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**Optimal sample size for composite sampling with subsampling, when estimating proportion of pecky rice grains in a field**

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1           The proportion of pecky rice grains has been empirically estimated using  
2 composite sampling with subsampling. The procedure is summarized as follows: (1) a  
3 fixed number of rice plants ( $n_1$ ) are drawn at random in the paddy field; (2) all the rice  
4 grains in the collected rice plants are mixed well to form a composite; (3) a portion of the  
5 grains ( $n_2$ ) are drawn at random from the composite; and (4) the collected grains are  
6 examined by eye to estimate the proportion of pecky rice grains. We propose a method to  
7 determine the optimal sample size in estimating the proportion of defective items by this  
8 kind of composite sampling with subsampling. Spatial heterogeneity in the proportion of  
9 defective items is included in the estimation. We use Taylor's power law to describe the  
10 density-dependent change of spatial heterogeneity. In controlling the precision of the  
11 estimate, we use the relative precision ( $D$ ) that is defined by the coefficient of variation of  
12 the estimated proportion. We propose a rejection procedure where the product is rejected  
13 if the estimate of proportion with  $D = 0.25$  is larger than a predetermined tolerable  
14 threshold of proportion. We further consider another control criterion where the  
15 consumer's risk ( $\beta$ ) is controlled by a zero-tolerance method. The relation between two  
16 control criteria is examined.

17

18 **Keywords:** Consumer's risk; Increment sampling; Relative precision; Spatial  
19 heterogeneity; Taylor's power law

20

# 1. INTRODUCTION

The relative significance of insect pest species in paddy fields has greatly changed in the past 50 years in Japan (Kiritani 2006). The populations of the three classical major pests, the rice stem borer, *Chilo suppressalis*, the green rice leafhopper, *Nephotettix cincticeps*, and the small brown planthopper, *Laodelphax striatellus*, have greatly decreased in this time (Yamamura et al. 2006). The agricultural loss caused by these insects decreased accordingly. On the other hand, the agricultural loss caused by several rice bugs has increased since about 1995. The rice bugs are becoming the most serious insect pests in paddy fields. These rice bugs consist of several species of Pentatomidae, Coreidae, Alydidae and Miridae. The rice leaf bug, *Trigonotylus caelestialium* (Kirkaldy), is especially important in the northern part of Japan. These insects suck the rice grain to generate pecky rice grains. The existence of pecky rice grains causes serious problems even if the proportion of pecky rice grains is quite small. The grade of rice falls from first grade to second grade if the proportion of colored grains including pecky rice grains is larger than 0.001 (Ministry of Agriculture Forestry and Fisheries 2001). The market price of rice seriously decreases due to this downgrading. For example, the price of 30 kg rice grains may change from 7500 yen to 7000 yen.

The proportion of pecky rice grains is usually quite small, and hence a composite sampling procedure with subsampling has been empirically used in estimating the proportion. The procedure is summarized as follows: (1) a fixed number of rice plants are drawn at random in the paddy field and brought to the laboratory; (2) all the rice grains in the collected rice plants are mixed well to form a composite; (3) a portion of grains are drawn at random from the composite; and (4) the selected grains are examined by eye to estimate the proportion of pecky rice grains. A plant corresponds to the quantity called an increment. A rice grain corresponds to a sampling item.

Various composite sampling procedures that examine composites of sampling

1 items instead of examining individual sampling items have been developed as  
2 cost-effective procedures (Boswell et al. 1988; Lovinson et al. 1994; Lancaster and  
3 Keller-McNulty 1998; United States Environmental Protection Agency 2000; Patil  
4 2002). Some of these procedures are used for classification purposes, for example, to find  
5 HIV-infected persons effectively (Dorfman 1943; Sterrett 1957; Bhattacharyya et al.  
6 1979; Emmanuel et al. 1988; Zenios and Wein 1998; Johnson and Patil 2001). Other  
7 procedures of composite sampling are used for estimation purposes. The parameters of  
8 interest are either continuous variables or binary variables. In applying the composite  
9 sampling to continuous variables, the theory has been developed for various sampling  
10 schemes that allow the subsampling from composites (Brown and Fisher 1972; Rohde  
11 1976; Elder et al. 1980; Rohlf et al. 1996). In applying the composite sampling to binary  
12 variables, however, the application is mostly confined to the procedure called group  
13 testing (Chiang and Reeves 1962; Thompson 1962; Swallow 1985; Burrows 1987;  
14 Swallow 1987; Chen and Swallow 1990; Gastwirth and Johnson 1994; Hughes-Oliver  
15 and Swallow 1994; Chick 1996; Zenios and Wein 1998; Brookmeyer 1999; Colón et al.  
16 2001; Tebbs et al. 2003; Hsu 2005; Bar-Lev et al. 2006; Yamamura and Hino 2007). In a  
17 group testing procedure for estimating the proportion of defective items, the sampling  
18 items are drawn at random and mixed, and all the items in the composite are used to  
19 examine the existence of defective items. This procedure is repeated several times to  
20 obtain an estimate of the proportion of defective items.

21         The sampling procedure for estimating the proportion of pecky rice grains is  
22 different from group testing procedures in two aspects: (1) rice grains are not drawn at  
23 random in the field, but rice grains are instead drawn as increments (i.e., clusters) given  
24 by rice plants; and (2) only a portion of the rice grains in the composite is measured by  
25 using subsampling from the composite. In this paper, we discuss the method of  
26 determining the sample size in estimating the proportion of defective items by this kind of  
27 sampling. In controlling the precision of the estimate, we use the relative precision ( $D$ )

1 that is defined by the coefficient of variation (CV) of the estimated proportion. We use  
2 Taylor's power law to describe the relation between the mean and spatial heterogeneity in  
3 the proportion of defective items. We propose a rejection procedure where the product is  
4 rejected if the estimate of proportion with  $D = 0.25$  is larger than a predetermined  
5 tolerable threshold of proportion. We further consider another control criterion where the  
6 consumer's risk ( $\beta$ ) is controlled by a zero-tolerance method. The relation between two  
7 control criteria is examined.

## 2. SPECIFIC MODEL

11 We use the following notations.

12  $s_i$  = the number of grains in the  $i$ th plant,

13  $n_1$  = the number of drawn rice plants,

14  $n_2$  = the number of rice grains drawn from the composite ( $n_2 \leq s_i n_1$ ),

15  $P_i$  = the probability that a rice grain around the  $i$ th plant is pecky,

16  $P_0$  = the average of  $P_i$  over the sampling field, i.e.,  $P_0 = E(P_i)$ ,

17  $X_i$  = the number of pecky rice grains in the  $i$ th plant,

18  $Y$  = the total number of pecky rice grains in the composite, i.e.,  $Y = \sum_1^{n_1} X_i$ ,

19  $Z$  = the number of pecky rice grains in the  $n_2$  grains that are drawn from the composite.

21 We want to estimate  $P_0$ , that is, the average of the proportion of pecky rice grains. The  
22 proportion of pecky rice grains per plant fluctuates depending on the spatial position of  
23 the rice plants in the field. We assume that the proportion of pecky rice grains fluctuate  
24 following a distribution. This type of estimation is sometimes called 'model-based  
25 approach' (Lohr 1999, p47; Thompson 2002, p22). For simplicity, we first assume a  
26 specific form of distribution in describing the spatial heterogeneity. A beta distribution is

frequently used to describe the heterogeneity in the proportions. The proportion of pecky rice grains is usually very small. A beta distribution can be approximately described by a gamma distribution when the average proportion is small, and hence we use a gamma distribution that is more tractable than a beta distribution. The probability density of  $P_i$  is given by

$$f(p) = \frac{1}{\Gamma(k)} \lambda^k p^{k-1} \exp(-\lambda p), \quad (2.1)$$

where  $k$  and  $\lambda$  are the shape parameter and scale parameter, respectively. The mean ( $P_0$ ) and variance ( $V(P_i)$ ) are given by  $k/\lambda$  and  $k/\lambda^2$ , respectively. Thus, we are estimating the parameter of the model,  $k/\lambda$ , in this case. The number of pecky rice grains in the  $i$ th plant ( $X_i$ ) for a given  $P_i$  is given by a binomial distribution, but we can use a Poisson distribution as an approximation if the  $P_i$  is sufficiently small. If we use a distribution which is conditional to  $s_i$ , we have

$$\Pr(X_i = x | P_i = p) = \frac{1}{x!} (s_i p)^x \exp(-s_i p), \quad (2.2)$$

Then, the probability density of  $X_i$  is given by

$$\begin{aligned} \Pr(X_i = x) &= \int_0^{\infty} \Pr(X_i = x | P_i = p) f(p) dp \\ &= \frac{\Gamma(k+x)}{x! \Gamma(k)} \left(1 + \frac{s_i}{\lambda}\right)^{-k} \left(\frac{s_i}{\lambda + s_i}\right)^x, \end{aligned} \quad (2.3)$$

which is a negative binomial distribution with mean  $s_i k/\lambda$  and variance  $s_i k(\lambda + s_i)/\lambda^2$ .

For simplicity, we assume that the number of grains in a plant ( $s_i$ ) is almost the same for all plants, and we denote it by  $s$  by omitting the subscript. We assume that  $s$  is

1 known to us beforehand. Then, the distribution of  $Y$  is given by the  $n_1$  times convolution  
 2 of (2.3). We readily obtain the following distribution due to the reproducibility of the  
 3 negative binomial distribution (Minotani 2003).

$$4 \quad \Pr(Y = y) = \frac{\Gamma(n_1 k + y)}{y! \Gamma(n_1 k)} \left(1 + \frac{s}{\lambda}\right)^{-n_1 k} \left(\frac{s}{\lambda + s}\right)^y. \quad (2.4)$$

6  
 7 The mean and variance of  $Y$  are given by  $sn_1 k/\lambda$  and  $sn_1 k(\lambda + s)/\lambda^2$ , respectively.

8 The probability distribution of the number of pecky rice grains ( $Z$ ) in the  $n_2$  grains  
 9 that are obtained by a subsampling from the composite is most exactly expressed by a  
 10 hypergeometric distribution.

$$11 \quad \Pr(Z = z | Y = y) = \frac{\binom{y}{z} \binom{n_1 s - y}{n_2 - z}}{\binom{n_1 s}{n_2}}. \quad (2.5)$$

13  
 14 If the proportion of pecky rice grains in the composite ( $Y/(n_1 s)$ ) is sufficiently small, we  
 15 can approximately consider that each pecky rice grain in the composite is drawn by an  
 16 equal probability,  $n_2/(n_1 s)$ . Kuno (1991) used this form of binomial approximation of  
 17 hypergeometric distribution in deriving the sample size for zero-tolerance method.

$$18 \quad \Pr(Z = z | Y = y) = \binom{y}{z} \left(\frac{n_2}{n_1 s}\right)^z \left(1 - \frac{n_2}{n_1 s}\right)^{y-z}. \quad (2.6)$$

20  
 21 Then, the number of pecky rice grains ( $Z$ ) in the subsample is given either by a compound  
 22 distribution (i.e., a stopped-sum distribution by the terminology of Johnson et al. 2005) or  
 23 a mixture distribution; a compound negative binomial distribution that is compounded  
 24 with Bernoulli distribution of the parameter  $n_2/(n_1 s)$ ; or a mixture binomial distribution  
 25 where the number of trials ( $Y$ ) follows a negative binomial distribution. The compound

1 distribution or the mixture distribution yields the negative binomial distribution where the  
 2 mean is multiplied by  $n_2/(n_1s)$  while the shape parameter is the same (Shimizu 2006).

$$3 \Pr(Z = z) = \frac{\Gamma(n_1k + z)}{z! \Gamma(n_1k)} \left(1 + \frac{n_2}{n_1\lambda}\right)^{-n_1k} \left(\frac{n_2}{n_1\lambda + n_2}\right)^z. \quad (2.7)$$

5  
 6 The mean and variance of  $Z$  are given by  $n_2k/\lambda$  and  $n_2k(n_1\lambda + n_2)/(n_1\lambda^2)$ , respectively. The  
 7 estimate of  $P_0$  is given by

$$8 \hat{P}_0 = Z/n_2. \quad (2.8)$$

10  
 11 Hence, (2.7) yields the following mean and variance of the estimate.

$$12 E(\hat{P}_0) = k/\lambda = P_0, \quad (2.9)$$

$$13 V(\hat{P}_0) = \frac{k(n_1\lambda + n_2)}{n_1n_2\lambda^2}. \quad (2.10)$$

### 15 16 3. GENERAL MODEL

17 We can extend the above argument to general distributions of the proportion of  
 18 pecky rice grains. The mean and variance of pecky rice grains ( $X_i$ ) in the  $i$ th plant with a  
 19 known  $s_i$  are given by

$$20 E(X_i) = \int_0^\infty E(X_i | P_i = p) f(p) dp$$

$$21 = \int_0^\infty s_i p f(p) dp = s_i P_0, \quad (3.1)$$

$$22 V(X_i) = \int_0^\infty E((X_i - s_i P_0)^2 | P_i = p) f(p) dp$$

$$23 = \int_0^\infty (E(X_i - s_i P_i)^2 + (s_i P_i - s_i P_0)^2 | P_i = p) f(p) dp$$



$$\begin{aligned}
&= \int_0^{\infty} (s_i p + s_i^2 (p - P_0)^2) f(p) dp \\
&= s_i P_0 + s_i^2 V(P_i).
\end{aligned}
\tag{3.2}$$

3

4 The rearrangement of (3.1) and (3.2) yields the following equation.

5

$$P_0 = E\left(\frac{X_i}{s_i}\right), \tag{3.3}$$

$$V(P_i) = V\left(\frac{X_i}{s_i}\right) - E\left(\frac{X_i}{s_i^2}\right). \tag{3.4}$$

8

9 We can obtain the moment estimates of  $P_0$  and  $V(P_i)$  by substituting the mean and  
10 variance of  $X_i/s_i$  and the mean of  $X_i/s_i^2$  into (3.3) and (3.4). Numerical examples of  
11 calculation are shown in the electronic material that is stored in JABES site  
12 (<http://www.amstat.org/publications/jabes/data.shtml>). As for the mean and variance of  
13 the total number of pecky rice grains in the composite ( $Y$ ), we have the following  
14 equation.

15

$$E(Y) = \sum_{i=1}^{n_1} s_i P_0, \tag{3.5}$$

$$V(Y) = \sum_{i=1}^{n_1} (s_i P_0 + s_i^2 V(P_i)). \tag{3.6}$$

18

19 For simplicity, we again assume that the number of grains in a plant ( $s_i$ ) is almost the  
20 same for all plants, and we denote it by  $s$  by omitting the subscript. We assume that  $s$  is  
21 known to us beforehand.

22 The probability distribution of the number of pecky rice grains ( $Z$ ) in the  $n_2$  grains  
23 that are obtained by a subsampling from the composite is expressed by a hypergeometric  
24 distribution given by (2.5). The mean and variance are given by

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$$E(Z | Y = y) = \frac{n_2 y}{n_1 s}, \tag{3.7}$$

$$\begin{aligned} V(Z | Y = y) &= \frac{n_2(n_1 s - n_2)}{n_1 s - 1} \frac{y}{n_1 s} \left(1 - \frac{y}{n_1 s}\right) \\ &\approx \frac{n_2(n_1 s - n_2)}{n_1 s} \frac{y}{n_1 s} \\ &= y \frac{n_2}{n_1 s} \left(1 - \frac{n_2}{n_1 s}\right). \end{aligned} \tag{3.8}$$

We again used a binomial approximation where  $y$  is the number of trials and  $n_2/(n_1 s)$  is the probability of occurrence. This approximation will be valid because we are considering a situation where the proportion of pecky rice grains in the composite ( $Y/(n_1 s)$ ) is sufficiently small. The expectation of  $\hat{P}_0$  is given by

$$\begin{aligned} E(\hat{P}_0) &= \frac{1}{n_2} \sum_{y=0}^{\infty} \sum_{z=0}^y z \Pr(Z = z | Y = y) \Pr(Y = y) \\ &= P_0. \end{aligned} \tag{3.9}$$

Thus,  $\hat{P}_0$  is an unbiased estimate of  $P_0$ . The variance of  $\hat{P}_0$  is given by

$$\begin{aligned} V(\hat{P}_0) &= \frac{1}{n_2^2} \sum_{y=0}^{\infty} \sum_{z=0}^y [z - E(Z)]^2 \Pr(Z = z | Y = y) \Pr(Y = y) \\ &= \frac{1}{n_2^2} \sum_{y=0}^{\infty} \sum_{z=0}^y \left[ (z - E(Z | Y = y))^2 + (E(Z | Y = y) - E(Z))^2 \right] \Pr(Z = z | Y = y) \Pr(Y = y) \\ &\approx \frac{1}{n_2^2} \sum_{y=0}^{\infty} \left[ y \frac{n_2}{n_1 s} \left(1 - \frac{n_2}{n_1 s}\right) \right] \Pr(Y = y) + \frac{1}{n_2^2} \left(\frac{n_2}{n_1 s}\right)^2 V(Y) \\ &= \frac{P_0}{n_2} + \frac{V(P_i)}{n_1}, \end{aligned} \tag{3.10}$$

1 where we used the binomial approximation of (3.8). The rearrangement of (3.9) and  
2 (3.10) yields the following equation.

$$3 \quad V(P_i) = n_1 V(\hat{P}_0) - \left( \frac{n_1}{n_2} \right) E(\hat{P}_0). \quad (3.11)$$

5  
6 If we could estimate the mean and variance of  $\hat{P}_0$  by repeating the composite sampling in  
7 the same field, we can obtain the moment estimates of  $P_0$  and  $V(P_i)$  by using (3.9) and  
8 (3.11), although such an estimation is not practical in our case.

#### 11 4. DEFINITION OF PRECISION

12 If the distribution of  $\hat{P}_0$  could be approximately described by a normal  
13 distribution with a mean  $P_0$  and a fixed variance  $V(\hat{P}_0)$ , the 95% confidence interval of  
14  $\hat{P}_0$  is given by  $\hat{P}_0 \pm 1.96\sqrt{V(\hat{P}_0)}$ . We can keep the width of confidence interval at a  
15 constant by controlling  $V(\hat{P}_0)$  at a constant. However,  $P_0$  does not have negative  
16 quantity;  $P_0$  will be rather determined by a multiplicative manner than by an additive  
17 manner. Hence, it will be preferable to keep the relative width of confidence interval at a  
18 constant instead of keeping the absolute width of confidence interval at a constant. Then,  
19 instead of controlling the quantity of  $V(\hat{P}_0)$  at a constant, we control the precision by the  
20 relative precision ( $D$ ) defined by the coefficient of variation (CV) of the estimates (Kuno  
21 1986):

$$22 \quad D = \sqrt{V(\hat{P}_0)} / P_0. \quad (4.1)$$

24  
25 The required quantity of  $D$  changes depending on the purpose of the control. By  
26 substituting (3.10) into (4.1), we obtain

1

$$2 \quad D^2 = \frac{1}{n_2 P_0} + \frac{V(P_i)}{n_1 P_0^2}. \quad (4.2)$$

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4 For a fixed set of  $n_1$  and  $D$ , we can calculate the required quantity of  $n_2$  by

5

$$6 \quad n_2 = \frac{n_1 P_0}{D^2 n_1 P_0^2 - V(P_i)}. \quad (4.3)$$

7

8 We have an inequality,  $sn_1 \geq n_2$ . Hence, (4.3) indicates that  $n_1$  must satisfy the following  
9 condition:

10

$$11 \quad n_1 \geq \frac{P_0 + sV(P_i)}{D^2 s P_0^2}. \quad (4.4)$$

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## 5. TAYLOR'S POWER LAW

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$$21 \quad \log_e(\sigma^2) = \log_e(a) + b \log_e(\mu), \quad (5.1)$$

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The spatial distribution of the proportion of pecky rice grains will change depending on the spatial distribution of rice bugs. The distribution of insects can be generally described by Taylor's power law (Taylor 1961; Taylor et al. 1978; Taylor et al. 1979; Taylor 1984). Let  $\mu$  and  $\sigma^2$  be the spatial mean and variance of the number of insects, respectively. Then, we frequently find a linear relation called Taylor's power law:

where  $a$  and  $b$  are constants. The parameter  $b$  usually lies between 1 and 2. This linear relation is approximately generated if the density of individuals increases with increasing occupied area. A nearly exact linear relation emerges when the quantity of (instantaneous

1 increasing rate of density)/(instantaneous expansion rate of occupied area) is constant  
 2 (Yamamura 2000). Taylor's power law will be also applicable to the variance of the  
 3 distribution of the proportion of pecky rice grains because the proportion of pecky rice  
 4 grains will be approximately proportional to the incidence of rice bugs.

$$5 \log_e[V(P_i)] = \log_e(a) + b \log_e(P_0). \quad (5.2)$$

7  
 8 We obtain the following equations by substituting (5.2) into (4.2) and (4.3).

$$9 \quad D^2 = \frac{1}{n_2 P_0} + \frac{a P_0^{b-2}}{n_1}, \quad (5.3)$$

$$10 \quad n_2 = \frac{n_1}{D^2 n_1 P_0 - a P_0^{b-1}}. \quad (5.4)$$

11  
 12  
 13 The range of  $n_1$  given by (4.4) is expressed by

$$14 \quad n_1 \geq \frac{sa P_0^{b-1} + 1}{D^2 s P_0}. \quad (5.5)$$

## 15 16 17 18 6. CONTROL OF PRECISION

19 We can obtain the combination of  $n_1$  and  $n_2$  that achieves the relative precision  $D$   
 20 by using (5.4). However, we have a contradiction in this respect; we must know the  
 21 quantity of  $P_0$  beforehand to estimate  $P_0$  with a specified precision by using (5.4). We can  
 22 avoid this contradiction by determining the critical quantity of  $P_0$  that is tolerable. Let us  
 23 denote the critical quantity by  $P_c$ . The derivative of (5.3),  $\partial(D^2)/\partial P_0$ , is negative at least  
 24 if  $b < 2$ . Therefore, if we use a set of  $n_1$  and  $n_2$  that achieves a given relative precision ( $D$ )  
 25 under  $P_c$ , we can achieve a smaller  $D$  for all  $P_0$  values that are larger than  $P_c$ . Thus, the

1 precision of the estimates becomes superior for a larger  $P_0$ ; we can enhance the precision  
 2 of estimates for a worse case than  $P_c$ . In that sense, we can control the precision by using  
 3 the set of  $n_1$  and  $n_2$  that are calculated at the critical proportion  $P_c$ .

4 We can calculate the optimal combination of  $n_1$  and  $n_2$  that minimizes the total  
 5 cost of inspection. Let  $c_1$  be the cost that is required to collect one rice plant, and let  $c_2$  be  
 6 the cost that is required to examine one rice grain. Then, the total cost ( $c_{\text{total}}$ ) is given by

$$8 \quad c_{\text{total}} = c_1 n_1 + c_2 n_2. \quad (6.1)$$

9  
 10 Let  $n_1^*$  and  $n_2^*$  be the optimal quantities of  $n_1$  and  $n_2$ , respectively, that minimize the total  
 11 cost to achieve a fixed amount of  $D$ . We can calculate  $n_1^*$  by solving  $\partial c_{\text{total}} / \partial n_1 = 0$  after  
 12 substituting (5.4) into (6.1) to eliminate  $n_2$ .

$$13 \quad n_1^* = \sqrt{\frac{c_2}{c_1}} \frac{\sqrt{a}}{D^2} P_c^{0.5b-1.5} + \frac{a}{D^2} P_c^{b-2}. \quad (6.2)$$

14  
 15 The corresponding quantity of  $n_2^*$  is calculated by using (5.4). Actual sample size is an  
 16 integer, and hence the exact optimal quantity of  $n_1$  is either integer just below  $n_1^*$  or just  
 17 above  $n_1^*$ .

18  
 19 To minimize the quantity  $D$  for a fixed total cost ( $c_{\text{total}}$ ), let  $n_1'$  and  $n_2'$  be the  
 20 optimal quantities of  $n_1$  and  $n_2$ , respectively. Then  $n_1'$  is found to be

$$21 \quad n_1' = \frac{c_{\text{total}} \sqrt{a P_c^{b-1}}}{\sqrt{c_1} \left( \sqrt{c_2} + \sqrt{a c_1 P_c^{b-1}} \right)}. \quad (6.3)$$

22  
 23 The corresponding quantity of  $n_2'$  is calculated by using (6.1).

24  
 25 It should be noted that the cost function of (6.1) is different from that of a

1 two-stage sampling. The total cost in (6.1) is more precisely described by

$$2 \quad 3 \quad c_{\text{total}} = c_0 + c_1 n_1 + c_2 n_2, \quad (6.4)$$

4  
5 where  $c_0$  is the cost for making a composite. If we adopt a two-stage sampling in which  
6 grains are drawn separately from each sampled plant, we can estimate the proportion of  
7 pecky rice grains by using the known formula for two-stage sampling for proportion  
8 (Cochran 1977, p279). In a two-stage sampling, the total cost is roughly given by

$$9 \quad 10 \quad c_{\text{total}} = (c_0 + c_1)n_1 + c_2 n_2, \quad (6.5)$$

11  
12 where the cost for preparing composites becomes  $n_1$  times larger than that of a composite  
13 sampling. Hence, a two-stage sampling is scarcely adopted for the estimation of the  
14 proportion of pecky rice grains except for experimental purposes.

## 15 16 17 7. REJECTION PROCEDURE USING $D = 0.25$

18 In judging the difference in the abundance of insect pests, half of the quantity of  
19 the density is frequently used empirically in Japan. In the official experiments used to  
20 evaluate the effectiveness of pesticides, for example, the abundance of insects in treated  
21 fields is judged to be smaller than that in control fields if the observed difference is larger  
22 than 50% of the quantity of the abundance in control fields (Japan Plant Protection  
23 Association 2003). The definition in (4.1) indicates that the standard error (SE) is given  
24 by  $DP_0$ . The 95% confidence limits are given by  $\pm 1.96 \times \text{SE}$  in a case of a normal  
25 distribution with a fixed variance. If we use  $D = 0.25$ , therefore, the 95% confidence  
26 interval of  $\hat{P}_0$  is approximately given by  $[0.5\hat{P}_0, 1.5\hat{P}_0]$  under the normal approximation

1 with a fixed variance. Hence, we empirically use  $D = 0.25$  as a standard, although  $\hat{P}_0$  will  
2 not exactly follow a normal distribution.

3 In the actual inspection of the proportion of pecky rice grains, we must judge the  
4 acceptance of product by using  $\hat{P}_0$ . We consider a rejection procedure where we reject  
5 the product of a field if we obtain  $\hat{P}_0 > P_c$ . The probability of acceptance is about 0.975 at  
6  $P_0 = 0.5P_c$ , 0.5 at  $P_0 = P_c$ , and 0.025 at  $P_0 = 1.5P_c$ , if the distribution of  $\hat{P}_0$  follows a  
7 normal distribution with a fixed variance, under the sampling procedure that controls the  
8 relative precision at  $D = 0.25$ . Therefore, the producer's risk (i.e., the probability of false  
9 rejection of a superior product) is 0.025 at  $P_0 = 0.5P_c$ . The consumer's risk (i.e., the  
10 probability of false acceptance of an inferior product) is 0.025 at  $P_0 = 1.5P_c$ . Actual  
11 distribution of  $\hat{P}_0$  will not follow a normal distribution with a fixed variance. However,  
12 we will be able to expect that a superior product having  $P_0 < 0.5P_c$  is almost certainly  
13 accepted while an inferior product having  $P_0 > 1.5P_c$  is almost certainly rejected.

## 14 15 16 8. CONTROL OF CONSUMER'S RISK

17 We can exactly control the consumer's risk (that is denoted by  $\beta$ ), if we assume a  
18 specified distribution for the distribution of  $P_i$ . Let us consider a sampling inspection  
19 where the product of a field is rejected if the final sample contains at least one pecky rice  
20 grain. We call this rejection procedure as 'zero-tolerance method'. The zero-tolerance  
21 method is not adopted in actual examination of pecky rice grains, but it is used in various  
22 inspections such as the import plant quarantine inspection in Japan (Yamamura and  
23 Sugimoto 1995), because it requires the smallest sample size. The sample size ( $n$ ) in the  
24 Japanese official procedure of import plant quarantine inspection was principally  
25 calculated by using the following formula that is based on the Poisson distribution.



$$n = -\frac{\log_e(\beta)}{P_c}. \quad (8.1)$$

2

3 In most of the standards in industrial inspection such as international standards (ISO) and  
 4 Japanese industrial standards (JIS), the consumer's risk is set at  $\beta = 0.1$  while the  
 5 producer's risk (that is usually denoted by  $\alpha$ ) is set at 0.05. However, in the Japanese  
 6 import plant quarantine inspection, the consumer's risk was set at  $\beta = 0.05$  in principle,  
 7 because the primary purpose of the quarantine inspection lies in the protection of  
 8 consumer's risk rather than producer's risk. If we use  $\beta = 0.05$ , (8.1) is approximately  
 9 given by  $3/P_c$ , and hence we can easily calculate the sample size by a mental calculation.  
 10 This rule is sometimes called the 'rule of three' (Jovanovic and Levy 1997; van Belle  
 11 2002; Iwasaki 2005).

12 The probability that no pecky rice grains are included in the final sample in the  
 13 composite sampling is given by the zero-term of (2.7) if we assume a gamma distribution  
 14 for  $P_i$ . We calculate the sample size so that we have  $\Pr(Z = 0) < \beta$ . By equating the mean  
 15 and variance of (2.1) to  $P_0$  and  $aP_0^b$ , respectively, we obtain  $k = P_0^{2-b}/a$  and  $\lambda = P_0^{1-b}/a$ .  
 16 By substituting  $k = P_0^{2-b}/a$  and  $\lambda = P_0^{1-b}/a$  into the zero-term of (2.7), we obtain

17

$$\left(1 + \frac{n_2 a P_0^{b-1}}{n_1}\right)^{-\frac{n_1}{a P_0^{b-2}}} < \beta. \quad (8.2)$$

19

20 The first derivative of the left hand side of (8.2) about  $P_0$  is negative at least if  $1 < b < 2$ .  
 21 Therefore, we can obtain the combination of  $n_1$  and  $n_2$  to achieve the above inequality for  
 22 all  $P_0$  satisfying  $P_c < P_0 \leq 1$ , by finding the quantities that satisfy  $\Pr(Z = 0 | P_0 = P_c) = \beta$ .  
 23 Hence, we have the following relation.

24

$$n_2 = \frac{n_1}{aP_c^{b-1}} \left( \beta \frac{aP_c^{b-2}}{n_1} - 1 \right). \quad (8.3)$$

2

3 If the heterogeneity  $V(P_i)$  approaches zero while  $P_0$  is kept at a constant in (2.1), the  
 4 quantity of  $\lambda$  increases to infinity while  $k/\lambda$  is kept at a constant. Then, the zero-term of  
 5 (2.7) becomes  $\exp(-n_2P_0)$ . Therefore, (8.3) reduces to (8.1) where  $n$  is replaced by  $n_2$ . If  
 6  $c_1 > 0$ , the corresponding optimal quantity of  $n_1$  is given by the smallest integer that  
 7 satisfies  $sn_1 \geq n_2$ , because  $n_1$  does not influence the consumer's risk if there is no  
 8 heterogeneity.

9 Let  $n_1^\#$  and  $n_2^\#$  be the optimal quantities of  $n_1$  and  $n_2$ , respectively, that minimize  
 10 the total cost to achieve a fixed amount of  $\beta$ . We can calculate  $n_1^\#$  by solving  
 11  $\partial c_{\text{total}} / \partial n_1 = 0$  after substituting (8.3) into (6.1) to eliminate  $n_2$ .

12

$$n_1^\# = - \frac{aP_c^{b-2} \log_e(\beta)}{1 + W \left( \frac{a(c_1/c_2)P_c^{b-1} - 1}{\exp(1)} \right)}, \quad (8.4)$$

14

15 where  $W$  is the Lambert W-function. The corresponding quantity of  $n_2^\#$  is calculated by  
 16 using (8.3). Actual sample size is an integer, and hence the exact optimal quantity of  $n_1$  is  
 17 either integer just below  $n_1^\#$  or just above  $n_1^\#$ .

18

19

20

## 9. APPLICATION

21

22

23

We must first estimate the parameters of Taylor's power law ( $a$  and  $b$ ) for the  
 proportion of pecky rice grains. We collected data from 16 paddy fields (each area ranges  
 from 75 to 150 m<sup>2</sup>) in Niigata Agricultural Research Institute, Crop Research Center (37°

1 26° N, 138° 52' E). The rice leaf bug, *Trigonotylus caelestialium*, is the primary species  
 2 causing pecky rice grains in these fields. Three varieties were used: Wasejiman (5 fields),  
 3 Koshi-ibuki (5 fields), and Koshi-hikari (6 fields). We selected 20 plants at random from  
 4 each field. We recorded the number of pecky rice grains ( $X_i$ ) and the total number of  
 5 grains ( $s_i$ ) separately for each plant. The data used in this estimation are stored in the  
 6 JABES web-site (<http://www.amstat.org/publications/jabes/data.shtml>). We can estimate  
 7 the mean and variance for each field by the moment method by using (3.3) and (3.4).  
 8 However, we instead obtained maximum likelihood estimates, that will be more reliable,  
 9 by maximizing the sum of the logarithm of (2.3). The procedure given in Appendix A of  
 10 Yamamura and Sugimoto (1995) was used for the estimation. We then obtained 16 pairs  
 11 of estimates,  $\hat{k}$  and  $\hat{\lambda}$ . The quantities of  $P_0$  and  $V(P_i)$  were estimated by  $\hat{k}/\hat{\lambda}$  and  
 12  $\hat{k}/\hat{\lambda}^2$ , respectively. Then, we estimated the power law relation from the 16 pairs of  $\hat{P}_0$   
 13 and  $\hat{V}(P_i)$  by using a linear regression of the form of (5.2) (Figure 1). The explanatory  
 14 variable,  $\hat{P}_0$  in this case, has some measurement errors, but a linear regression will  
 15 suffice in estimating the parameters of power law (Perry 1981). The estimated parameters  
 16 ( $\pm$ SE) were  $\widehat{\log(a)} = -2.19 \pm 0.81$  and  $\hat{b} = 1.60 \pm 0.13$ . If we used the moment method in  
 17 estimating  $P_0$  and  $V(P_i)$ , the estimated parameters ( $\pm$ SE) were  $\widehat{\log(a)} = -2.41 \pm 0.66$  and  
 18  $\hat{b} = 1.58 \pm 0.11$  (See the electronic material that is stored in JABES site). The curves in  
 19 Figure 2 show the combination of  $n_1$  and  $n_2$  that satisfy  $D < 0.25$  for all  $P_0$  in a range of  $P_0$   
 20  $> P_c$ . The combination is shown for several quantities of  $P_c$ . The number of grains in a  
 21 plant was set at 1400, which seems to be the average number of grains per plant. The  
 22 required  $n_2$  decreases in a decelerating manner with increasing  $n_1$ .

23 We must estimate the costs ( $c_1$  and  $c_2$ ), to determine the optimal sample size.  
 24 About 60 seconds are required in drawing a rice plant and in shelling the rice grains.  
 25 About 0.12 seconds are required to examine a rice grain on average. We thus use  $c_1/c_2 =$   
 26  $60/0.12 = 500$ . The grade of rice falls from the first grade to the second grade if the  
 27 proportion of pecky rice grains is larger than 0.001 (Ministry of Agriculture Forestry and

Figure 1

Figure 2

1 Fisheries 2001). Thus, we use  $P_c = 0.001$ . Equation (6.2) indicates that the optimal  $n_1$  is  
 2 58 in this case. Then, (5.4) indicates that the corresponding  $n_2$  is about 31000. We can  
 3 alternatively obtain the optimal combination of  $n_1$  and  $n_2$  in a graphical manner. We have  
 4  $n_2 = (c_{\text{total}}/c_2) - (c_1/c_2)n_1$  from (6.1). In our case, we have  $n_2 = (c_{\text{total}}/c_2) - 500n_1$ . The  
 5 minimization of  $c_{\text{total}}$  is equivalent to the minimization of the intercept,  $c_{\text{total}}/c_2$ . Hence, we  
 6 can visually find the optimal combination of  $n_1$  and  $n_2$  for  $P_c = 0.001$  by finding the point  
 7 where the curve of  $P_c = 0.001$  contacts a line with a slope of  $-500$  (see Figure 2).

8 If we explicitly assume a gamma distribution for the distribution of  $P_i$ , we can use  
 9 (2.7) to obtain the ‘exact’ confidence interval that is defined by the inverse of testing. By  
 10 equating the mean and variance of (2.1) to  $P_0$  and  $aP_0^b$ , respectively, we obtain  $k = P_0^{2-b}/a$   
 11 and  $\lambda = P_0^{1-b}/a$ . After substituting the parameters  $k = P_0^{2-b}/a$ ,  $\lambda = P_0^{1-b}/a$ ,  $n_1 = 58$ , and  $n_2 =$   
 12 31000 into (2.7), we obtain the lower 95% exact confidence limit by numerically finding  
 13  $P_0$  where the upper 2.5% point coincides to  $\hat{P}_0$ . Similarly, we obtain the upper 95% exact  
 14 confidence limit by numerically finding  $P_0$  where the lower 2.5% point coincides to  $\hat{P}_0$ .  
 15 For example, if we obtain an estimate  $\hat{P}_0 = 0.001$ , i.e.,  $Z = 31$ , the exact confidence  
 16 interval is [0.00060, 0.00164]. This exact confidence interval is close to the confidence  
 17 interval that is calculated by the normal approximation,  $\hat{P}_0 \pm 1.96D\hat{P}_0$ , that is [0.00051,  
 18 0.00149]. Thus, the normal approximation seems satisfactory in this case.

19 We can calculate another optimal sample size by controlling the consumer’s risk  
 20 if we assume a gamma distribution for the distribution of  $P_i$ . By substituting the cost ratio  
 21 ( $c_1/c_2 = 500$ ) into (8.4) and (8.3), we estimate the optimal size of  $n_1$  and  $n_2$  to be  $n_1^\# = 5.5$   
 22 and  $n_2^\# = 5001$ , respectively (Figure 3). The exact optimal size of  $n_1$  and  $n_2$  were 6 and  
 23 4775, respectively. Equation (8.1) indicates that the required sample size is 2996 if we  
 24 perform a simple random sampling. Thus, the required number of grains increases from  
 25 2996 to 4775 if we use a composite sampling with subsampling instead of using a simple  
 26 random sampling, although we can greatly reduce the cost required for sampling by  
 27 adopting composite sampling.

Figure 3

1           The optimal sample size for controlling the consumer's risk at  $\beta = 0.05$  by a  
 2 zero-tolerance method (i.e.,  $n_1^\# = 5.5$  and  $n_2^\# = 5001$ ) was much different from the  
 3 optimal sample size for controlling the relative precision at  $D = 0.25$  (i.e.,  $n_1^* = 58$  and  $n_2^*$   
 4  $= 31000$ ). The zero-tolerance method requires a much smaller cost for inspection, but we  
 5 must tolerate a larger producer's risk if we use such a small sample size. The conceptual  
 6 difference between two rejection procedures is shown in Figure 4. The broken curve in  
 7 Figure 4 indicates the operating characteristic curve (OC-curve) for the zero-tolerance  
 8 method using  $P_c = 0.001$  and  $\beta = 0.05$  under the assumption that  $P_i$  fluctuates following a  
 9 gamma distribution. The probability of acceptance is exactly 0.05 at  $P_0 = 0.001$  by its  
 10 definition. However, the probability of acceptance is small even if  $P_0$  is much smaller  
 11 than  $P_c$ ; for example, the probability of acceptance is 0.18 even if  $P_0 = 0.0005$ . Let us next  
 12 consider the rejection procedure where we reject the product if we obtain  $\hat{P}_0 > P_c$  under  
 13 the sampling procedure that controls  $D = 0.25$  for  $P_c = 0.001$ . The solid curve in Figure 4  
 14 indicates that the producer's risk is much smaller in this rejection procedure under the  
 15 assumption that  $P_i$  fluctuates following a gamma distribution. The probabilities of  
 16 acceptance at  $P_0 = 0.0005$ , 0.001, and 0.0015 are 0.995, 0.502, and 0.046, respectively.  
 17 As we expected for general distributions, a superior product having  $P_0 < 0.5P_c$  is almost  
 18 certainly accepted while an inferior product having  $P_0 > 1.5P_c$  is almost certainly rejected  
 19 if we use  $D = 0.25$ .

Figure 4

## 10. DISCUSSION

23           We proposed a method to find the optimal sample size for the composite sampling  
 24 with subsampling. This method will be applicable to various sampling procedures that  
 25 have the following characteristics. (1) The purpose of sampling is the estimation of the  
 26 proportion of defective items in a lot. In our case, a defective item corresponds to a pecky

1 rice grain; a lot corresponds to a paddy field. (2) The proportion of defective items is  
2 sufficiently small. (3) The sampling items are drawn by increments, that is, several items  
3 are drawn at the same position. In our case, an increment corresponds to a plant. (4) All  
4 collected items are mixed well to yield a composite. (5) A portion of the collected items  
5 are examined by performing a subsampling from the composite.

6 Composite sampling with subsampling has been widely used in the inspection of  
7 agricultural products. In the procedure to estimate the proportion of commingling of  
8 genetically modified organisms (GMOs) of corn, for example, sampling items are drawn  
9 by increments, and the increments are mixed and subsequently subsampled to form  
10 ‘laboratory sample’ (Japanese Ministry of Health Labor and Welfare 2001). Similar  
11 sampling procedures are used in several international standards (ISO 1990, 1999, 2000,  
12 2002, 2003) and FGIS (Federal Grain Inspection Service 1995). When these types of  
13 sampling are used for the estimation of the proportion of defective items, the required  
14 sample size is sometimes calculated by assuming a simple random sampling. Such a  
15 sample size is valid only if the defective items are distributed at random in the lot, that is,  
16 only if there is no spatial heterogeneity in  $P_i$ . The variance (3.10) becomes  $P_0/n_2$  if  $V(P_i) =$   
17  $0$ ; that is, the variance becomes identical to the variance of the average of  $n_2$  Poisson  
18 variables of mean  $P_0$ . However, if the distribution of defective items is highly aggregated  
19 in the lot, the variance will be severely underestimated if we use the formula for a simple  
20 random sampling. We should use appropriate equations such as (3.10) if large  
21 heterogeneity is suspected. The corresponding optimal sample size should be calculated  
22 by using (6.2) and (5.4). Similarly, if we perform zero-tolerance method, we should use  
23 (8.4) and (8.3) instead of (8.1) in determining the sample size if large heterogeneity is  
24 suspected.

25 In constructing the optimal sampling design, we should first estimate the  
26 parameters of Taylor’s power law unless we have clear evidence that the variance  $V(P_i)$  is  
27 constant irrespective of  $P_0$ . If we examine the number of defective items of each

1 increment separately, we can estimate  $P_0$  and  $V(P_i)$  of each lot by using the moment  
2 method by using (3.3) and (3.4). Alternatively, if we can repeat composite sampling  
3 several times in each lot, we obtain  $\hat{E}(\hat{P}_0)$  and  $\hat{V}(\hat{P}_0)$  for each lot. Then, we can estimate  
4  $P_0$  and  $V(P_i)$  of each lot by the moment method by using (3.9) and (3.11). We can estimate  
5 the parameters of Taylor's power law by using a linear regression such as that in Figure 1  
6 by using several pairs of the estimates of  $P_0$  and  $V(P_i)$ . If we have a clear evidence that the  
7 variance  $V(P_i)$  is constant irrespective of  $P_0$ , only a single estimate of  $V(P_i)$  is required;  
8 we can obtain the optimal sample size by substituting  $a = \hat{V}(P_i)$  and  $b = 0$  to (6.2) and  
9 (5.4) in this case.

10 We estimated Taylor's power law in the proportion of pecky rice grains that were  
11 primary caused by the rice leaf bug, *T. caelestialium*. The parameter  $b$  of Taylor's power  
12 law may change depending on the species; the parameter  $b$  is influenced by the dispersal  
13 rate and reproduction rate of each species (Yamamura 2000). The parameter  $b$  generally  
14 becomes close to 1 if the insect has a high tendency of dispersal, while it becomes close to  
15 2 if the insect has a low tendency of dispersal (Yamamura 2000). Yamamura (2001)  
16 estimated the parameter  $b$  of the distribution of 4 insect pests that have quite different  
17 abilities of dispersal in cabbage fields. The estimated  $b$  for the green peach aphid *Myzus*  
18 *persicae*, eggs of the diamondback moth *Plutella xylostella*, eggs of the small white  
19 butterfly *Pieris rapae crucivora*, and eggs of the beet semi-looper *Autographa nigrisigna*,  
20 were 1.74, 1.52, 1.28, and 1.15, respectively. The decreasing order of the estimated size  
21 of  $b$  coincides with the increasing order of dispersal ability. Pecky rice grains in Japan are  
22 mostly caused by either of the three species of bugs: the rice leaf bug *T. caelestialium*, the  
23 sorghum plant bug *Stenotus rubrovittatus*, and the rice bug *Leptocorisa chinensis*  
24 (Watanabe and Higuchi 2006). The optimal sample size calculated in this paper will be  
25 applicable for most of the northern part of Japan (including Hokuriku, Tohoku, and  
26 Hokkaido districts) where *T. caelestialium* is the primary species. However, if we apply  
27 the method to the districts where *S. rubrovittatus* or *L. chinensis* are the primary species,

1 it will be preferable to re-estimate the parameters of Taylor's power law for these species.

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4

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## FIGURE CAPTIONS

Figure 1. Taylor's power law between the mean and variance of the proportion of pecky rice grains. Three rice varieties are indicated by different symbols. The linear regression was calculated including three rice varieties:

$$\log_e[\hat{V}(P_i)] = -2.19 + 1.60 \log_e(\hat{P}_0), R^2 = 0.91.$$

Figure 2. Sample size to achieve a given relative precision ( $D$ ). The curves indicate the combination of  $n_1$  and  $n_2$  that achieve  $D < 0.25$  for all  $P_0$  in the range of  $P_0 > P_c$ . Five curves for different values of  $P_c$  are shown. The solid circle indicates the optimal combination of  $n_1$  and  $n_2$  that was calculated by using (6.2) for  $P_c = 0.001$  and  $(c_1/c_2) = 500$ . The broken line indicates a slope of  $-500$ . The shaded area indicates the nonexistent combination of  $n_1$  and  $n_2$  where the required number of drawn grains exceeds the total number of drawn grains, i.e., the region of  $n_2 > sn_1$ . The following parameters were used:  $s = 1400$ ,  $a = \exp(-2.19)$ , and  $b = 1.60$ .

Figure 3. Sample size to achieve a given consumer's risk ( $\beta$ ). The curves indicate the combination of  $n_1$  and  $n_2$  that achieve  $\beta < 0.05$  for all  $P_0$  in the range of  $P_0 > P_c$ . Five curves for different values of  $P_c$  are shown. The solid circle indicates the optimal combination of  $n_1$  and  $n_2$  that was calculated by using (8.4) for  $P_c = 0.001$  and  $(c_1/c_2) = 500$ . The broken line indicates a slope of  $-500$ . The meaning of shaded area is the same as that in Figure 2. The following parameters were used:  $s = 1400$ ,  $a = \exp(-2.19)$ , and  $b = 1.60$ .

Figure 4. Conceptual difference between two kinds of control, the control of precision and control of consumer's risk. The operating characteristic curves (OC-curves)

1 are compared under the assumption that the probability that a rice grain around the  
2  $i$ th plant is pecky ( $P_i$ ) fluctuates following a gamma distribution spatially. The  
3 broken curve indicates the OC-curve for the zero-tolerance method using  $P_c =$   
4  $0.001$  and  $\beta = 0.05$ , i.e.,  $n_1^\# = 5.5$  and  $n_2^\# = 5001$ . The solid curve indicates the  
5 OC-curve for the rejection procedure where we reject the product if we obtain  
6  $\hat{P}_0 > P_c$  under the sampling procedure that controls  $D = 0.25$  for  $P_c = 0.001$ , i.e.,  
7  $n_1^* = 58$  and  $n_2^* = 31000$ . The following parameters were used:  $a = \exp(-2.19)$   
8 and  $b = 1.60$ .



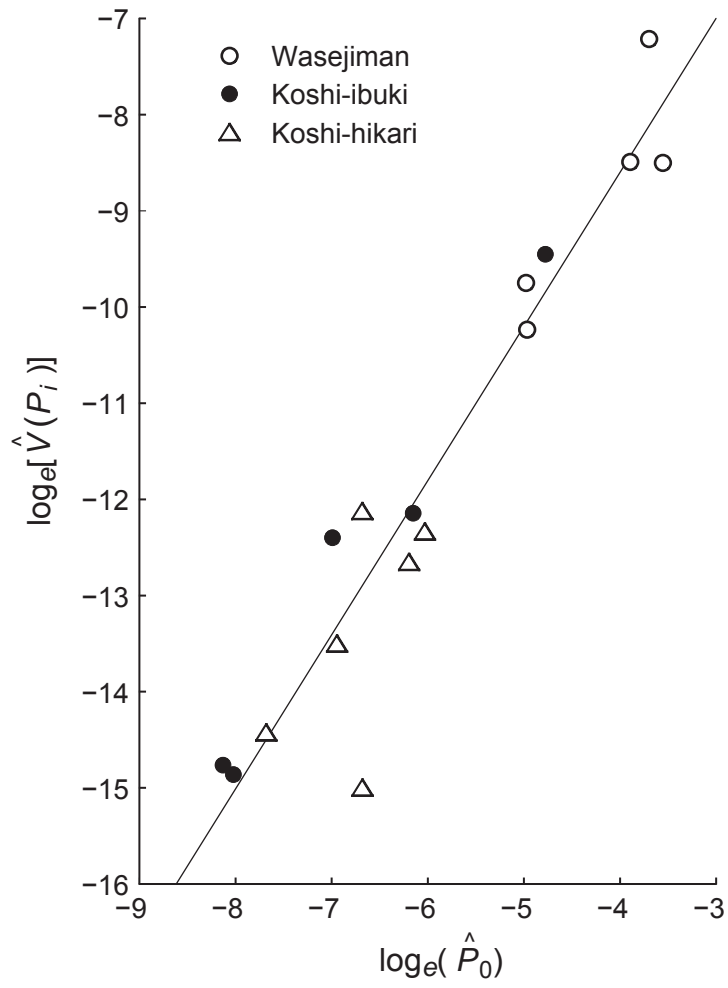


Figure 1

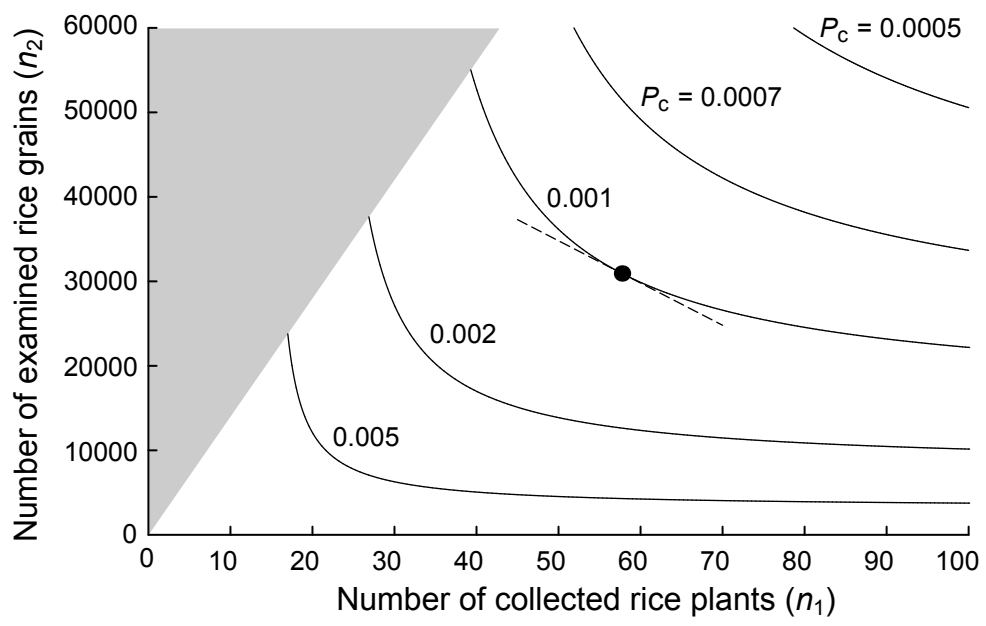


Figure 2

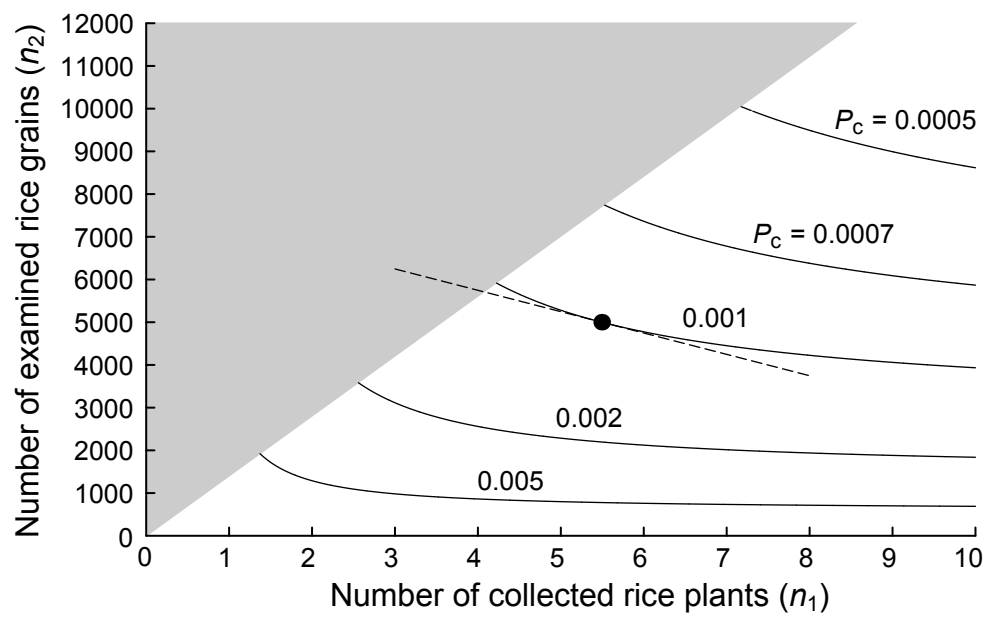


Figure 3

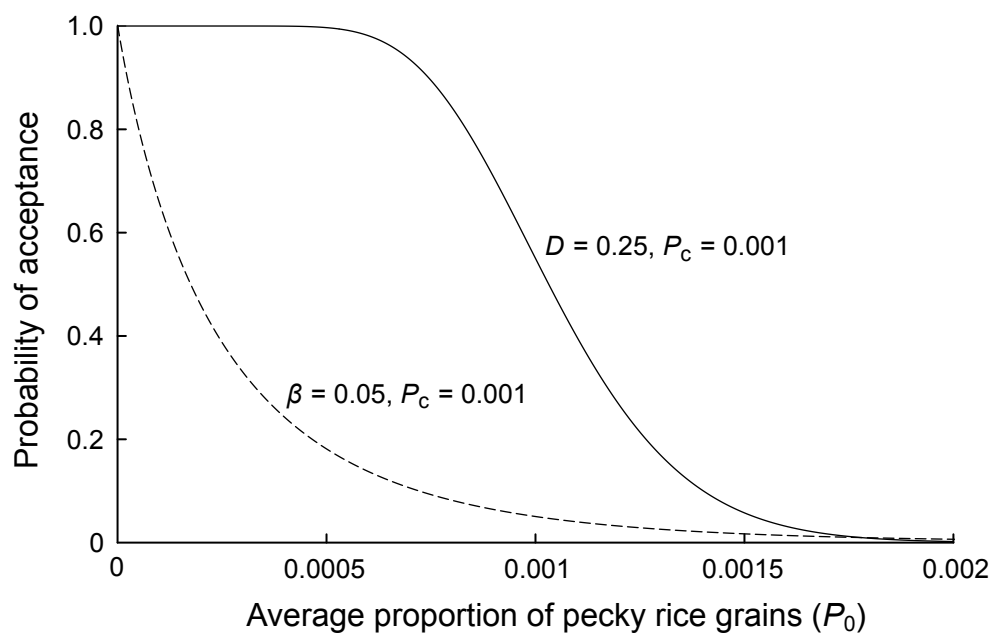


Figure 4