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Vol. 43, No. 1, Spring 1997

Validation of Arthropod Sampling Plans Using a Resampling Approach: Software and Analysis

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ABSTRACT Many sampling plans have been developed for a wide variety of arthropods of economic importance. However, relatively few plans have been tested adequately to gauge their utility in the field. The software presented here should facilitate a validation approach in which actual field data sets are resampled numerous times to arrive at average performance values and associated variances. The major strength of this resampling approach is that analyses are based on actual sampling distributions of arthropod populations, not those specified by a theoretical model. A limitation is that this approach does require additional planning and effort to collect an adequate number of independent data sets. The software (Resampling for Validation of Sample Plans [RVSP]) can be used to test 2 fixed-precision sequential sampling plans based on enumerative counts and 2 (1 sequential and 1 fixed) sampling plans based on binomial counts. The software is user friendly and permits easy entry of sample plan parameters and data sets. We present details of the required input data and output generated by RVSP. We further provide example analyses for 3 pest insect species to demonstrate the use of RVSP for evaluating several different sampling plans.

RELIABLE AND COST-EFFECTIVE SAMPLING METHODS ARE CRITICAL TO THE development of monitoring systems for pest management and can enhance research activities that address issues in population ecology and population dynamics. The specifics of developing sampling protocols for particular arthropods depend on a number of considerations, including whether absolute or relative population estimates are needed, the spatial scale over which the protocols are intended to operate, and whether one wishes to estimate or merely classify population density. Many excellent references are available detailing the rationales and techniques for developing sampling plans for insects and mites (e.g., Morris 1960, Southwood 1978, Nyrop and Binns 1991, Shelton and Trumble 1991, Pedigo and Buntin 1994). Ideally, sampling plans should be developed from robust data sets covering the geographic area of the taxa and encompassing the range of environmental conditions likely to be encountered for particular species in specific environments. In practice, sampling plans often are developed from a fairly restricted range of observations from a small area but then are used over a wide area representing a novel array of environmental and agronomic conditions. Given this practical limitation, it is important that the sample plan be evaluated in terms of expected performance in the field so that the limits of its utility can be better defined. This verification of utility, or validation, may be particularly crucial for sampling plans developed for pest management application in which a decision rule (e.g., economic threshold level) has been integrated into the sampling protocol. An incorrect decision regarding pest control may have important economic and environmental consequences. Likewise, sample plans developed for estimation of population density that provide estimates of uncertain precision may compromise the efficiency and productivity of field research efforts.

Several approaches have been proposed for analyzing and validating arthropods sampling plans. Here we present a resampling technique that uses actual field counts to evaluate and test the performance of commonly used sample plans. First, we briefly discuss the different approaches that are available for testing sample plans. We then discuss our resampling approach and provide a detailed description of computer software that we have developed for per-

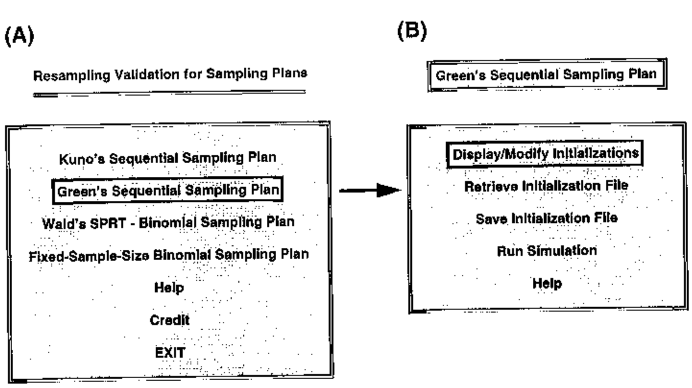

Fig. 1. (A) Opening screen of RVSP providing user with options for testing 4 common sampling plans and (B) example window for selecting options to run analyses using Green's sequential sampling plan.

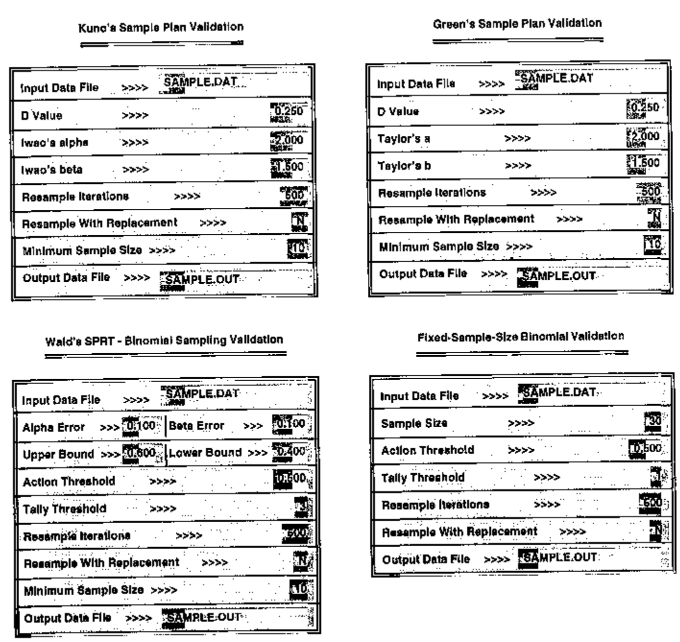

Fig. 2. Parameter input windows for the 4 sample plans that can be tested with RVSP. Each highlighted item can be entered by the user.

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forming these analyses. Finally, we demonstrate the resampling approach by evaluating sample plans developed for three pest insect species and discuss its general utility.

Analysis and Validation of Sampling Plans

Recently, a fairly extensive set of Monte Carlo-based tools have been developed for constructing and analyzing arthropod sampling plans. For example, Trumble et al. (1989) presented an approach for testing fixed-precision sampling plans based on Green's (1970) method, which uses the Taylor (1961) power law to predict sample variance from the sample mean. They used a computer to randomly select sample units from a negative binomial distribution until sampling was terminated by the specified sequential stop lines. They further incorporated variability in the power law relationship by assuming a normal error distribution about the regression line. After many iterations (500), the average precision, as well as the variability in precision, could be estimated as a function of mean density. A similar approach was used by Nyrop and Binns (1991), Binns (1994), and Nyrop and van der Werf (1994) to evaluate the performance characteristics of Iwao's (1975) and Wald's (1947) sequential sampling plans and fixed-sample-size plans for classifying population density relative to a critical density. Their goals were to examine the accuracy of decision-making and estimate the associated sample size required to reach a decision. These tools have been used relatively widely by entomologists (see Nyrop and Binns 1991, Binns 1994).

Monte Carlo tools are valuable because they can be used to evaluate and fine-tune various sampling plans during their construction phase. They also are easy to use (FORTRAN programs are available, see Nyrop and Binns [1991]) and provide smooth analytical output. However, they are of limited value in validating the performance of sampling plans under field conditions. First, they assume a specific underlying statistical distribution (e.g., negative binomial, poisson) that may not mimic the actual sampling distributions of individuals in all instances. Further, it is assumed implicitly that the underlying sampling relationships (e.g., Taylor power law, Iwao's patchiness regression, empirical mean density-proportion infested regression) describe adequately the sampling distribution of populations in novel situations.

An alternative approach, which circumvents these limitations, is to resample field data, independent of that used in plan construction, to evaluate sample plan performance. This approach was first proposed by Hutchison et al. (1988a) to validate the behavior of 2 fixed-precision sequential sampling plans for estimating population density of the pea aphid, *Acyrthosiphon pisum* (Harris), in alfalfa. The approach is appealing intuitively because it makes no a priori assumptions about the sampling distribution of individuals in the field, and resampling directly mimics the process of data collection in the field with the advantage that the results of many different sampling outcomes from that field can be generated and quantified. Recently, this approach was used to validate fixed-precision sequential sampling plans for sweetpotato whitefly, *Bemisia tabaci* (Gennadius), in cotton (Naranjo and Flint 1995) and *Frankliniella* spp. in staked tomatoes (Cho et al. 1995).

Resampling for Sample Plan Analysis and Validation

Resampling techniques, including randomization, Monte Carlo, the jackknife, and the bootstrap have found wide use in the analysis of biological and ecological data (e.g., Fisher 1936, Efron and Tibshirani 1991, Manly 1991, Crowley 1992), and it is anticipated that their use will continue to expand, particularly with the growing

(A) (B)

Field Data Set File:	Input Data File:	
	Columns 1-13	*Columns 14-26*
3	SPW1.DAT	SPW1.OUT
0	SPW2.DAT	SPW2.OUT
5	SPW3.DAT	SPW3.OUT
3	SPW4.DAT	SPW4.OUT
4	SPW5.DAT	SPW5.OUT
2	SPW6.DAT	SPW6.OUT
2	SPW7.DAT	SPW7.OUT
0	SPW8.DAT	SPW8.OUT
3	SPW9.DAT	SPW9.OUT
10	SPW10.DAT	SPW10.OUT
.	.	.
.	.	.
.	.	.
2	SPW63.DAT	SPW63.OUT
5	SPW64.DAT	SPW64.OUT
6	SPW65.DAT	SPW65.OUT
19	SPW66.DAT	SPW66.OUT
1	SPW67.DAT	SPW67.OUT
0	SPW68.DAT	SPW68.OUT
8	SPW69.DAT	SPW69.OUT
7	SPW70.DAT	SPW70.OUT
24	SPW71.DAT	SPW71.OUT
1	SPW72.DAT	SPW72.OUT
2	SPW73.DAT	SPW73.OUT

Fig. 3. Example of (A) field data file and (B) input data file necessary to run analyses with RVSP. SPW, sweetpotato whitefly.

RESAMPLING VALIDATION OF GREEN'S SEQUENTIAL PLAN

DATA SETS RESAMPLED WITHOUT REPLACEMENT

SEQUENTIAL PLAN PARAMETERS

Taylor's a:	2.079	Desired Precision:	0.25
Taylor's b:	1.675	Minimum Sample Size:	10

	Observed Stats			Average Stats Over 500 Simulations						
datafile	Mean	SD	N	Mean	D	Dmax	Dmin	D-SD	N	Nmx
SPW2.DAT	0.03	0.21	481	0.03	0.68	1.00	0.39	0.131	113	204
SPW3.DAT	0.03	0.17	481	0.03	0.61	1.00	0.44	0.103	113	183
SPW4.DAT	0.05	0.23	481	0.06	0.48	0.74	0.31	0.074	90	159
SPW5.DAT	0.09	0.33	481	0.09	0.44	0.79	0.29	0.069	76	116
SPW6.DAT	0.27	0.57	481	0.27	0.30	0.49	0.19	0.042	52	71
SPW7.DAT	1.21	1.30	481	1.24	0.19	0.28	0.12	0.026	32	39
SPW8.DAT	0.35	0.62	80	0.35	0.26	0.33	0.19	0.020	48	59
SPW9.DAT	1.05	1.17	80	1.05	0.19	0.26	0.14	0.020	33	38
SPW10.DAT	1.09	1.38	320	1.12	0.21	0.32	0.13	0.033	33	41
SPW11.DAT	2.66	1.94	80	2.68	0.15	0.19	0.09	0.019	25	28
SPW12.DAT	2.30	2.14	80	2.33	0.18	0.26	0.11	0.028	26	30
SPW13.DAT	9.32	9.12	320	9.41	0.21	0.49	0.10	0.071	17	21
SPW14.DAT	0.50	0.75	80	0.51	0.23	0.31	0.15	0.025	42	49
SPW15.DAT	1.11	1.19	80	1.13	0.19	0.27	0.12	0.022	33	37
SPW16.DAT	12.10	9.01	80	12.08	0.19	0.28	0.10	0.032	15	18
.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.
SPW64.DAT	60.41	38.41	75	60.42	0.19	0.32	0.08	0.039	10	11
SPW65.DAT	27.25	23.54	75	28.07	0.24	0.35	0.11	0.047	12	15
SPW66.DAT	82.75	58.83	75	83.19	0.22	0.34	0.09	0.043	10	10
SPW67.DAT	59.79	50.15	75	60.19	0.26	0.42	0.11	0.052	10	12
SPW68.DAT	63.39	48.91	75	63.38	0.23	0.38	0.11	0.048	10	11
SPW69.DAT	36.67	25.74	75	36.59	0.21	0.40	0.11	0.044	11	13
SPW70.DAT	8.63	7.78	75	8.59	0.21	0.35	0.10	0.054	17	21
SPW71.DAT	3.24	2.84	75	3.23	0.20	0.29	0.13	0.028	19	21
SPW72.DAT	3.23	4.20	75	3.28	0.25	0.42	0.15	0.057	23	29
SPW73.DAT	2.27	2.30	75	2.23	0.20	0.28	0.13	0.022	26	31

Fig. 4. Example of a portion of a summary output file for Green's sequential sampling plan showing sample plan parameters and observed and resampled statistics for each field data file.

availability of inexpensive computing resources (Noreen 1989). In Monte Carlo, repeated samples are drawn from a theoretical distribution or some defined stochastic process such as a simulation model. In contrast, the jackknife and bootstrap methods are based on resampling from sets of real observations. The jackknife consists of drawing a finite number of repeated samples, each one consisting of all but ≥1 observation(s) omitted in turn. The bootstrap consists of drawing repeated samples, all with a sample size equal to the original number of observations. All these techniques conceptually are easy to comprehend and often can provide high levels of statistical power, particularly in instances where the assumptions of parametric methods cannot be met (Efron and Tibshirani 1986, Crowley 1992).

The resampling approach we describe here is a hybrid between the bootstrap and Monte Carlo techniques. It deviates from the bootstrap because the sample size drawn from a data set during any resampling bout is not equal necessarily to the total number of observations in that data set. More significantly, our resampling approach differs from Monte Carlo because the underlying sampling distribution of the arthropod population is defined by actual field data rather than a theoretical model. Thus, it is possible to test sample plans on a more realistic and unbiased basis. By using independent field data, it is possible to test simultaneously the accuracy of the basic statistical model underlying the sampling plan (e.g., Taylor power law, Iwao's patchiness regression, various proportion infested-mean density models) and the sampling error associated with the selection (sequential or otherwise) of sample units from the field.

The major limitation of this resampling approach is that additional field data, independent of that used to develop the sampling plan, must be collected. Ideally, these independent data need to cover the range of population densities under which the sample plan likely will be used. Often, this task can be accomplished by withholding a certain amount of data during the developmental phase. We currently are evaluating the amount of data (both the number of data sets and the number of sample units per data set) necessary to perform a robust analysis of sample plan performance. Also, because real data are being used, the output generated by resampling rarely resembles the smooth analytical output generated by resampling from a theoretical distribution. This tends to complicate analyses and may sometimes make it difficult to interpret general patterns. This limitation can be overcome somewhat by fitting smooth functions (see example analyses below). Finally, in addition to the effort needed to collect the independent data, extra time and effort are needed to conduct the actual analyses. To ameliorate this latter constraint, and to encourage and facilitate the wider use of resampling as a tool for sample plan evaluation, we have developed easy-to-use public-domain software. Below we describe the software and present example analyses.

General Description. Resampling for Validation of Sample Plans (RVSP) is a user friendly computer program designed specifically for the analysis and validation of 4 sample plans that are commonly used for estimating or classifying arthropod density. The current version of RVSP can be used to evaluate 2 fixed-precision sampling plans based on enumerative counts and 2 sample plans based on binomial counts (Fig. 1). Presently, RVSP can be used only to test sampling models with simple variance structures. However, the pro-

RESAMPLING VALIDATION OF WALD'S SEQUENTIAL BINOMIAL PLAN

DATA SETS RESAMPLED WITHOUT REPLACEMENT

SEQUENTIAL PLAN PARAMETERS

Action Threshold (Prop Inf):			0.570
Lower Bound :	0.470	Slope :	0.572
Upper Bound :	0.670	Upper Intercept :	2.653
Alpha Error (I) :	0.100	Lower Intercept :	-2.653
Beta Error (II) :	0.100		
Tally Threshold :	3	Min Sample Size:	10

	Observed Stats			Average Stats Over 500 Simulations								
datafile	PI	Mean	N	PI	PImx	PImn	PI-SD	N	Nmx	Nmn	N-SD	OC
SPW2.DAT	0.002	0.03	481	0.002	0.100	0.000	0.013	10	10	10	0.0	1.000
SPW3.DAT	0.000	0.03	481	0.000	0.000	0.000	0.000	10	10	10	0.0	1.000
SPW4.DAT	0.000	0.05	481	0.000	0.000	0.000	0.000	10	10	10	0.0	1.000
SPW5.DAT	0.002	0.09	481	0.003	0.100	0.000	0.016	10	10	10	0.0	1.000
SPW6.DAT	0.002	0.27	481	0.002	0.100	0.000	0.015	10	10	10	0.0	1.000
SPW7.DAT	0.129	1.21	481	0.131	0.375	0.000	0.102	10	16	10	0.5	1.000
SPW8.DAT	0.000	0.35	80	0.000	0.000	0.000	0.000	10	10	10	0.0	1.000
SPW9.DAT	0.125	1.05	80	0.122	0.375	0.000	0.093	10	16	10	0.4	1.000
SPW10.DAT	0.112	1.09	320	0.112	0.357	0.000	0.093	10	14	10	0.4	1.000
SPW11.DAT	0.512	2.66	80	0.465	0.900	0.100	0.129	30	77	10	17.7	0.902
SPW12.DAT	0.350	2.30	80	0.308	0.722	0.000	0.101	13	38	10	5.1	0.998
SPW13.DAT	0.903	9.32	320	0.908	1.000	0.714	0.079	11	21	10	1.6	0.000
SPW14.DAT	0.025	0.50	80	0.023	0.200	0.000	0.045	10	10	10	0.0	1.000
SPW15.DAT	0.125	1.11	80	0.125	0.375	0.000	0.091	10	16	10	0.5	1.000
SPW16.DAT	0.912	12.10	80	0.916	1.000	0.722	0.073	10	18	10	1.2	0.000
.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.
SPW64.DAT	1.000	60.41	75	1.000	1.000	1.000	0.000	10	10	10	0.0	0.000
SPW65.DAT	1.000	27.25	75	1.000	1.000	1.000	0.000	10	10	10	0.0	0.000
SPW66.DAT	1.000	82.75	75	1.000	1.000	1.000	0.000	10	10	10	0.0	0.000
SPW67.DAT	1.000	59.79	75	1.000	1.000	1.000	0.000	10	10	10	0.0	0.000
SPW68.DAT	1.000	63.39	75	1.000	1.000	1.000	0.000	10	10	10	0.0	0.000
SPW69.DAT	1.000	36.67	75	1.000	1.000	1.000	0.000	10	10	10	0.0	0.000
SPW70.DAT	0.880	8.63	75	0.887	1.000	0.680	0.085	11	25	10	2.4	0.000
SPW71.DAT	0.480	3.24	75	0.422	1.000	0.100	0.119	23	66	10	12.2	0.956
SPW72.DAT	0.427	3.23	75	0.375	0.900	0.000	0.129	19	73	10	12.1	0.964
SPW73.DAT	0.387	2.27	75	0.338	0.818	0.000	0.114	16	65	10	9.5	0.994

Fig. 5. Example of a portion of a summary output file for Wald's sequential probability ratio test sampling plan showing sample plan parameters and observed and resampled statistics for each field data file.

(A)

GREEN'S SAMPLING PLAN - STATISTICS FOR EACH PASS

Data Sets Resampled Without Replacement

PASS	MEAN	VAR	STD	SE	D	N
1	4.18	11.77	3.43	0.73	0.17	22
2	4.24	22.59	4.75	1.04	0.24	21
3	4.67	31.53	5.62	1.23	0.26	21
4	5.19	32.66	5.72	1.25	0.24	21
5	6.16	54.47	7.38	1.69	0.27	19
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
496	4.19	22.56	4.75	1.04	0.25	21
497	3.30	6.04	2.46	0.51	0.16	23
498	4.52	16.26	4.03	0.88	0.19	21
499	4.75	30.93	5.56	1.24	0.26	20
500	4.80	31.54	5.62	1.26	0.26	20

(B)

WALD'S SAMPLING PLAN - STATISTICS FOR EACH PASS

Data Sets Resampled Without Replacement

PASS	MEAN	VAR	STD	SE	PROP	OC
1	4.57	19.67	4.43	0.68	0.595	0.000
2	5.41	32.38	5.69	1.38	0.647	0.000
3	6.60	22.27	4.72	1.49	1.000	0.000
4	10.10	61.88	7.87	2.49	0.900	0.000
5	6.08	22.08	4.70	1.30	0.692	0.000
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
496	8.82	70.76	8.41	2.54	0.727	0.000
497	7.30	63.12	7.94	2.51	0.800	0.000
498	3.36	11.05	3.32	1.00	0.364	1.000
499	10.50	53.17	7.29	2.31	1.000	0.000
500	4.31	18.72	4.33	0.80	0.483	1.000

Fig. 6. Example of a portion of optional iteration by iteration output tables for (A) Green's plan and (B) Wald's sequential probability ratio test that can be generated by RVSP for each field data set.

gram is modular and virtually any sample plan or models based on more complex, nested variance structure could be included. Furthermore, RVSP does not keep track of the actual spatial arrangement of sample units from the field; each sample unit has an equal probability of being selected. This deviates from the systematic pattern of sample unit collection common to many field sampling protocols. RVSP assumes that the overall sample is representative, and this assumption would only be violated if there were strong gradients in population density within the field. The program is menu-based and permits the easy entry of sample plan parameters and data files using the cursor keys (Fig. 2). RVSP also contains help screens to advise the user on program operation. RVSP is a DOS program that will run on any PC; it also can be executed in a DOS-shell from the Windows environment.

Basically, RVSP uses a uniform random number generator to select sample units from an actual data set until either the sequential rule is satisfied or a fixed sample size has been drawn, depending on the sample plan tested. This process is repeated numerous times (default = 500) for each data set. Based on these iterations, RVSP then calculates averages and variances for precision and sample size, as well as operating characteristics for the binomial plans that classify population densities as either above or below a critical level (e.g., an action or economic threshold). Details on these calculations are given below. RVSP automatically provides a summary table and also can provide a detailed iteration by iteration output table. Data from both tables can be imported easily into spreadsheet and graphical programs for further examination and analysis.

Sample Plans Covered–Enumerative. RVSP can be used to analyze Green's (1970) and Kuno's (1969) fixed-precision sequential sampling plans based on enumerative counts. Green's plan is based on the Taylor (1961) power law, $s^2 = am^b$, which models the relationship between the sample mean (m) and variance (s^2). The sequential sampling model stop line is given as:

$$T_n \geq (an^{1-b}/D^2)^{1/(2-b)} \qquad (1)$$

where T_n is the cumulative count from n sample units, D is precision

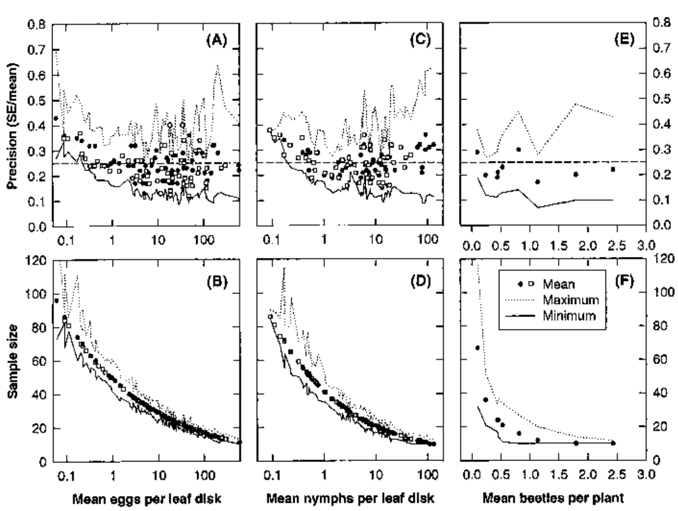

Fig. 7. Analyses of Green's sequential sampling plan using independent field data for (A and B) sweetpotato whitefly eggs on cotton, (C and D) sweetpotato whitefly nymphs on cotton, and (E and F) striped cucumber beetle adults on squash. The dashed horizontal lines in A, C, and E represent the desired level of precision (0.25). Symbols denote mean values; dotted and solid lines denote extreme values for each data set and are not intended to represent a continuous function. Different symbols in A–D represent field samples from Maricopa, AZ, in 1993 (open boxes) and 1995 (closed circles).

(ratio of standard error to mean), and a and b are parameters of the Taylor power law. Kuno's plan uses Iwao's (1968) patchiness regression, $\overset{*}{m} = \alpha + \beta m$, to model the mean–variance relationship, where $\overset{*}{m}$ is Lloyd's (1967) mean crowding index and the variance is given as $s^2 = (\alpha + 1)m + (\beta - 1)m^2$. The sequential sampling model stop line is given as:

$$T_n \geq (\alpha + 1)/(D^2 - [\beta - 1]/n) \qquad (2)$$

where Tn and D are as described above and α and β are parameters of the patchiness regression.

Sample Plans Covered–Binomial. RVSP also can be used to analyze Wald's (1947) sequential probability ratio test and fixed-sample-size plans based on binomial counts. The program does not explicitly require the parameters of the relationship relating the proportion of infested sample units to mean density. The only input required by RVSP is the specification of the action or economic threshold and upper and lower decision boundaries (sequential model only) in terms of proportion infested. Because these values are derived from the underlying proportion infested-mean density model of the sample plan, any of a number of models (e.g., Kono and Sugino 1958, Gerrard and Chiang 1970, Wilson and Room 1983, Binns and Bostanian 1990) can be used. By generating operating characteristic and average sample number curves as functions of mean density (described below), RVSP automatically tests the validity of the underlying model. This test of validity accounts for and quantifies the impact of variability and/or systematic deviations of field observations from the model in terms of the accuracy and efficiency of management decisions.

Wald's (1947) sequential plan allows population density to be classified as either above or below a critical density. For binomial count data, upper (u) and lower (l) sampling stop lines are defined as:

$$T_{u(n)} \geq Bn + A \qquad (3a)$$

$$T_{l(n)} \leq Bn - C$$

where n is the number of sample units examined; $T_{(n)}$ is the cumulative number of sample units infested; and A, B, and C are parameters derived as standard functions of specified type I (α) and II (β) error rates, and of upper (p_1) and lower (p_0) boundaries bracketing the critical density, given in terms of proportion infested:

$$B = \ln\{[1 - p_0/1 - p_1]\}/\ln\{[p_1(1 - p_0)/p_0(1 - p_1)]\} \qquad (3b)$$

$$A = \ln\{[1 - \beta]/\alpha\}/\ln\{[p_1(1 - p_0)/p_0(1 - p_1)]\} \qquad (3c)$$

$$C = \ln\{\beta/[1 - \alpha]\}/\ln\{[p_1(1 - p_0)/p_0(1 - p_1)]\} \qquad (3d)$$

The α error rate defines the probability that some control tactic would be implemented when actual pest density is just below the action threshold and β defines the probability that no control tactic would be implemented when density is just above the action threshold.

The fixed-sample-size plan is based on a user-specified sample size to determine the proportion of sample units infested. This value then can be compared to an action or economic threshold level, also specified as a proportion infested.

Data Requirements. The number of independent field data sets needed to run RVSP will depend on the particular sampling model being tested and how rigorously one wishes to test the model. At a minimum, the data sets should cover the range of population densities likely to be encountered by users of the sample plan. Likewise, the required number of observations in each data set will depend on the sample model being tested, the sample unit size, the specified precision or error rates, the width of decision boundaries, and whether resampling is run with or without replacement. Our experience indicates that ≈50 observations per data set should provide a representative sample and will satisfy most testing requirements. Our experience also suggests that as few as 10 independent data sets may adequately define sample plan performance, so long as these data sets uniformly cover the range of densities of interest (see example analyses below). Although the quality of testing will undoubtedly increase with more data sets, we recommend, as a general guideline, that at least 10–20 independent data sets be used. As previously noted, the development of more definitive guidelines is the subject of ongoing research.

When running in "resample without replacement" mode (each sample unit can be selected only once per sample iteration), RVSP will test the adequacy of each data set before executing. A warning message is given if the anticipated sample size is >75% but ≤90% of the observations available in a given data set and the user will be given the option of continuing or not. The data set will not be executed if the sample size exceeds 90% of the observations available, and execution will terminate for a given data set if the actual sample size exceeds the number of observations during any resampling iteration. Estimates for the anticipated sample size n_a are calculated as:

Green's plan $$n_a = ae^{[(b-2)\ln m]}/D^2 \quad (4)$$

Kuno's plan $$n_a = \{[\alpha + 1]/m + [\beta - 1]\}/D^2 \quad (5)$$

Wald's SPRT $$n_a = -\{\ln[(1-\beta)/a]\ln[\beta/(1-\alpha)]\}/\{\ln[p_1/p_0]\ln[(1-p_0)/(1-p_1)]\} \quad (6)$$

Fixed plan n_a = minimum sample size (7)

where parameters are as defined above for equations 1–3. The anticipated sample size for Wald's sequential probability ratio test is somewhat conservative in that equation 6 estimates the average sample size when mean density equals the action threshold. The 90% limit ensures that there will be enough sample units to complete all iterations given that the actual number of sample units needed is only an estimate based on original sample plan parameters. It also permits RVSP to adequately estimate the between-iteration variability. RVSP also checks to see that at least one sample unit in the field data set is >0 before executing that data set. None of the anticipated sample size safeguards operate when the user specifies the "resample with replacement" mode. In this mode, the same sample unit could be selected more than once for each sampling iteration.

RVSP Input Requirements. In this section we describe the specific data that need to be entered to run a resampling analysis for any of the 4 sample plans.

Data Files. RVSP requires 2 types of data files. One type of data file, referred to from here forward as field data files, are ASCII text files that contain observations from a particular sampling bout. For example, these would be the counts recorded from a specific field on a particular date. These data should be the actual enumerative counts, not binomial counts, and they need to be input so that there is 1 observation per line of the file (see Fig. 3A). The 2nd type of data file, referred to from here on as the input data file, is an ASCII text file that contains the names of one or more field data set files and the associated output file(s) that RVSP can optionally generate if the user wants an iteration by iteration summary for each field data set. This enables a batch execution of the analysis when the user has a number of independent field data sets to test. The format of the input data file is rigid, requiring the name of the field data set to occupy columns 1–13 and the output file name to occupy columns 14–26 (Fig. 3B). Only 1 field data and output file can be specified per line and the user must enter output file names even if iteration by iteration summaries are not desired. Both types of data files can be made easily using DOS-Edit, or a wordprocessor, or spreadsheet capable of writing or saving ASCII text files.

General Inputs. Beside field and input data files, there are several other input requirements that are common to all 4 sample plans that are entered in RSVP through input windows (see Fig. 2). The number of times to resample each field data set can be specified by the user. The default is 500 and probably is adequate for most purposes; however, this number can be changed as needed to improve precision or decrease execution time. The user also is given the choice of sampling with or without replacement. Each sample unit can be selected only once during each iteration when sampling without replacement (default setting). This mode duplicates most closely the selection of sample units in the field, where any given sample unit can only occur once (although the same number of organisms may be observed on other sample units in the same field). The option to sample with replacement is provided so that analyses can be performed using field data sets that may not be adequate for the high levels of precision or low error rates specified by the user. Overall, our experience suggests that there is little difference between the 2 modes in program output when there are enough observations to sample without replacement. We currently are looking at this issue in more depth in terms of the minimum sample size that would be necessary for a robust analysis. Another general input is the minimum sample size, which is the number of sample units that need to be drawn before terminating a single sampling bout. Most sample plans that are implemented in the field include this parameter so that a minimum sample size is taken regardless of population density. This parameter is equal to sample size in the fixed-sample-size plan and is modified for Kuno's plan in relation to the constraint that $n > (\beta - 1)/D^2$ (Kuno 1969). Finally, the user must specify the name for the summary output file. This ASCII text file is generated by RVSP

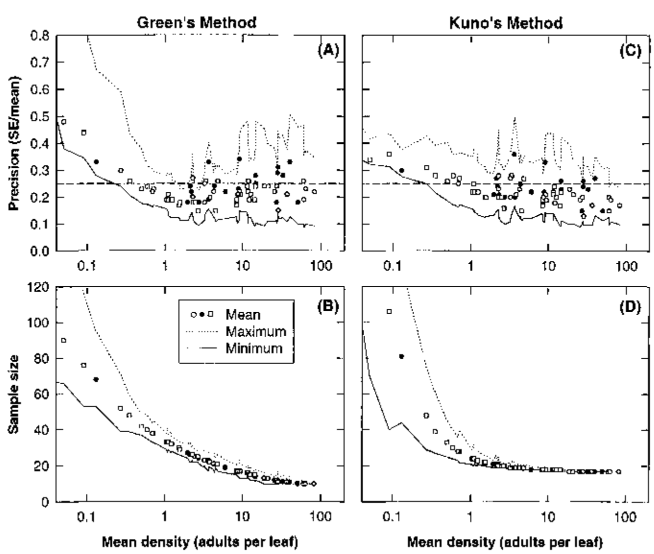

Fig. 8. Comparative analyses of (A and B) Green's and (C and D) Kuno's sequential sampling plan using independent field data for sweetpotato whitefly adults on cotton. The dashed horizontal lines in A and C represent the desired level of precision (0.25). Symbols denote mean values; dotted and solid lines denote extreme values for each data set and are not intended to represent a continuous function. Different symbols represent field samples from Maricopa, AZ, in 1994 (open boxes) and Phoenix, AZ, in 1993 (closed circles) and 1994 (shaded circles).

and contains summary statistics for each field data file executed (Figs. 4 and 5). At execution, the program also provides an option to print this summary table directly.

Plan-Specific Inputs. Beyond the common general inputs, each plan requires its own set of parameters (see Fig. 2). Testing of Kuno's plan requires input of the desired level of fixed-precision (SE/mean) and the slope (β) and intercept (α) of Iwao's patchiness regression. Green's plan also requires input of the desired level of precision and a and b of the Taylor power law. Note that if ln$a$ is determined as the y-intercept of the regression of lns^2 on ln$m$ it must be exponentiated. To test Wald's sequential probability ratio test, the user must enter α and β error rates (default $\alpha = \beta = 0.1$), the tally threshold (t) for determining whether a sample unit is infested. The user also must enter upper and lower decision boundaries and the action threshold, all given in terms of proportion infested with at least t individuals.

Other Options. For each sample plan, RVSP gives the user the option of saving the parameters entered in the input window and of retrieving previously saved parameter files (see Fig. 1B). This simplifies data entry if multiple runs of each input data file are planned with only 1 or 2 changes in plan parameters. Individual help screens also are provided to explain required inputs for each sample plan.

RVSP Output. RVSP automatically creates a summary file under the name of the output data file. This file contains sample plan parameters and summary statistics for each field data set (Figs. 4 and 5). The user also can request that this summary table be printed directly. RVSP checks for a connected printer and informs the user of any other problems before printing. Optionally, RVSP also can create an output file of results for each individual iteration of a field data set if the user wishes to perform further analyses (Fig. 6). These individual files are saved under file names specified in the input data file (see Fig. 3B). For 500 iterations, these files occupy ≈30 K of disk space each. Output from both types of tables can be imported into spreadsheet and graphics programs for further examination and analysis.

For Green's and Kuno's plan, the output file tabulates the mean, standard deviation, and n of the original data set; and the mean, standard deviation, maximum and minimum of precision, and required sample size over all resampling iterations (e.g., Fig. 4). For Wald's sequential probability ratio test, the output file tabulates the proportion infested, mean, and n of the original data set; and the mean, standard deviation, maximum and minimum of proportion infested, and required sample size over all resampling iterations (see Fig. 5). The operating characteristic, which is the probability of not intervening relative to true pest density, is calculated after the sequential decision rule is satisfied (equation 3). It is estimated directly as the proportion of iterations in which the proportion infested does not exceed the lower sequential stop line. The operating characteristic function can be generated by plotting these probabilities against the true mean of the sample. Likewise, the average sample number function can be generated by plotting average sample size against mean density. Similar to Wald's, the fixed-sample-size plan output tabulates the proportion infested, mean, standard deviation, and n of the original data set; and the mean, standard deviation,

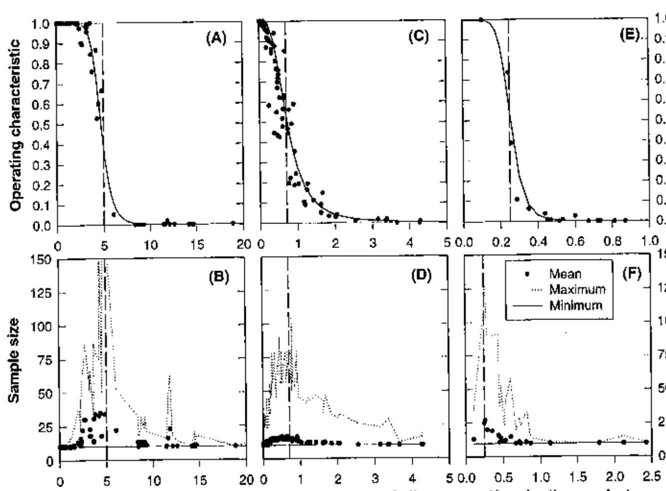

Fig. 9. Analyses of Wald's sequential probability ratio test sampling plan using independent field data for (A and B) sweetpotato whitefly adults on cotton, (C and D) pink bollworm eggs on cotton, and (E and F) striped cucumber beetle adults on squash. The dashed vertical lines denote the action threshold for each insect. The operating characteristic (OC) curves in A, C, and E were fitted to the resampling results using a 4-parameter logistic model, $OC = d + (a - d)/(1 + [x/c]^b)$, where x is mean density and a–d are fitted parameters . Dotted and solid lines in the average sample number graphs denote extreme values for each data set and are not intended to represent a continuous function.

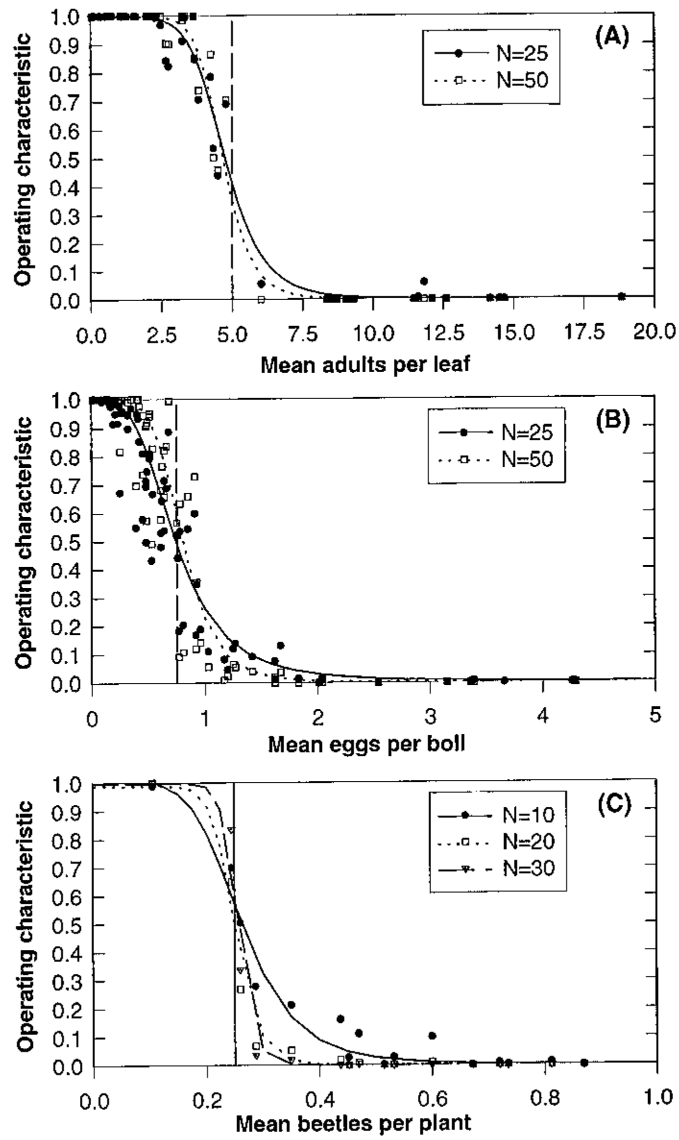

Fig. 10. Comparative analyses of fixed-sample-size sampling plans using independent field data for (A) sweetpotato whitefly adults on cotton, (B) pink bollworm eggs on cotton, and (C) striped cucumber beetle adults on squash. The dashed vertical lines denote the action threshold for each insect. The operating characteristic (OC) curves were fitted to the resampling results using a 4 parameter logistic model, $OC = d + (a - d)/(1 + [x/c]^b)$, where x is mean density and a–d are fitted parameters.

maximum and minimum of proportion infested over all resampling iterations. The operating characteristic is estimated directly as the proportion of iterations in which the proportion infested did not exceed the action threshold. RVSP provides only an estimate of the operating characteristic for Walds's and the fixed-sample-size plan because mean density is estimated with error from field data sets. Confidence intervals about the operating characteristic could be constructed by using the standard deviation provided in the output table under observed statistics. The operating characteristic and average sample number also can be plotted as functions of the proportion of infested sample units if validity of the proportion infested-mean density model is not of interest.

Example Analyses of Sample Plans

To demonstrate the use of RVSP, we present here a series of analyses for 3 pest insect species for which we have developed sample plans and for which we have independent field data sets available for testing sample plan performance (Table 1). Species include the sweetpotato whitefly and the pink bollworm, *Pectinophora gossypiella* (Saunders), in cotton; and the striped cucumber beetle, *Acalymma vittatum* (F.), on cucurbits (primarily squash). Independent field data sets for sweetpotato whitefly were collected as part of several ongoing efforts to study population dynamics and develop pest management strategies in cotton (Naranjo et al. 1995, Flint et al. 1996). Field data sets for eggs and nymphs were collected in cotton fields in Maricopa, AZ, in 1993 and 1995, with the sample size of each data set ranging from 60 to 120. The sample unit for eggs and nymphs was a 4-cm^2 leaf disk extracted near the petiole of 5th mainstem node leaves. Field data sets for adults were collected at Phoenix, AZ, in 1993 and at Maricopa and Phoenix, AZ, in 1994, with sample sizes ranging from 60 to 320. The sample unit for adults was a whole 5th mainstem node leaf of cotton. Data sets for pink bollworm eggs also were collected over several years in conjunction with various studies of populations dynamics and biological control (Hutchison et al. 1988b, 1991; Naranjo et al. 1992; Naranjo and Martin 1993). Here the sample unit was an individual cotton boll, ≈14–21 d old. Data sets were collected from fields in the Palo Verde Valley, CA, in 1986–1987; Maricopa and Gilbert, AZ, in 1990; and Maricopa and Phoenix, AZ, in 1991–1992. Pink bollworm data sets had sample sizes of 50–250. Data sets for striped cucumber beetle adults were collected from southern Minnesota (Anoka, Dakota, Dodge, Mower, Steele, and Wright counties) cucurbit fields (squash, pumpkin, cucumber) during 1994–1995 (Burkness 1996). For this analysis, the sample unit was 4 whole consecutive plants, ranging from the cotyledon to the 4 true-leaf stage. Each data set had a sample size of 48.

Green's and Kuno's Plans. We demonstrated the use of RVSP for testing fixed-precision plans by examining the performance of existing sample plans for egg, nymphs, and adults of sweetpotato whitefly; and adults of striped cucumber beetle (see Table 1). We set the desired precision to 0.25, set the minimum sample size to 10, and resampled field data sets without replacement 500 times. We summarized the output of RVSP by plotting mean, maximum and minimum values for actual precision, and sample size as a function of mean density; and calculated means for precision and sample size over all populations densities.

Results highlight the stochastic nature of fixed-precision sampling in the field (Figs. 7 and 8) that has been observed previously (Hutchison et al. 1988a, Cho et al. 1995, Naranjo and Flint 1995). The mean value of actual precision (denoted by symbols) may be near that desired, but extreme values of actual precision (denoted by dotted and solid lines) may be >> or << 0.25 during any one sampling bout. Because precision is a measure of variability, values >0.25 indicate that the sample plan performed poorer than expected, whereas values <0.25 indicate the sample plan performed better than expected. In general, all the fixed-precision sample plans performed poorly at low densities (<0.2 insects per sample unit), particularly for sweetpotato whitefly where the mean values of actual precision exceeded 0.25 in all cases and minimum values of precision for any one sampling bout exceeding 0.25 in many cases (Figs. 7 A and C, 8 A and C). At higher mean densities, the actual mean value of precision was better than desired in more cases than not for eggs and adults but roughly better than or worse than the desired precision with equal frequency for nymphs of sweetpotato whitefly. These patterns were fairly consistent for field data sets collected over different years or from different sites (denoted by different symbols in Figs. 7 and 8). For striped cucumber beetle adults, Green's plan resulted in better than desired mean precision in all but 2 instances. Still, there was considerable variability in actual precision from one sample bout to the next. As expected, sample size requirements declined rapidly with increases in mean density; however, there was less

Table 1. Sample plan parameters and number of independent field data sets used in example analyses with RVSP

Plan	Insect/stage	Taylor's		Iwao's		Wald's		Wald's and Fixed		Field data sets[a]	Sample plan reference
		a	*b*	α	β	p_0	p_1	Threshold	Tally		
Green's	SPW eggs	2.986	1.766	—	—	—	—	—	—	124	Naranjo and Flint 1994
	SPW nymphs	2.537	1.688	—	—	—	—	—	—	100	Naranjo and Flint 1994
	SPW adults	2.079	1.675	—	—	—	—	—	—	72	Naranjo and Flint 1995
	SCB adults	0.800	1.286	—	—	—	—	—	—	9	Burkness 1996
Kuno's	SPW adults	—	—	−0.530	2.030	—	—	—	—	72	Naranjo and Flint 1995
Wald's	SPW adults	—	—	—	—	0.47	0.67	0.57	3	72	Naranjo et al. 1996
	PBW eggs	—	—	—	—	0.02	0.22	0.12	1	85	Hutchison et al. 1986
	SCB adults	—	—	—	—	0.15	0.35	0.25	2	20	Burkness 1996
Fixed	SPW adults	—	—	—	—	—	—	0.57	3	72	Naranjo et al. 1996
	PBW eggs	—	—	—	—	—	—	0.12	1	85	Hutchison et al. 1986
	SCB adults	—	—	—	—	—	—	0.25	2	20	Burkness 1996

SPW, sweetpotato whitefly; SCB, striped cucumber beetle; PBW, pink bollworm.

[a] The number of independent field data sets available to test a specific sample plan. See text for descriptions of data sets.

variability among sampling bouts for any one field data set, particularly at mean densities greater than ≈0.5 insects per sample unit (Figs. 7 B, D, and F; 8 B and D).

Differences in the performance of Green's and Kuno's plans for sampling adult sweetpotato whitefly were relatively minor (Fig. 8). Kuno's plan required a greater sample size at low densities (<0.2 adults per leaf) and, as a result, permitted mean density estimates with levels of precision closer to those specified in comparison with Green's plan. However, because of the minimum sample size requirement (see above), Kuno's plan also required, on average, a great sample size than necessary to achieve the desired precision at moderate to high mean densities.

Overall, fixed-precision sequential sampling plans for these 2 insect species performed adequately. Averaging results across all field data sets, actual mean precision was close to that specified in the sample plans, and extreme values were reasonable (Table 2). For example, over a range of densities from 0.03 to 83 sweetpotato whitefly adults per leaf, mean precision averaged 0.22–0.25 and, on average, was never worse than 0.40.

RVSP also can be used to evaluate optimum sample unit size by combining actual estimates of precision with sampling cost data. For example, Burkness (1996) used RVSP and Green's plan to estimate the actual relative net precision for 7 different sample units (1–7 whole plants) for striped cucumber beetle and then compared these results with conventional relative net precision calculations (e.g., Pedigo et al. 1972). The conventional estimates, based on all observations (n = 48), indicated that a 1-plant sample unit was most cost-effective whereas the resampling analysis showed that 2- and 3-plant sample units were best. The latter analysis is based on the repeated sequential selection of observations (n generally < 48) and likely is more indicative of performance in the field if a sequential sampling plan is used. This outcome suggests that selection of an optimal sample unit should be done in tandem with sample size validation to maximize the probability of selecting the most efficient sample unit.

Wald's Plan. Next we demonstrate the use of RVSP for testing Wald's plan for classifying population densities of sweetpotato whitefly adults, pink bollworm eggs and striped cucumber beetle adults relative to defined action thresholds for these pests. We set p_0 and p_1 at ± 0.10 of the action threshold and set nominal error rates at $\alpha = \beta = 0.10$. For the classification of population density two important factors are the operating characteristic function, which is defined as the probability of taking no action relative to true mean density, and the associated average sample size function, which is the mean sample size required to reach a decision. These functions are shown for the 3 species in Fig. 9. We used a 4-parameter logistic model (SigmaPlot, Jandel Scientific 1994) to fit a smooth curve for the operating characteristic function. When $\alpha = \beta$, the operating characteristic should ideally equal 0.5 at the action threshold density. The deviations from this ideal for sweetpotato whitefly (Fig. 9A) indicate errors in the sampling model for predicting mean density from the proportion of infested sample units. Fortunately, this error is conservative, resulting in a higher probability of applying a control tactic at densities slightly lower than the action threshold.

We can estimate the actual α and β error rates (type I and II errors, respectively) by solving the operating characteristic function at mean densities associated with p_0 and p_1, respectively. For sweetpotato whitefly, actual α and β error rates were 0.164 and 0.063; for pink bollworm, 0.003 and 0.103; and for striped cucumber beetle, 0.047 and 0.080, respectively. Recall that nominal rates for these error terms were specified at 0.10. It is not unusual for actual error rates to deviate from nominal rates, and it has been suggested that α and β be considered variables of Wald's sequential probability ratio test that can be adjusted to achieve desired operating characteristic and average sample number functions (Nyrop and Binns 1991). Changes in α, β, p_0, and p_1 can be made easily in RVSP to explore sensitivities in the operating characteristic and average sample number functions.

On average, relatively few sample units were needed before the sequential stop lines terminated sampling; however, there was considerable variability in sample size, particularly at densities near the action threshold (Fig. 9 B, D, and F). For all 3 insect species, the specified minimum sample size of 10 truncated the lower boundary of the sample size function. Thus, even at densities near the action threshold, there were sampling bouts in which a decision to treat or not could have been made with fewer than 10 binomial sample units.

Fixed-Sample-Size Plan. Finally, we demonstrate the use of RVSP for testing fixed-sample-size plans based on binomial count data. We examined sample plans based on different sample sizes for sweetpotato whitefly adults, pink bollworm eggs, and striper cucumber beetle adults. As expected, increasing the sample size increased the steepness of the operating characteristic functions and, thus, improved the probabilities of making a correct decision relative to implementing control (Fig. 10). Doubling the sample size from 25 to 50 for sweetpotato whitefly improved the operating characteristic function (Fig. 10 A). The α error rate dropped from 0.201 to 0.158 and the $ error rate declined from 0.099 to 0.046. Likewise, the operating characteristic function improved for pink bollworm when the sample size was doubled (Fig. 10 B). Here, the α error rate remained unchanged at 0.004 and the β error rate declined from 0.084 to 0.033. In contrast, the operating characteristic function for striped cucumber beetle was very good for a fixed sample size of 30 (Fig. 10 C) and did not change perceptibly with $n > 30$ (not shown). The operating characteristic function was still good with a sample size as low as 10. The α error rates steadily declined from 0.081 to 0.023 to 0.005 with n = 10, 20, and 30, respectively. The corresponding β error rates were 0.17, 0.018, and 0.003.

Direct comparisons of the sequential and fixed-sample-size plans suggest tradeoffs in efficiency. For instance, the average sample size needed to classifying the density of sweetpotato whitefly rarely ex-

Table 2. Summary of performance for Green's plan for sweetpotato whitefly on cotton and striped cucumber beetle on squash

Field data sets (site/yr)	Averaged over all densities: Precision Mean	Precision Max	Precision Min.	Sample size Mean	Sample size Max	Sample size Min.	Range of densities
Sweetpotato whitefly eggs							
Maricopa 1993	0.24	0.35	0.15	31.9	36.0	28.8	0.06–809.35
Maricopa 1995	0.25	0.43	0.13	31.6	38.9	26.3	0.09–293.72
Sweetpotato whitefly nymphs							
Maricopa 1993	0.25	0.37	0.17	32.3	37.9	28.0	0.09–47.98
Maricopa 1995	0.26	0.44	0.13	27.3	35.8	21.8	0.17–131.75
Sweetpotato whitefly adults							
Phoenix 1993	0.25	0.40	0.14	20.7	26.0	17.1	0.13–50.29
Maricopa 1994	0.25	0.39	0.15	33.4	45.3	26.3	0.03–20.94
Phoenix 1994	0.22	0.34	0.11	17.1	20.3	14.9	0.69–82.75
Striped cucumber beetle adults							
Minnesota 1994–1995	0.22	0.36	0.12	24.4	38.6	15.0	0.10–2.43

ceeded 30 even at densities near the action threshold; however, during some sample bouts, the sample size could exceed 100. The fixed-sample-size plan with $n = 25$ had an operating characteristic function similar to that of Wald's plan and would be more efficient at densities near the action threshold. However, the fixed plan would be less efficient at low and high densities where Wald's plan could classify density with fewer samples, even during extreme sampling bouts. Similar contrasts can be drawn from the other 2 species examined in our analyses. For sweetpotato whitefly, we ultimately decided to implement a fixed sample size model to ensure adequate coverage of a cotton field before making a control decision (Naranjo et al. 1996).

General Utility of the Resampling Approach

The desired precision specified in a sequential sample plan is not the precision that will result from any one sample from a field but, instead, is the average precision that would be expected over a large number of individual sampling bouts. Likewise, error rates associated with making the proper decision to control a pest population are those that would be expected, on average, over a large number of trials. There are at least 3 sources of error that cause deviation from this expected performance: (1) statistical variation associated with fitting the model on which the sampling plan is based (e.g., the Taylor power law or the empirical proportion infested-mean density regression), (2) deviations in the actual sampling distribution of populations from that used to construct the sample plan, and (3) sampling error, including variability in the sequential selection of samples in the field.

A Monte Carlo method that uses a theoretical distribution may be satisfactory to account for errors 1 and 3 as long as deviations from the actual sampling distributions are minimal but can only adequately account for the first type of error if distributional deviations are greater. In contrast, resampling from actual field data simultaneously accounts for all these sources of error and their consequences in terms of sample plan performance. Several analyses that have contrasted the 2 approaches suggest that a Monte Carlo approach may provide misleading results. Using the resampling approach, Hutchison (1994) found that Green's plan required a greater sample size than necessary (better than expected precision was achieved) over a range of pea aphid densities. In contrast, a Monte Carlo approach assuming a negative binomial distribution and incorporating variability in the mean–variance relationship suggested that the sample plan was fairly accurate at achieving the prescribed precision over these same densities. A similar contrast between the 2 approaches for testing Green's plan for adult sweetpotato whitefly also yielded discrepancies (Naranjo and Flint 1995). Here, resampling of field data suggested that precision was better than desired at densities <15 adults per leaf and worse than expected at higher densities. The Monte Carlo analysis indicated essentially the opposite. Finally, the Monte Carlo program of Nyrop and Binns (1991) for estimating expected operating characteristic functions based on Wald's sequential probability ratio test indicated expected α and β error rates of 0.148 and 0.158, respectively, when classifying the density of sweetpotato whitefly adults relative to an action threshold of 5 per leaf with a tally count of 3 (Naranjo et al. 1996). These same error rates were 0.164 and 0.063, respectively, in our analyses above. Thus, the sample plan is much better at protecting against the possibility of taking no action when pest density is above the action threshold than Monte Carlo results indicated.

It is difficult to generalize about the respective robustness of these 2 approaches on the basis of a few contrasting examples. As noted earlier, the Monte Carlo technique can be valuable in sample plan development and even may be useful in field validation if assumptions about sampling distributions are carefully considered and appropriate selection of theoretical models is made. Perhaps, it would be most prudent to use both approaches early on in the development and implementation of a sampling program. If both approaches yield similar results, it might be more efficient to use Monte Carlo to adjust plan parameters because of the analytical and more easily interpretable output. Nonetheless, the resampling technique presented here represents the most robust method for verifying actual field performance and has the added advantage of requiring no restrictive assumptions. We hope that the software described here will facilitate routine resampling of real data sets as one of the primary methods for sample plan analysis and validation.

Software Availability

The RVSP software is public domain and can be downloaded from the Internet at World-Wide Web pages maintained at our respective institutions. The Western Cotton Laboratory URL is http://gears.tucson.ars.ag.gov/wcrl/ and the University of Minnesota URL is http://www.mes.umn.edu/~vegipm/hlab/research/hlab.htm. The downloadable version is provided as a self-extracting .ZIP file and includes the software, a user's manual (a condensed version of this article), and a set of example field data sets that can be used to familiarize the user with operation of the software. Software and documentation also can be obtained directly from the authors.

Acknowledgments

We thank Vincent Jones (University of Hawaii), Roger Moon (University of Minnesota), and James Walgenbach (North Carolina State University) for their helpful comments on earlier drafts of the manuscript. This is publication 22,520 of the Minnesota Agricultural Experiment Station.

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Received for publication 24 April 1996; accepted 3 September 1996.

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