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Variable intensity and fixed-size sampling plans: Comparative analysis using simulated *Nephotettix* spp. (Homoptera: Cicadellidae) populations in wet paddy ecosystem in Malaysia

[Pelan pensampelan keamatan berubah dan bersaiz tetap: Analisis perbandingan dengan populasi *Nephotettix* spp. (Homoptera: Cicadellidae) yang disimulasikan dalam ekosistem sawah di Malaysia]

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Key words: rice, sample plan, VIS, bootstrap, Taylor's coefficients, simulation, Malaysia

Abstrak

Kajian ini membandingkan pelan pensampelan keamatan berubah (VIS) dan bersaiz tetap (FSS) untuk serangga perosak padi bena hijau (GLH) *Nephotettix* spp. dalam ekosistem sawah. Pelan-pelan pensampelan dijana berdasarkan model regresi varians-min dalam Hukum Kuasa Taylor. Bagi setiap pelan, sebanyak 100 replikat simulasi dijanakan serentak dengan kaedah 'bootstrap' untuk setiap tahap ketepatan iaitu 0.20, 0.25 dan 0.30 dengan ambang tindakan ekonomi 2 ekor bena hijau/rumpun. Simulasi dilaksanakan pada empat set data yang dicerap dari suatu petak penyelidikan di Universiti Putra Malaysia. Hasil daripada simulasi menunjukkan bahawa pelan VIS memerlukan sampel yang sedikit dibandingkan dengan FSS, terutama pada tahap kepadatan GLH yang rendah dan tinggi apabila min kepadatan sangat berbeza daripada ambang tindakan. Pelan VIS berbeza daripada pelan pensampelan bersaiz tetap yang memerlukan sampel yang banyak untuk sentiasa mengekalkan tahap ketepatannya, terutama pada tahap kepadatan yang rendah. Anggaran min kepadatan oleh kedua-dua pelan hampir sama walaupun anggaran FSS lebih dekat dengan nilai kepadatan sebenar. Anggaran min kepadatan oleh VIS berubah-ubah dibandingkan dengan nilai yang dianggar dengan FSS kerana perbezaan saiz sampel. Kajian ini mendapati bahawa pelan FSS menghasilkan 98–100% ketepatan sebenar berbanding dengan ketepatan yang diperlukan pada kepadatan yang tinggi dan sederhana. Keadaan ini meningkatkan kos dan masa untuk membuat keputusan tindakan. Pada tahap kepadatan yang rendah pula, pelan FSS memerlukan lebih banyak sampel untuk mengekalkan ketepatan sebenar walaupun pada tahap yang lebih rendah daripada ketepatan yang diperlukan. Jelas pelan VIS lebih cekap daripada FSS untuk menganggarkan kepadatan dan membuat keputusan kerana saiz sampel boleh berubah berdasarkan nilai ambang tindakan.

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Abstract
This study compares the variable intensity sampling (VIS) and fixed-size sampling (FSS) plans for the green rice leafhopper (GLH), *Nephotettix* spp., in wet paddy ecosystem. The sampling plans were generated based on a regression model of variance-mean relationship in Taylor's Power Law. In each plan, 100 simulated replicates were generated simultaneously using a bootstrap approach for each of 0.20, 0.25 and 0.30 levels of precision with 2 hoppers/hill as the economic threshold. The simulations were performed on four independent data sets collected from an experimental plot at Universiti Putra Malaysia. Results obtained show that VIS requires the least number of samples compared to FSS, especially at low and high densities of GLH, i.e. when the mean density is greatly different from the threshold. VIS differs from other fixed precision level sampling plans which require large sample sizes to maintain a constant precision, especially at a low population density. The mean densities estimated by both plans are quite similar, though the FSS estimation was closer to the mean density of the actual data. The mean densities estimated by VIS are more variable than those estimated by FSS due to greater variability in sample size generated by VIS. This study indicates that FSS generated 98–100% of actual precision relative to the required precision, at high and intermediate densities. This increases the cost and time needed for decision making. At low densities, FSS required more samples to maintain the actual precision even at levels less than that desired. Hence in comparison, VIS plan is more efficient than FSS for density estimation and decision making, due to the flexibility of sample size required in relation to threshold values.

Introduction

Computer simulation provides a systematic way of creating virtual data, enabling examination of behaviour of a bigger data set, hence a better analysis of operational performance of certain procedures, e.g. monitoring and surveillance schemes that usually involve sampling plans (Hutchison et al. 1988; Nyrop and Binns 1991; Binns and Nyrop 1992). Moreover, simulation provides an inexpensive method of creating data, evaluating and validating the sampling plan, and saves cost since field work is obviated and the same computer programs can be reused in some applications (Hutchison 1994).

Simulation procedures have been used in studying many insects and their activities (e.g. Hassan and Wilson 1993) in various crop ecosystems. There are also procedures frequently applied in developing sampling plans in monitoring and decision making such as Kuno's and Green's fixed-precision stop lines on the pea aphids in alfalfa (Hutchison et al. 1988); for sequential sampling plan on the spruce bud moths (Regniere et al. 1988), the mango leafhoppers (Corey 1988), the green peach aphids on potato (Hollingsworth and Gatsonis 1990), the rice planthoppers (Shepard et al. 1986; Shepard, Ferrer et al. 1988; Shepard, Minnick et al. 1988; Shepard et al. 1989), the European red mites on apple (Nyrop and Binns 1992), and the pests and predators of wet paddy ecosystem (Hassan and Rashid 1997a, b); and for variable intensity sampling plan in cabbage pests (Hoy et al. 1983; Hoy 1991; Shelton et al. 1994).

Generally, there are two primary approaches in simulation as used for developing and validating sampling plans. First, the Monte Carlo method (Hoy et al. 1983; Nyrop and Binns 1991, 1992; Binns 1994) which requires the population to fit a conventional probability distribution, such as

Poisson or Negative Binomial (Hoy et al. 1983; Nyrop and Binns 1991). Second, the bootstrap approach method (Hutchison et al. 1988; Cho et al. 1995; Naranjo and Hutchison 1996) which assumes no specific underlying distribution of the data but resamples data files containing actual sample counts for the species of interest (Efron and Tibshirani 1986, 1993; Hutchison et al. 1988; Jones 1990; Naranjo and Hutchison 1996).

Variable intensity sampling (VIS) was initially developed as a new method for decision making in cabbage pest management (Hoy et al. 1983, 1991). This plan is more efficient and reliable than fixed-size and sequential sampling plans because the effort required for a precise density estimate is expended only when necessary, and samples are taken throughout the entire field within a designated sampling pattern (Hoy et al. 1983). In a designated sampling pattern, the field is divided into several segments, and some segments are selected for examination. The sample size for this plan is flexible depending on information obtained from each previous sample. Although the primary objective of VIS is not to classify population for decision making, in practice this plan can be used for management decision since it requires a range of critical densities or threshold (Binns and Nyrop 1992; Shelton et al. 1994). This procedure is suitable for situations in which spatial heterogeneity in a pest's density occurs in the field since it is based on the negative binomial distribution (Binns and Nyrop 1992; Jones 1994). Hoy et al. (1983) developed a simulation methodology for VIS for the cabbage looper, *Trichoplusia ni* (Hubner) and the imported cabbageworm, *Pieris rapae* (L.), based on the negative binomial distribution.

In this paper, we have generated a simulation scenario of variable intensity and fixed-size sampling using a resampling method on direct counting of insects from established data sets. The bootstrap technique is used to generate simulation of samples on previous *Nephotettix* spp. (Homoptera: Cicadellidae) (the green leafhopper, GLH) data sets with no assumption on the underlying mathematical distribution of insects. Instead, the dispersion indices based on Taylor's Power Law (1961, 1984) variance-mean model was used since it provides a widely proven species attribute relating mean and variance of insect population (Wilson and Room 1983; Hassan 1996; Hassan and Rashid 1997a, b). In this paper, attributes including statistics on mean density, variability, actual precision and sample size requirement are compared at three levels of reliability between variable intensity (VIS) and fixed-size (FSS) samplings.

Materials and methods

Data collection

Visual counts of arthropods per hill were recorded from experimental plots at Universiti Putra Malaysia, Serdang, Selangor (3 ° 2' N, 101 ° 42' E) in 1991. Weekly direct visual counting was done on GLH, the major species selected for analysis in this paper. Twenty hills per plot were examined at 3-h intervals, during each 24-h duration. At each site, the sampling path taken by walking through the field was varied from diagonal to zig-zag and semi-circle to ensure a good coverage of the entire field. Waterproof torchlights with 6V superheavy *Eveready®* batteries were used to examine the plants during the night sampling. The arthropods examined were easily recognised under this light.

Dispersion analysis

The density data were arranged according to factorial combinations of sampling date, sampling time and replicates. PROC MEANS of SAS (SAS Institute Inc. 1985) was then used to generate means and variances of pooled data of adults and nymphs of the GLH for each time interval samples at each sampling occasion. Dispersion indices were calculated using Taylor's (1961, 1984) Power Law ($\ln s^2$ =

ln$a$ + $b$ln$\bar{x}$) which is the regression of ln variance (s^2) on ln mean ($\bar{x}$). The intercept a represents a correction term related to sample size, and b is a species-specific aggregation constant. The regression analysis was conducted using General Linear Models Procedure of SAS (SAS Institute Inc. 1985). The goodness-of-fit of the linear regression model was evaluated using estimates of r^2. Student t-test was used to determine if the slope b of the regression was significantly different from unity, where >1, 1 and <1 described clumped, random and regular distributions respectively. The dispersion parameters of GLH were partly reported by Hassan (1996).

Development of sampling plans

The VIS plan was developed based on that of Hoy et al. (1983), but using Taylor's Power Law to derive coefficients a and b for GLH. Both VIS and FSS plans were developed at three precision levels of 0.20, 0.25 and 0.30. These levels balance precision and practical considerations, and are acceptable for most pest management purposes (Southwood 1978). The sample size needed to achieve the required and predetermined precision was calculated as a function of the mean, the 95% confidence interval (CI) for the mean threshold ($\bar{x}_{\text{thr}}$), and the ensuing algorithms for development of the plans are described in our previous paper (Rashid et al. 1998). The maximum sampling intensity (n_{max}) was used for all time intervals in the FSS plan.

Validation of sampling plans

A bootstrap simulation program was written in *Microsoft® QBasic.* Input parameters included the Taylor's coefficients, the action threshold, the number of simulation replicates, the minimum and maximum number of sampling units, and the desired precision levels. During simulation, a random number generator was used for each run to select successive samples from a given data set given the required sample size and predetermined time intervals. Both VIS and FSS plans were executed simultaneously at each simulation replicate thus enabling simultaneous counts of arthropod from the same selected sample. All the sampling units were examined by the FSS plan.

Simulations were performed on four independent data sets (four dates of sampling) of GLH collected from an experimental plot located at Universiti Putra Malaysia (UPM) in 1991, with 160 hill samples each date. These data sets were classified based on the threshold (2 hoppers/ hill) into three categories: category 1 – low density represented by the first sampling, category 2 – intermediate density shown by the second and third samplings, and category 3 – high density represented by the fourth sampling. Separate simulations were run for each category. During simulation, six hills were selected at each time interval for 10 time intervals as one simulation replicate or run. Therefore, 60 hills were determined as needed to be examined for FSS plan at each simulation. For each plan and desired precision level (D_0), 100 simulation runs were performed. Relative frequency histograms were established and summary statistics were calculated detailing actual precision levels, mean densities and sample sizes obtained, based on 100 simulation runs for each combination of density category, type of sampling and desired precision level.

Results and discussion

Dispersion analysis

Taylor's Power Law regression provided a good fit between population parameters of GLH and some other paddy arthropods (Hassan 1996). The coefficients of determination (r^2) ranged from 0.63 to 0.99, and 0.94 for GLH. In contrast, regressions using Iwao's (1968) patchiness concept yielded relatively lower r^2 (Hassan 1996). Therefore, Taylor's regression parameters were justifiably used to model the functional relationship between mean and variance in VIS and FSS plans. The slope and intercept of the regression line (n = 138) obtained in this paper were 1.16 and 1.48 respectively;

the dispersion pattern of GLHs was established as mostly clumped (Hassan 1996).

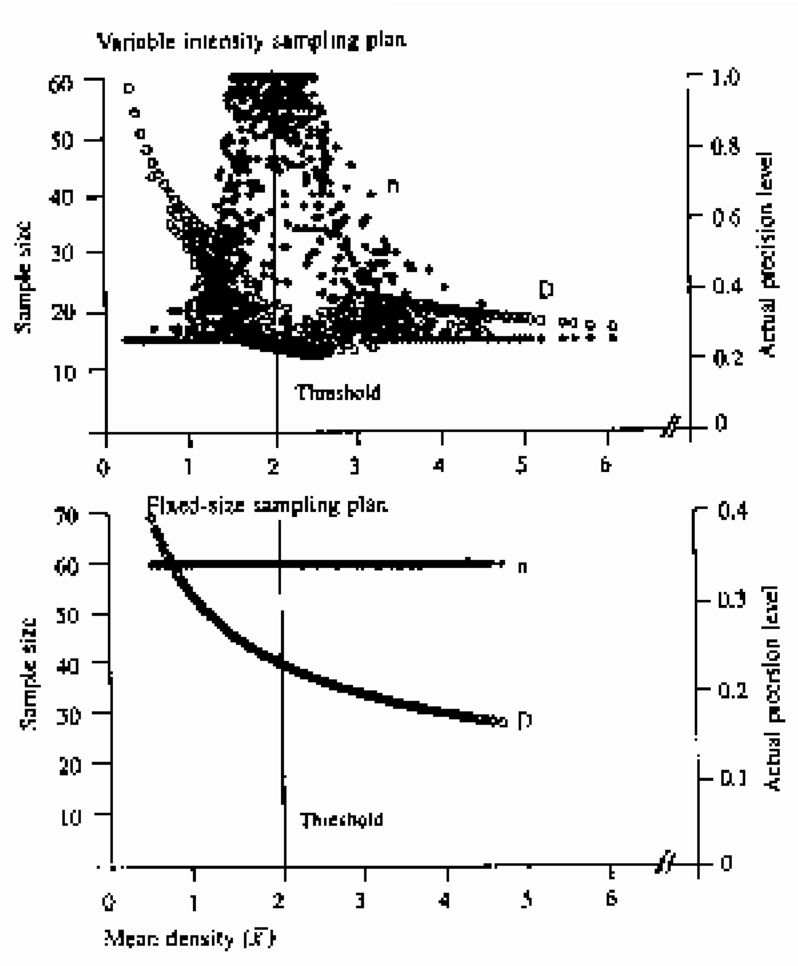
Validation of sampling plans

Statistics for both plans of 100 simulation runs at each sampling date are summarised in *Table 1*. In general, the VIS required fewer samples than FSS, especially at low and high densities (*Figure 1* to *Figure 5*). The relative frequency histograms of actual precision level obtained, mean density and sample size variability at three desired precision levels for low, intermediate and high densities are presented in *Figure 2* to *Figure 5*. The results also suggest that VIS requires minimum sample size when the mean density is greatly different from the threshold and larger sample size when mean density is closer to the threshold *(Figure 1)*. This differs from other predetermined fixed precision level sampling plans such as Kuno's (1969) and Green's (1970) sequential sampling plans, which require large sample sizes to maintain a constant precision or a fixed width confidence interval, especially at a lower density. In VIS, small sample size, nevertheless, yielded higher actual precision levels at low and high densities (*Table 1* and *Figure 1*). These are remarkably beneficial characteristics of VIS and other decision making sampling schemes which were designed for smaller sample size requirement hence lower cost incurred. Initially, estimation of density was the major objective of VIS plan (Hoy et al. 1983), but it evolved towards pest management decision-making purposes since VIS is similar to other sequential classification methods (Binns and Nyrop

Table 1. Statistics of fixed-size (60 hills) and variable intensity sampling based on 100 simulation runs for *Nephotettix* spp. at three desired precision levels, Universiti Putra Malaysia

Date	Statistics	Statistics from all samples (160 hills)	Av. statistics for 100 simulations at 3 desired precision levels					
			$D_0 = 0.20$		$D_0 = 0.25$		$D_0 = 0.30$	
			FSS	VIS	FSS	VIS	FSS	VIS
20 Feb. 1991	Mean density	0.98	1.00	0.95	0.94	0.87	0.99	0.95
	SEM	0.10	0.17	0.26	0.15	0.28	0.14	0.26
	D	–	0.31	0.62	0.29	0.60	0.31	0.62
	n	160.00	60.00	17.00	60.00	16.90	60.00	17.20
	% $D \leq D_0$	–	–	–	2.00	–	32.00	–
25 Feb. 1991	Mean density	1.58	1.59	1.52	1.58	1.46	1.58	1.47
	SEM	0.12	0.18	0.26	0.17	0.25	0.19	0.30
	D	–	0.25	0.36	0.25	0.39	0.25	0.39
	n	160.00	60.00	36.80	60.00	33.70	60.00	34.90
	% $D \leq D_0$	–	–	–	35.00	13.00	99.00	35.00
5 Mar. 1991	Mean density	2.26	2.24	2.28	2.26	2.28	2.22	2.24
	SEM	0.16	0.25	0.40	0.25	0.38	0.26	0.42
	D	–	0.22	0.25	0.22	0.26	0.22	0.26
	n	160.00	60.00	47.20	60.00	47.40	60.00	46.60
	% $D \leq D_0$	–	3.00	–	99.00	66.00	100.00	82.00
12 Mar. 1991	Mean density	3.62	3.62	3.65	3.56	3.70	3.59	3.70
	SEM	0.22	0.40	0.62	0.41	0.61	0.38	0.58
	D	–	0.18	0.32	0.18	0.33	0.18	0.32
	n	160.00	60.00	19.00	60.00	18.50	60.00	19.50
	% $D \leq D_0$	–	98.00	–	100.00	3.00	100.00	20.00

FSS = fixed-size sampling; SEM = standard error of mean; n = number of samples
VIS = variable intensity sampling; D = actual precision level



n = sample size
D = actual precision level

Figure 1. Relationship between calculated sample size and actual precision level for variable intensity sampling plan and fixed-size sampling plan to mean density (economic threshold chosen was 2 hoppers/hill for ***Nephotettix*** *spp., four sampling dates with 100 simulation runs)*

1992; Shelton et al. 1994). Nevertheless, the VIS plan does not consider the relative importance of classification errors since it was designed initially not for classification (Shelton et al. 1994).

The mean densities estimated by both plans were quite similar and their estimates were closer to the 160-hill fixed-size sample estimates *(Table 1)*. However, the standard errors of the mean of VIS were larger than those of FSS *(Table 1)*, hence resulting in broader 95% confidence intervals of the mean densities of VIS plan compared to FSS plan. This indicates that the mean densities estimated by VIS are more varied than those estimated by FSS (*Figure 2* to *Figure 5*) due to variability in sample size in algorithms of VIS.

In FSS, the actual precision level increases with increasing mean density *(Figure 1)*, hence increasing the reliability of estimates at high density with a larger sample size. However, sampling cost and time often limit sample size (Hassan and

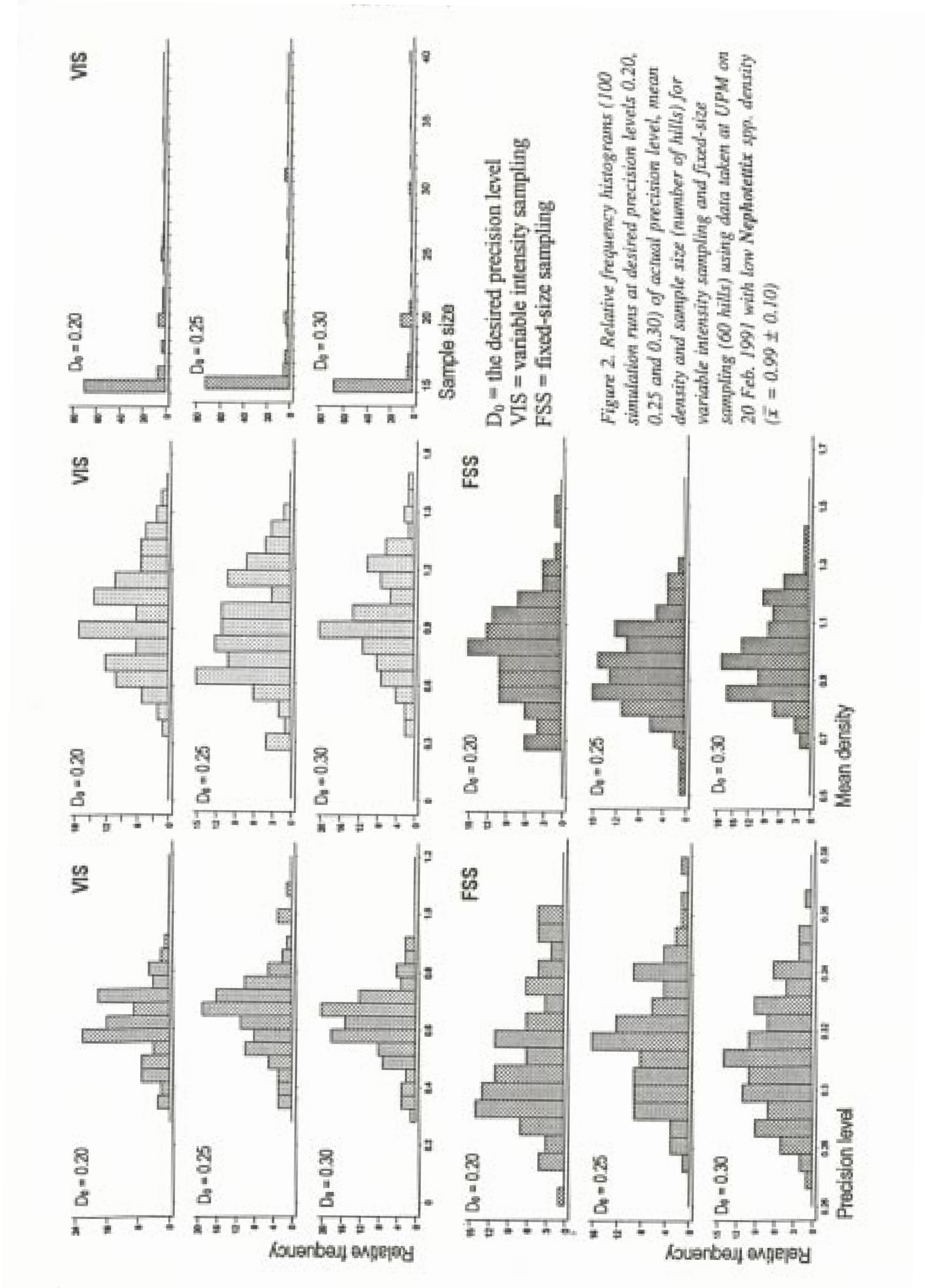


Figure 2. Relative frequency histograms (100 simulation runs at desired precision levels 0.20, 0.25 and 0.30) of actual precision level, mean density and sample size (number of hills) for variable intensity sampling and fixed-size sampling (60 hills) using data taken at UPM on 20 Feb. 1991 with low **Nephotettix** *spp. density ($\bar{x}$ = 0.99 ± 0.10)*

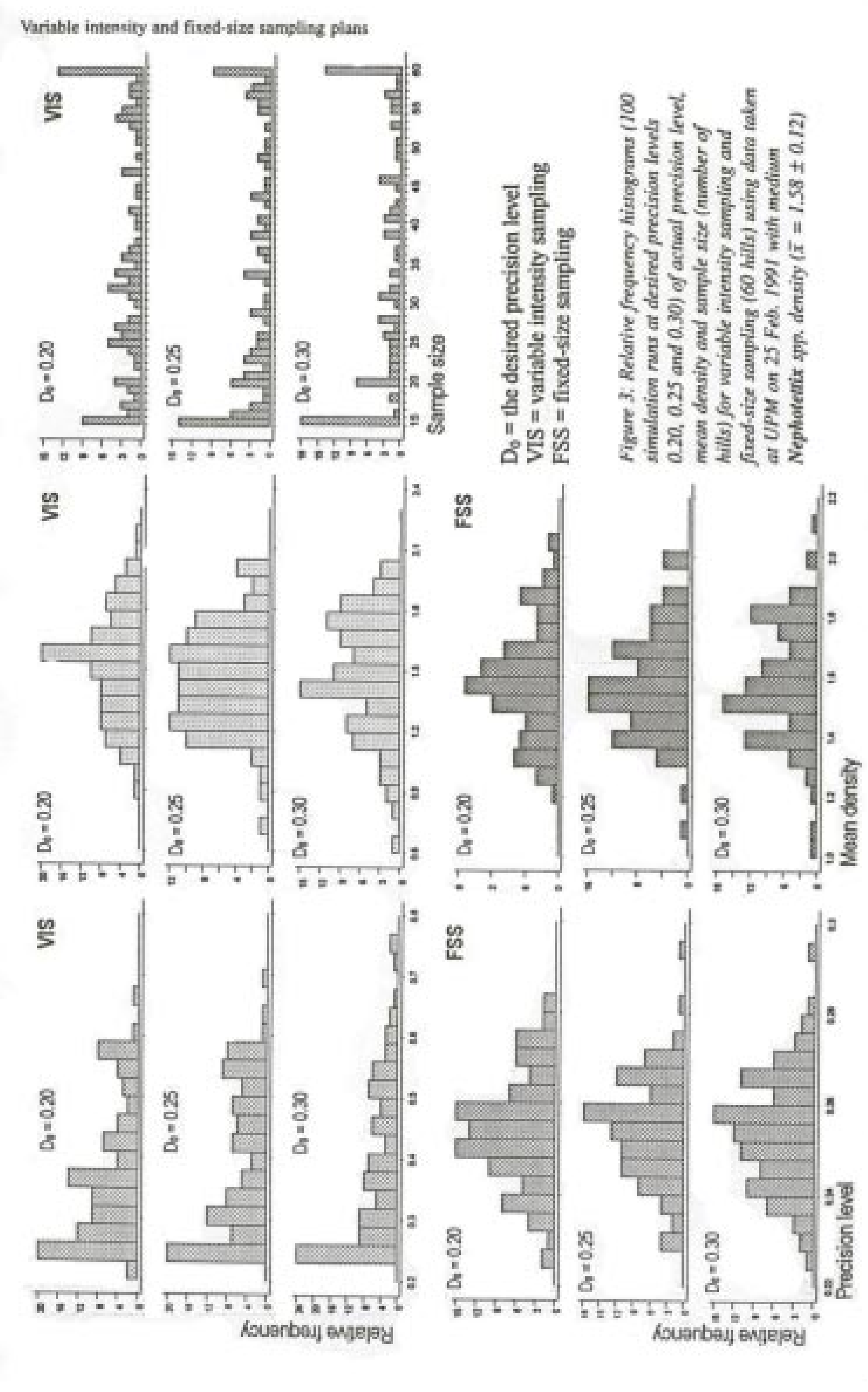


Figure 5: Relative frequency histograms (100 simulation runs at desired precision levels 0.20, 0.25 and 0.30) of actual precision level, mean density and sample size (number of hills) for variable intensity sampling and fixed-size sampling (60 hills) using data taken at UPM on 25 Feb. 1991 with medium Nephotettix spp. density ($\bar{x}$ = 1.58 ± 0.12)

Rashid 1997a). At low density, FSS requires more samples to maintain the actual precision level less than the desired precision level, especially at a higher precision requirement. Meanwhile, at high and intermediate densities, this plan generated 98–100% of actual precision level relative to the desired precision level *(Table 1).* Consequently, this plan leads to an increase in cost and time consumed in gathering more samples, while the predetermined precision level is already achieved, especially at a lower precision requirement. In contrast, higher percentage of the actual precision level less than the desired precision level in VIS plan occurred only for the third sampling (category 2) with 66–82% at a lower precision level *(Table 1)*, due to the larger sample size generated (*Figure 1*, *Figure 3* and *Figure 4*). Most of the relative frequencies of actual precision level estimated by FSS are normally distributed (*Figure 2* to *Figure 5*). In VIS, there is inconsistent distribution of relative frequency of actual precision level depending on the calculated sample size. Their relative frequencies at intermediate densities were skewed to the right with many more higher precision level estimates (particularly at a lower desired precision level), especially for a large sample size situation (*Figure 1*, *Figure 3* and *Figure 4*). *Table 1* clearly shows that the actual precision level equals 0.26 with 86% of them less than the desired precision level was generated by VIS at intermediate densities. However, as with other decision making schemes, VIS requires less precision at low or high densities for treatment decision hence incurring less cost and time.

In VIS, sample size varies depending on the actual (simulated) population mean densities in relation to the threshold (*Figure 2* to *Figure 5*). The sample size ranged from 15 to 40 at low densities *(Figure 2)* and from 15 to 60 at high densities *(Figure 5).* However, the minimum sample size required was 15 at both densities *(Figure 1)*, as clearly shown by the relative frequency for sample size obtained (*Figure 2* and *Figure 5*). Although the range of the required sample sizes is similar (15–60), the relative frequencies of sample required differ between the second *(Figure 3)* and the third samplings *(Figure 4).* The second sampling shows that the relative frequencies of small and high sample sizes were similar *(Figure 3)*, whereas a larger sample size is required for the third sampling *(Figure 4).* Therefore, these results suggest that most decisions would be to continue sampling in the third sampling since the larger sample sizes indicate that the estimated mean densities are closer to the threshold. Conversely, in the first and fourth samplings, fewer samples were required indicating that the estimated mean is far from the threshold, hence the decision is either ‘not to treat’ or ‘to treat’ (Binns and Nyrop 1992; Hoy et al. 1983; Shelton et al. 1994).

This study indicates that VIS plan is more efficient and reliable than FSS as a decision making tool as well as for density estimation, due to the flexibility of the sample size in relation to the mean threshold. The advantages of this plan are reduction in cost and time in gathering samples when the population mean density is either low or high. Nevertheless, the density estimations by both plans are similar. A good estimate of precision level is shown in FSS plan compared to the VIS. However, high precision level consideration is a lesser-important requisite for generating and operating plans used in making treatment decision in pest management (Shelton et al. 1994).

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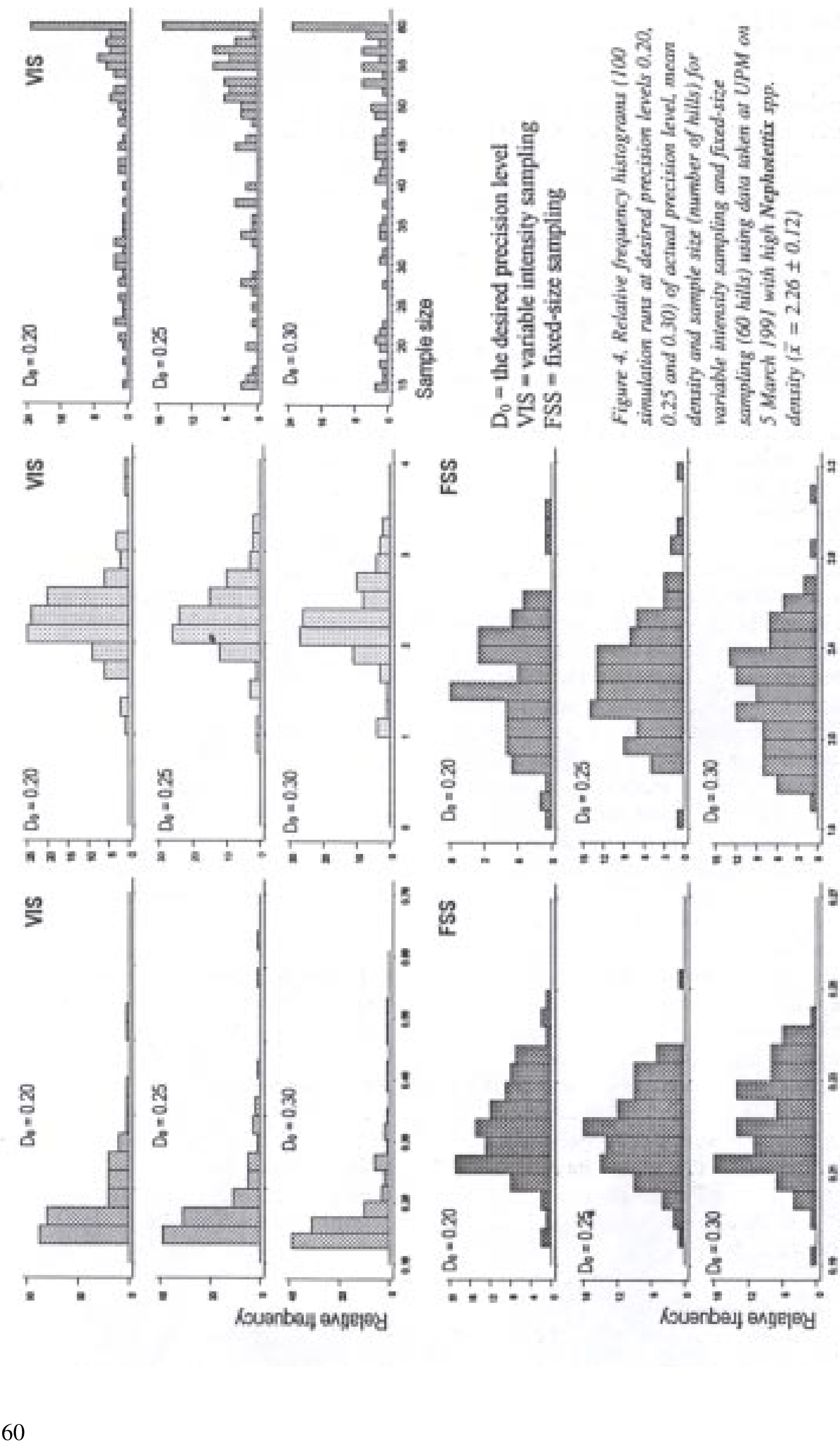
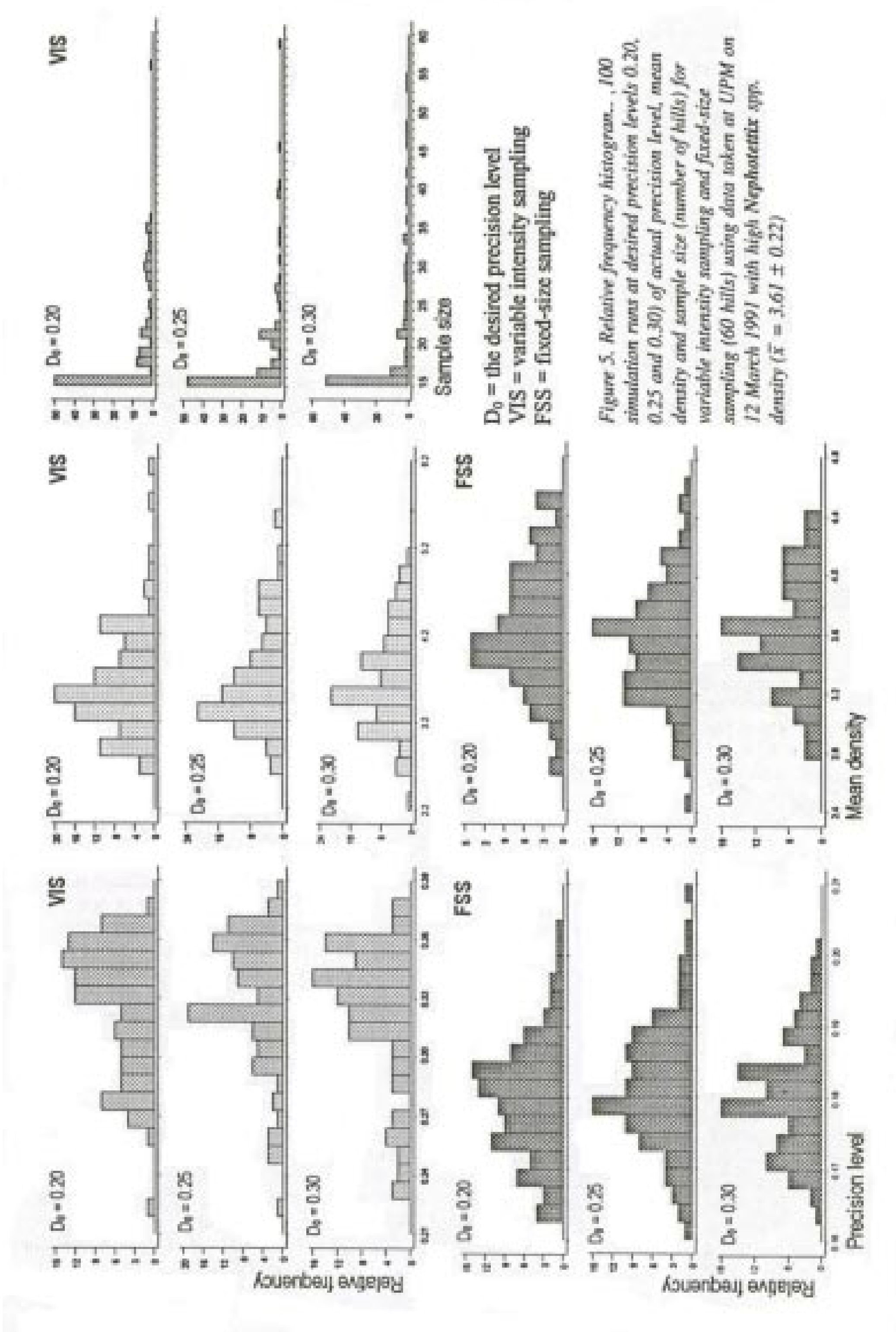


Figure 4. Relative frequency histograms (100 simulation runs at desired precision levels 0.20, 0.25 and 0.30) of actual precision level, mean density and sample size (number of hills) for variable intensity sampling and fixed-size sampling (60 hills) using data taken at UPM on 5 March 1991 with high **Nephotettix** *spp. density ($\bar{x}$ = 2.26 ± 0.12)*



D_0 = the desired precision level
VIS = variable intensity sampling
FSS = fixed-size sampling

*Figure 5. Relative frequency histogram... 100 simulation runs at desired precision levels 0.20, 0.25 and 0.30) of actual precision level, mean density and sample size (number of hills) for variable intensity sampling and fixed-size sampling (60 hills) using data taken at UPM on 12 March 1991 with high **Nephotettix** spp. density ($\bar{x}$ = 3.61 ± 0.22)*

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