th>( m )</th>
<th>( S_\varepsilon^2 )</th>
<th>MSE</th>
<th>( r^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.5264</td>
<td>0.7079</td>
<td>43</td>
<td>0.3605</td>
<td>0.0021</td>
<td>0.1239</td>
<td>0.871</td>
</tr>
<tr>
<td>2</td>
<td>-1.4683</td>
<td>1.0037</td>
<td>43</td>
<td>0.1412</td>
<td>0.0072</td>
<td>0.1378</td>
<td>0.907</td>
</tr>
<tr>
<td>3</td>
<td>-1.9400</td>
<td>1.0854</td>
<td>38</td>
<td>0.0735</td>
<td>0.0020</td>
<td>0.1075</td>
<td>0.954</td>
</tr>
<tr>
<td>4</td>
<td>-2.4697</td>
<td>1.2237</td>
<td>39</td>
<td>1.1020</td>
<td>0.0026</td>
<td>0.1039</td>
<td>0.938</td>
</tr>
<tr>
<td>5</td>
<td>-2.8547</td>
<td>1.3387</td>
<td>38</td>
<td>1.1269</td>
<td>0.0024</td>
<td>0.0903</td>
<td>0.953</td>
</tr>
<tr>
<td>6</td>
<td>-3.2251</td>
<td>1.4166</td>
<td>38</td>
<td>1.3966</td>
<td>0.0028</td>
<td>0.1091</td>
<td>0.952</td>
</tr>
<tr>
<td>7</td>
<td>-3.5072</td>
<td>1.4099</td>
<td>38</td>
<td>1.5406</td>
<td>0.0028</td>
<td>0.1163</td>
<td>0.948</td>
</tr>
<tr>
<td>8</td>
<td>-3.8035</td>
<td>1.4284</td>
<td>36</td>
<td>1.6552</td>
<td>0.0058</td>
<td>0.2017</td>
<td>0.912</td>
</tr>
<tr>
<td>9</td>
<td>-4.1793</td>
<td>1.5238</td>
<td>33</td>
<td>1.7730</td>
<td>0.0065</td>
<td>0.1899</td>
<td>0.920</td>
</tr>
<tr>
<td>10</td>
<td>-4.3908</td>
<td>1.5427</td>
<td>31</td>
<td>1.8431</td>
<td>0.0072</td>
<td>0.1909</td>
<td>0.919</td>
</tr>
</tbody>
</table>

\( ^a \)Tally threshold.

### Table 2. Parameters used to construct binomial sequential classification sampling plans for \( T. palmi \) at two intervention thresholds \( (m_{IT})^3 \)

<table>
<thead>
<tr>
<th>( m_{IT} )</th>
<th>( T )</th>
<th>( P_{IT}^c )</th>
<th>( P_0^d )</th>
<th>( P_1^e )</th>
<th>Sampling stop line</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Intercepts</td>
</tr>
<tr>
<td>5</td>
<td>1</td>
<td>0.842</td>
<td>0.708</td>
<td>0.937</td>
<td>±2.529</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.722</td>
<td>0.531</td>
<td>0.830</td>
<td>±3.142</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>0.562</td>
<td>0.456</td>
<td>0.673</td>
<td>±6.515</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>0.458</td>
<td>0.343</td>
<td>0.584</td>
<td>±4.642</td>
</tr>
<tr>
<td>10</td>
<td>1</td>
<td>0.951</td>
<td>0.865</td>
<td>0.989</td>
<td>±1.711</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.902</td>
<td>0.778</td>
<td>0.972</td>
<td>±2.007</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>0.826</td>
<td>0.723</td>
<td>0.907</td>
<td>±3.346</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>0.757</td>
<td>0.623</td>
<td>0.872</td>
<td>±3.234</td>
</tr>
</tbody>
</table>

\( ^a \)Wald's (1947) sequential probability ratio test parameters \( a \) and \( \beta \) set at 0.01.

\( ^b \)Tally threshold.

\( ^c \)Proportion threshold expressed as proportion of leaves with \( > T \) thrips.

\( ^d \)Proportion of leaves with \( > T \) thrips that constitutes the null hypothesis for the sequential classification sampling plan.

\( ^e \)Proportion of leaves with \( > T \) thrips that constitutes the alternative hypothesis for the sequential classification sampling plan.
Fig. 1. Operating characteristics (OC) and average number of sample (ASN) curves for binomial sequential classification sampling plans of *T. palmi* at the intervention threshold of 5 thrips per leaf at varying tally thresholds based on the empirical *P*_{1T}–*m* relationship.

was approximately doubled when *T* was increased from 1 to 3, regardless of *m*_{1T} values. Boeve and Weiss (1997) reported that increasing *T* values at a given *m*_{1T} reduced the corresponding proportion infested (*P*_{1T}) with increasing the variability of the sampling plans, especially *P*_{1T}=0.5. This increased variability was reflected in increased ASN curves and width of the sampling stop lines (Table 2).

An increase in *T* decreases the efficiency of a binomial plan (Feng et al., 1994). In this study, increasing the *T* value from 1 to 3 increased the number of samples required to make a management decision. The expected ASN for *T*=1 was considerably less than the expected ASN for *T*= 3 relative to the *m*_{1T} values (Figs. 2 and 3). With *m*_{1T}=5, the expected average ASN was 32 and 65 leaves at *T*=1 and 3, respectively. Sampling time is an important consideration when judging the efficiency of the sampling program. The requisite increase in sample size can be offset by the much higher efficiency of binomial plan compared to complete enumeration plans (Jones, 1994). Boeve and Weiss (1997) reported that the binomial sequential sampling was highly efficient for decision making for the cereal aphids compared with conducting complete counts.

Increasing *T* values will also increase the cost per sample unit because of the additional time it takes to count *T* individual pests in a sampling unit. For *T. palmi*, however, this factor may not necessarily become an obstacle to the use of *T*=3 because *T. palmi* usually is concentrated
within 2–3 leaflets, which may reduce the difficulty of counting *T* thrips. Naranjo et al. (1996) reported that the differential costs of higher tally thresholds did not change the pattern seen for ASN in the sequential sampling plans of *Bemisia tabaci* (Grannadius).

The OC and ASN curves were built around the thresholds of 5 and 10 thrips per leaf using \(a = \beta = 0.01\) in this study. The expected ASN values increased as \(a\) and \(\beta\) declined; however, the expected OC changes little (Nyrop and Binns, 1992). Nyrop and Binns (1991) suggested that \(a\) and \(\beta\) should be considered parameters rather than fixed values in the development of sequential sampling stop lines, and their values should be chosen on the basis of desired OC and ASN functions. Reducing \(a\) and \(\beta\) values in the sequential sampling plans of *B. tabaci* would be greater sample size requirements with little or no gain in the accuracy of decision making (Naranjo et al., 1996).

**Sampling plan validation**

Eight independent data sets, representing density ranges from 0.17 to 18.3 thrips per leaf, were used for the resampling simulation. This range of densities is frequently observed in potato fields. The upper \(P_a\) and lower \(P_l\) boundaries at \(T = 3\), bracketing the critical density, were calculated using Eqs. 3 and 4 for each action threshold (Table 2), and nominal error rates were set at \(a = \beta = 0.01\).

The slopes in the actual OC function were steeper compared with the expected OC func-
Fig. 3. Analysis of Wald’s sequential probability test sampling plan using independent field data for \( T.\ palmi \) at \( m_{\text{fr}} = 5 \) (A and C) and 10 (B and D). The dashed vertical lines denote the intervention thresholds. The operating characteristic (OC) curves in A and B were fitted to the resampling results using a 4-parameter logistic model, \( \text{OC} = \frac{d + (a - d)}{1 + (x/c)^e} \), where \( x \) is mean density and \( a - d \) are fitted parameters (Naranjo and Hutchison, 1997).

These steeper slopes indicate that the sampling plan can be accomplished with a high probability of making a correct decision relative to implementing control. When \( a = \beta \), the OC function should ideally equal 0.5 at the action threshold density. The small deviations from this ideal in this sampling plan indicate insignificant errors in the sampling model for predicting mean density from the proportion infested sample units. For the action threshold of 5, actual \( a \) and \( \beta \) error rates were 0.0145 and 0.0025, respectively; for the threshold of 10, 0.0003 and 0.0005. Recall that the nominal error rates were specified at 0.01. It is not unusual for actual error rates to deviate from nominal rates; it has been suggested that \( a \) and \( \beta \) are considered variables of Wald’s SPRT (Naranjo and Hutchison, 1997).

The ASN curves (Fig. 3, C and D) from the independent data sets corresponded with the expected ASN functions in Figs. 1 and 2, and, on average, relatively few sample sizes were needed before the sequential sampling stop lines terminated sampling. However, there was considerable variability in sample size, particularly at the densities near the action thresholds. Regardless of the action thresholds, small sample sizes were required at the densities farther from the action thresholds.

**Sampling plan implementation**

Based on the results of the above analysis, we can conclude that a binomial sampling plan with \( T = 3 \) was best for the classification of density based on sequential sampling for both action thresholds of 5 and 10 thrips per leaf. In general, the variance in classifying density declined with increasing \( T \) up to a point based on the empirical binomial model (Feng et al., 1994; Naranjo et al., 1996).
To apply the above sampling stop lines to potato fields (Table 2), an appropriate economic injury level or action threshold should be selected based on crop stage, management costs, and level of risk accepted (Feng et al., 1994; Boeve and Weiss, 1997). The sampling plan for $m_{IT}=5$ (Fig. 1) should be considered for potato plants at early developmental stages (late August–early September), which are more susceptible to feeding damage by *T. palmi*. At this crop stage, potato plants are usually heavily infested by immigrants from the adjacent harvesting sweet potato and soybean fields in Cheju Island (Lee, 1996). Therefore, a lower action threshold ($m_{IT}$) is required at this crop stage compared to later crop stages. The sampling plan for $m_{IT}=10$ (Fig. 2) is primarily for use in sampling potatoes after the immigrants are established.

Action thresholds are dynamic and fluctuate with changes in management costs and crop values (Johnston and Bishop, 1987). Thus, a tolerant level of economic damage should be considered when choosing an appropriate sampling plan. Action thresholds (5 and 10 thrips per leaf) used in this study are set empirically based on the grower’s experience. Sampling plans reported here can be adjusted and recalculated using more sound economic injury levels, whenever available, as intervention thresholds.

If the total number of leaves containing $T \leq 3$ thrips in a minimal sample of 30 leaves is above the upper stop line or below the lower stop line, sampling is terminated and a decision as to whether or not to spray is achieved. This minimum sample size was set empirically and may need to be raised or lowered slightly, depending on field validation and the level of risk that the user is willing to accept. If the total number of leaves containing $T \leq 3$ thrips falls between the upper and lower stop lines, sampling is continued until a conclusion is drawn. In practice, the sampling plan should be truncated after sampling more than 50 leaves; if the total number of leaves containing $T \leq 3$ remains between the upper and lower stop lines after inspecting $\geq 50$ leaves, the thrips density should be considered over the action threshold.

The binomial sampling plans presented here should greatly enhance the efficiency of monitoring populations of *T. palmi* for pest management decision-making in Korea. In this study, by increasing the tally threshold from one to three, both robustness and performance of binomial sequential classification sampling can be significantly enhanced. Therefore, using $T=3$ in sampling of *T. palmi* populations can be advantageous over using empty sampling units. Prior to a large-scale implementation for a management of *T. palmi* on potato, the efficiency and performance of the binomial sequential sampling plan should be validated with a reliable economic threshold level.

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