Estimating stray dog populations with the regression method versus Beck's method: A comparison

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Shih-Yuan Fei, Jeng-Tung Chiang, Chang-Young Fei, Chung-Hsi Chou and Meng-Chih Tung

Abstract

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Keywords Animal welfare – Capture-recapture – Heterogeneous capture probabilities – Photographic survey – Population size – Stray dogs

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Abstract Statistical procedures for wildlife population estimation have been greatly improved since the last decade. For estimation of stray dog population size, however, the simple methods recommended by the 1990 WHO/WSPA guidelines seem to remain the popular favorites among researchers. Although the methods are very easy to use, their usefulness relies heavily on certain assumptions that are generally unrealistic. Using simulation studies, we conclude that Beck's method, one of the estimators recommended by the guidelines, performs fairly well and can be safely used to get a quick population estimate, as long as the underlying assumptions are not severely violated.

Keywords Animal welfare · Capture-recapture · Heterogeneous capture probabilities · Photographic survey · Population size · Stray dogs

1 Introduction

Stray dog population management is an area of concern for those who seek to improve the welfare of dogs. To carry out a relevant program, it is important to know the size

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of a stray dog population. Although it is impossible to take a census of stray dogs, several estimation methods have been proposed. Four wildlife techniques, total or indirect counts, estimates from rate of capture (or the regression method), estimates from recaptures, and estimates from photographic recaptures (or Beck's method) were described in the "Guidelines for Dog Population Management," published jointly in 1990 by the World Health Organization (WHO) and the World Society for the Protection of Animals (WSPA) to help obtain a population estimate in a defined area (WHO/WSPA 1990). Among them, estimates obtained from the regression method ($\hat{N}_R$) and from Beck's method ($\hat{N}_B$) are the two that attracted most attention. Although it has been almost 20 years since the publication of these guidelines, due to their easy-to-understand and user-friendly formulas, the two estimators remain popular choices for researchers involved in dog population and rabies management. In fact, the two methods are still recommended by the Terrestrial Animal Health Code 2010 (World Organization for Animal Health (OIE) 2010). Both methods require the use of photographic equipment to capture the dogs visually rather than physically. Assume that surveyors make a total of t photographic capture tours. For the jth tour, let M_j and m_j be the number of dogs captured and the number of dogs recaptured, respectively, and let x_j be the total number of distinct dogs captured in the previous $j-1$ tours. Define $y_j = M_j - m_j$, the number of new dogs captured at the jth tour. By plotting the number of new dogs captured on each tour (y_j) against the accumulated total number of distinct dogs previously captured (x_j), the dog population in an area can be estimated through extrapolation of the regression line to the horizontal axis. Specifically, the estimated population size based on the rate of capture is given by $\hat{N}_R = -a/b$, where $b = \sum_{j=1}^{t}(x_j - \bar{x})(y_j - \bar{y})/\sum_{j=1}^{t}(x_j - \bar{x})^2$ and $a = \bar{y} - b\bar{x}$ are the slope and intercept estimates for the simple linear regression line of y against x; $\bar{x}$ and $\bar{y}$ are the sample means of x and y, respectively. On the other hand, since m_j/x_j, $j = 2, \ldots, t$ stands for the recapture rates, each $M_j x_j/m_j = M_j/(m_j/x_j)$, $j = 2, \ldots, t$ can be used to estimate the population size. Evidently, $\hat{N}_B = \sum_{j=1}^{t}(M_j x_j)/\sum_{j=1}^{t} m_j$, a weighted average of them discussed in Beck (1973), provides a better population estimate with smaller variance.

Although the two estimates can be easily calculated once data are collected, problems may arise. If the two estimates are similar, there may not be a problem. But what if the two yield dramatically different estimates? Can one simply be favored over the other? Since the guidelines are neither written for survey specialists nor statisticians, they do not mention how the two estimates perform against each other. However, it might be worthwhile to look into the relative benefits of the two suggested methods.

Two assumptions are essential to the usefulness of the estimates: a closed population in which mortality, emigration, and recruitment are minimal during the survey; and that all individuals within the population have an equal probability of being counted. The assumption of a closed population that does not change demographically during the investigation period may not be seriously violated as long as the investigation can be completed in a short period of time. Equal catchability, on the other hand, does not appear to be a realistic assumption for stray dogs. As far as a photographic capture-recapture method is concerned, equal catchability means equal observability. However, some dogs are probably more easily spotted than others. Hence, capture probabilities may vary with individual dogs. It is also clear that a dog's activity pattern would influence its frequency of being observed. Because of food availability, human disturbance, weather conditions, etc., observability of a stray dog may change with days, weeks, and seasons. As a result, it does not seem reasonable to assume that capture probabilities stay constant all the time. Ignoring either type of variability in catchability likely yields an unreliable estimated population size. Hence, it should also be of interest to know how $\hat{N}_B$ and $\hat{N}_R$ perform should the two crucial assumptions fail to hold.

This article aims to provide some answers to the above-mentioned issues so that the two estimators can be used more effectively. The performances of the two estimators are compared through a series of simulation experiments.

2 Method

2.1 Capture-recapture

Capture-recapture is a method commonly applied to estimate wildlife population size, first used by Pierre Simon Laplace in 1786 to estimate the human population size in France. However, it was not until Petersen (1896) and Lincoln (1930) separately employed the technique to estimate population sizes of flatfish and aquatic birds that it became widely used in biology and ecology. Earlier treatments of the method all assumed a constant capture probability for all animals and for all sampling occasions. The work of Darroch (1958) appeared to be the first attempt to use a statistical model to allow varied capture probabilities. Since then, researchers have begun to establish a variety of models that are able to account for the variations in capture probabilities associated with time, behavior, and individual effects. Pollock (1974) and Otis et al. (1978) presented a set of models that allow capture probabilities to vary with time (M_t), trap response (M_b), individual animal (M_h), or all possible combinations of these three types of variations (M_{tb}, M_{th}, M_{bh}, and M_{tbh}). We focused only on models M_{th} and M_0 (the model with a constant capture probability) in this article.

2.1.1 Model M_0

Model M_0 assumes that the capture probability for each strayed dog is the same and stays constant for each sampling occasion. Although this model seems too good to be true, the two estimators are indeed appropriate for this unrealistic situation. However, the effectiveness of the two estimators and their relative performances remain to be seen.

2.1.2 Model M_{th}

Because every stray dog has its own territory (Beaver 1994; Dodman 2004), the probability of stray dogs being counted cannot be assumed equal for all individuals unless surveyors have absolute certainty of searching every nook and corner without a miss (and in addition, this must be done simultaneously). Generally speaking, places dogs look for food should be the most crowded, and these are also the places where surveyors are more likely to search. However, stray dogs may fight for access to food, and stronger dogs close to the food constantly chase weaker dogs away, resulting in a larger probability that the surveyor will count more strong dogs than weak ones. Moreover, some dogs are more nervous and vigilant and tend to avoid people and thus are less likely to be counted. This also rules out the unlikely scenario that the capture probabilities are equal for all dogs.

Capture probabilities may also vary with sampling occasions. For example, a cold, rainy day may hinder the chance of seeing a dog and therefore decrease overall capture probability. Hence, failure to account for time effect in capture probabilities may bias the result.

On the other hand, dogs' behaviors are not likely to be affected after being captured photographically, since dogs are not physically captured. Hence, we focused only on model M_{th}, which allows capture probabilities to vary with time and individual dogs. Since estimators $\hat{N}_B$ and $\hat{N}_R$ do not intend to deal with model M_{th}, they are unlikely the estimators of choice for dealing with situations described by model M_{th}. However, if a practitioner can have a better understanding about how individual dogs' capture probabilities vary and how the capture probabilities are likely to be influenced by the sampling occasions, information regarding how far $\hat{N}_B$ and $\hat{N}_R$ estimates deviate from the target values might be useful. With the information, practitioners might be able to adjust $\hat{N}_B$ and $\hat{N}_R$ values so that they can have some quick (though rough) estimates before exploring the need to use more refined estimators such as those established by Chao et al. (1992), Lee and Chao (1994) and Coull and Agresti (1999). With the goal in mind, we seek to investigate how $\hat{N}_B$ and $\hat{N}_R$ perform if they are used naively in the situations described by model M_{th}, and provide comments as to what happens when a poor estimator is used.

2.2 Simulation designs

We conducted simulation studies to provide insight into the performances of the two estimators. Two models were assumed to simulate the data: M_0, models with homogeneous capture probabilities, and M_{th}, models with heterogeneous capture probabilities that vary with sampling occasions and individual dogs. The former aimed to evaluate the relative performances of $\hat{N}_R$ and $\hat{N}_B$ under the unrealistic assumed situations, and the latter aimed to determine how much their performances would be affected should the crucial assumptions fail. Let n be the total number of successful simulation runs and $\hat{N}_r$ represent the population size estimate from the rth simulation run, $r = 1, \ldots, n$. Originally, we planned to run 1,000 simulation runs for each experimental condition. However, some runs yielded an estimate of infinity, especially when capture probabilities were low. We therefore excluded those runs and used n to denote the total number of runs that yielded a finite estimate. Although an estimator with an n closer or equal to 1,000 did not necessarily mean that the estimator was effective, it at least showed that the estimator was more likely to produce an estimate.

Performances of the estimators were compared in terms of the following four criteria: (i) n, the number of successful simulations runs; (ii) the mean bias of the n

simulation runs (Bias), $\sum_{r=1}^{n}(\hat{N}_r - N)/n$, or equivalently, $\bar{\hat{N}} - N$, the difference between the average population size estimate ($\bar{\hat{N}} = \sum_{r=1}^{n}\hat{N}_r/n$) and the true population size (N); (iii) sample standard deviation (SD), $\sqrt{\sum_{r=1}^{n}(\hat{N}_r - \bar{\hat{N}})^2/(n-1)}$; and (iv) root mean square error (RMSE), $\sqrt{\sum_{r=1}^{n}(\hat{N}_r - N)^2/n}$. Estimators are typically compared in terms of the last three criteria. For these three criteria, the smaller the value, the better the estimate. Bias measures the accuracy, and standard deviation measures the variability of an estimator. Unfortunately, an estimator with little bias and a small standard deviation is rare. RMSE, on the other hand, measures how far an estimator is off from the quantity to be estimated. RMSE incorporates both the bias of an estimator and its variance, and was therefore the primary measure upon which we relied on to evaluate the performances of the two estimators.

2.2.1 Model M_0

Let p_{ij} denote the capture probability of the ith dog in the jth survey occasion, where $i = 1, \ldots, N$ and $j = 1, \ldots, t$. Under model M_0, which assumes an equal capture probability for each dog and for each survey occasion, $p_{ij} = p$. Four levels of population size N (40, 100, 200, and 400) were considered. Simulation studies were designed to examine the behaviors of the two estimators with respect to eight levels of capture probability p (0.05, 0.10, 0.15, 0.20, 0.30, 0.40, 0.50, and 0.75), and three levels of number of survey occasions t (5, 7, and 10). For each combination of population size, capture probability, and number of survey occasions, 1,000 simulation runs were performed.

2.2.2 Model M_{th}

To assess the performance of estimators $\hat{N}_R$ and $\hat{N}_B$ in a situation related to model M_{th}, assume $p_{ij} = p_i e_j$, where p_i is the individual capture probability for the ith dog, e_j is the time effect of the jth survey occasion, and $0 < p_i, e_j < 1$. Assume, without loss of generality, that the population is composed of equal proportion of four types of stray dogs; that is, $p_1 = \cdots = p_{N/4} = p_1^*$, $p_{(N/4)+1} = \cdots = p_{2N/4} = p_2^*$, $p_{(2N/4)+1} = \cdots = p_{3N/4} = p_3^*$, and $p_{(3N/4)+1} = \cdots = p_N = p_4^*$. To see the possible impact arising from heterogeneous capture probabilities for individual dogs, 20 sets of individual capture probabilities were generated from four levels of $\bar{p}$ (0.2, 0.3, 0.4, and 0.5), and five levels of coefficient of variation (CV) (0, 0.2, 0.4, 0.6, and 0.8) were studied, where $\bar{p} = (p_1^* + p_2^* + p_3^* + p_4^*)/4$ is the average capture probability and CV$= [\sum_{i=1}^{4}(p_i^* - \bar{p})^2/4]^{1/2}/\bar{p}$ is the coefficient of variation. The use of CV introduced variability into the individual capture probabilities. A smaller CV value indicated less varied individual capture probabilities. This part of the simulation design was exactly the same as that in Chao et al. (1992), and the complete list is displayed in Table 1.

To determine the impact associated with number of survey occasions (t) and time effect on capture probabilities (e_j, $j = 1, \ldots, t$), we considered three levels of number of survey occasions (5, 7, and 10) and four levels of time effect (i.e. e_j, $j = 1, \ldots, 10$):

Table 1 Description of simulation design for individual capture probabilities

Case	$\bar{p}$	CV	p_1	p_2	p_3	p_4
1	0.2	0	0.20	0.20	0.20	0.20
2	0.2	0.2	0.16	0.16	0.24	0.24
3	0.2	0.4	0.12	0.12	0.28	0.28
4	0.2	0.6	0.10	0.14	0.16	0.40
5	0.2	0.8	0.10	0.10	0.12	0.48
6	0.3	0	0.30	0.30	0.30	0.30
7	0.3	0.2	0.24	0.24	0.36	0.36
8	0.3	0.4	0.18	0.18	0.42	0.42
9	0.3	0.6	0.15	0.21	0.24	0.60
10	0.3	0.8	0.15	0.15	0.18	0.72
11	0.4	0	0.40	0.40	0.40	0.40
12	0.4	0.2	0.32	0.32	0.48	0.48
13	0.4	0.4	0.24	0.24	0.56	0.56
14	0.4	0.6	0.20	0.28	0.32	0.80
15	0.4	0.8	0.20	0.20	0.24	0.96
16	0.5	0	0.50	0.50	0.50	0.50
17	0.5	0.2	0.40	0.40	0.60	0.60
18	0.5	0.4	0.30	0.30	0.70	0.70
19	0.5	0.6	0.25	0.35	0.40	1.00
20	0.5	0.8	0.10	0.10	0.90	0.90

low capture probabilities (0.2, 0.3, 0.25, 0.15, 0.1, 0.2, 0.25, 0.2, 0.1, and 0.15); middle capture probabilities (0.4, 0.5, 0.45, 0.6, 0.5, 0.4, 0.5, 0.6, 0.55, and 0.45); high capture probabilities (0.8, 0.7, 0.75, 0.85, 0.9, 0.9, 0.8, 0.7, 0.75, and 0.8); and mixed capture probabilities (0.1, 0.8, 0.4, 0.6, 0.1, 0.2, 0.9, 0.5, 0.3, and 0.5). Again, four levels of population size N (40, 100, 200, and 400) were assumed, and 1,000 simulation runs were performed for each experimental setting.

3 Results

3.1 *Model* M_0

Both estimators perform better as the population size grows. However, since the relative performances of the two stay the same no matter what the population size is, we provide only the results with population size 200 in Table 2.

In terms of the number of successful simulation runs (n), Table 2 shows that only when the capture probability (p) is as small as 0.05 and the number of survey occasions is as small as 5, $\hat{N}_B$ may fail to provide a finite population size estimate. As indicated, with $p = 0.05$ and $t = 5$, $\hat{N}_B$ successfully produce a finite estimate in 993 out of 1,000 simulation runs. Hence, even in this case, the failure rate is only 0.7 %.

Table 2 Simulation results for $\hat{N}_R$ and $\hat{N}_B$ under the assumption of equal capture probability for all individuals with $N = 200$

p	Estimator	$t = 5$					$t = 7$					$t = 10$				
		n	Estimate	Bias	SD	RMSE	n	Estimate	Bias	SD	RMSE	n	Estimate	Bias	SD	RMSE
0.05	$\hat{N}_R$	767	274	74	808.8	811.7	858	396	96	2088.6	2096.6	936	724	524	7599.6	7613.6
	$\hat{N}_B$	993	242	42	138.7	144.9	1,000	216	16	76.1	77.8	1,000	206	6	42.6	43
0.10	$\hat{N}_R$	918	331	133	1052.1	1059.6	989	975	775	22675.8	22677.6	1,000	213	13	68.7	69.9
	$\hat{N}_B$	1,000	208	8	44.7	45.3	1,000	203	3	27.5	27.7	1,000	202	2	17.9	18
0.15	$\hat{N}_R$	995	257	57	737.4	739.3	1,000	207	7	57.8	58.2	1,000	201	1	18.9	18.9
	$\hat{N}_B$	1,000	202	2	24.4	24.5	1,000	201	1	15.6	15.6	1,000	200	0	10.2	10.2
0.20	$\hat{N}_R$	1,000	207	7	45.7	46.1	1,000	201	1	20.5	20.6	1,000	200	0	10.3	10.3
	$\hat{N}_B$	1,000	201	1	17.3	17.3	1,000	201	1	10.7	10.7	1,000	200	0	6.9	6.8
0.30	$\hat{N}_R$	1,000	202	2	16.2	16.3	1,000	201	1	8.5	8.6	1,000	200	0	4.5	4.5
	$\hat{N}_B$	1,000	201	1	9.4	9.4	1,000	200	0	5.9	5.9	1,000	200	0	3.7	3.7
0.40	$\hat{N}_R$	1,000	201	1	8.2	8.2	1,000	200	0	4.6	4.6	1,000	200	0	2.6	2.6
	$\hat{N}_B$	1,000	200	0	5.8	5.8	1,000	200	0	3.7	3.7	1,000	200	0	2.3	2.3
0.50	$\hat{N}_R$	1,000	200	0	4.6	4.6	1,000	200	0	2.6	2.6	1,000	200	0	1.5	1.5
	$\hat{N}_B$	1,000	200	0	3.7	3.7	1,000	200	0	2.3	2.3	1,000	200	0	1.5	1.5
0.75	$\hat{N}_R$	1,000	200	0	1.3	1.3	1,000	200	0	0.9	0.9	1,000	200	0	0.6	0.6
	$\hat{N}_B$	1,000	200	0	1.2	1.2	1,000	200	0	0.8	0.8	1,000	200	0	0.5	0.5

On the other hand, $\hat{N}_R$ fails to provide a finite estimate more frequently. Hence, $\hat{N}_B$ has an advantage over $\hat{N}_R$ in this regard.

Next, for either estimator, no matter whether the mean bias, the standard deviation, or the root mean square error is concerned, when moving from the top to the bottom of Table 2, all the figures become smaller as the capture probabilities increase, an indication that the larger the capture probabilities, the better the estimates. However, for each $(\hat{N}_R, \hat{N}_B)$ pair, none of the figures associated with $\hat{N}_R$ is smaller than that of $\hat{N}_B$. $\hat{N}_R$ appears to never perform better than $\hat{N}_B$.

Furthermore, reading across Table 2 from left to right and focusing only on $\hat{N}_B$ and those of $\hat{N}_R$ with capture probability greater than or equal to 0.20, mean bias, standard deviation, and root mean square error all become smaller as number of survey occasions (t) increases, which implies that more survey occasions lead to better estimates. However, this is not necessarily true for $\hat{N}_R$ with a capture probability no greater than 0.15. As shown in the upper part of the table, the standard deviation of $\hat{N}_R$ can be a huge number, which provides evidence that $\hat{N}_R$ may not be a reliable estimator when the capture probability is small. And this holds even when the number of survey occasions is as large as 10. It follows that $\hat{N}_R$ can provide a reliable estimate only when the capture probabilities are not too small. Nevertheless, given the better performance and less variability of $\hat{N}_B$, it seems totally unnecessary to rely on $\hat{N}_R$ when the assumption of equal capture probability for all individuals strictly holds.

3.2 *Model* M_{th}

Since the simulation results are basically the same as far as the relative performances of the two estimators are concerned, only the results with a population size of 200 and a time effect associated with middle capture probabilities (i.e. $[e_j, j = 1, \ldots, 10] = [0.4, 0.5, 0.45, 0.6, 0.5, 0.4, 0.5, 0.6, 0.55, 0.45]$) are displayed in Table 3. Table 3 once again shows that $\hat{N}_B$ has an advantage over $\hat{N}_R$ in terms of number of successful simulation runs. $\hat{N}_R$ can yield an estimate of infinite much more frequently than $\hat{N}_B$. It appears that $\hat{N}_R$ is not worthy of serious consideration until number of survey occasions reaches 10.

To facilitate the comparisons of their relative performances, Figs. 1 and 2 plot the simulation results of the two estimators in terms of mean bias, and root mean square error, respectively. In each plot, the three 'x' connected by dashed lines correspond to the three estimates of $\hat{N}_R$, and the three 'o' connected by solid lines correspond to the three estimates of $\hat{N}_B$. However, for the case with $\bar{p} = 0.2$ and CV = 0.2, the corresponding $\hat{N}_R$ estimate associated with $t = 5$ is much larger than the upper limit of the vertical axis, and is therefore unable to be shown in the plot.

For every combination of $\bar{p}$ and CV, as shown in Table 3, $\hat{N}_B$ exhibits a smaller standard deviation than $\hat{N}_R$, indicating that $\hat{N}_B$ is the most stable estimator of the two. Generally speaking, $\hat{N}_B$ estimates do not vary greatly as long as the number of sampling occasions reaches five, while $\hat{N}_R$ estimates can still vary dramatically even with 10 sampling occasions. Given its instability, use of $\hat{N}_R$ as a population size estimator is not recommended.

Table 3 Simulation results for the two estimators ($\hat{N}_R$ and $\hat{N}_B$) under the assumption that capture probabilities vary with individual dogs and sampling occasions ($N = 200$, and $[e_j, j = 1, \ldots, 10]$ = [0.4, 0.5, 0.45, 0.6, 0.5, 0.4, 0.5, 0.6, 0.55, and 0.45])

Case	Estimator	$t = 5$					$t = 7$					$t = 10$				
		n	Estimate	Bias	SD	RMSE	n	Estimate	Bias	SD	RMSE	n	Estimate	Bias	SD	RMSE
1	$\hat{N}_R$	749	718	518	2564.4	2614.5	975	310	110	492.5	504.4	1,000	247	47	153.4	160.2
	$\hat{N}_B$	1,000	209	9	45.9	46.7	1,000	203	3	28.3	28.5	1,000	202	2	17.4	17.5
2	$\hat{N}_R$	731	1.8E16	1.8E16	5.0E17	5.0E17	981	371	171	2,435	2439.7	1,000	323	123	2530.8	2532.5
	$\hat{N}_B$	1,000	202	2	42.7	42.7	1,000	198	−2	28.3	28.4	1,000	195	−5	16.8	17.4
3	$\hat{N}_R$	795	620	420	2514.8	2548.1	985	271	71	770.2	773.1	1,000	215	15	136.3	137.0
	$\hat{N}_B$	1,000	181	−19	36.4	41.0	1,000	179	−21	23.8	31.8	1,000	179	−21	15.3	26.2
4	$\hat{N}_R$	843	427	227	1105.7	1128.2	989	255	55	690.8	692.6	1,000	192	−8	47.7	48.4
	$\hat{N}_B$	1,000	159	−41	30.6	51.3	1,000	159	−41	20.3	46.0	1,000	162	−38	13.7	40.6
5	$\hat{N}_R$	907	467	267	2977.1	2987.4	995	168	−32	86.4	92.2	1,000	162	−38	35.5	51.7
	$\hat{N}_B$	1,000	131	−69	22.6	73.0	1,000	133	−67	16.0	69.0	1,000	138	−62	11.7	63.3
6	$\hat{N}_R$	934	490	734	1114.5	1151.1	999	238	38	120.3	126.1	1,000	220	20	25.8	32.4
	$\hat{N}_B$	1,000	201	1	24.3	24.3	1,000	200	0	16.1	16.1	1,000	200	0	10.0	10.0
7	$\hat{N}_R$	950	511	311	1948.5	1972.2	999	228	28	70.2	75.4	1,000	214	14	23.5	27.5
	$\hat{N}_B$	1,000	196	−4	24.5	24.8	1,000	195	−5	16.5	17.2	1,000	195	−5	10.1	11.1
8	$\hat{N}_R$	970	383	183	658.6	683.1	1,000	208	8	132.2	132.3	1,000	198	−2	21.1	21.2
	$\hat{N}_B$	1,000	178	−22	21.4	30.6	1,000	179	−21	15.4	26.4	1,000	180	−20	10.0	22.0
9	$\hat{N}_R$	977	286	86	342.4	352.9	1,000	186	−14	38.3	40.7	1,000	186	−14	18.5	23.3
	$\hat{N}_B$	1,000	158	−42	18.3	45.8	1,000	161	−39	13.5	41.2	1,000	167	−33	9.5	34.7

Table 3 continued

Case	Estimator	$t = 5$					$t = 7$					$t = 10$				
		n	Estimate	Bias	SD	RMSE	n	Estimate	Bias	SD	RMSE	n	Estimate	Bias	SD	RMSE
10	$\hat{N}_R$	992	257	57	1,565.5	1565.7	1, 000	159	−41	29.6	50.6	1,000	165	−35	17.0	38.6
	$\hat{N}_B$	1, 000	131	−69	14.1	70.5	1, 000	136	−64	11.5	64.7	1,000	145	−55	9.1	56.0
11	$\hat{N}_R$	996	323	123	459.7	475.6	1, 000	220	20	26	33.0	1,000	213	13	12.7	18.3
	$\hat{N}_B$	1, 000	200	0	17.2	17.2	1, 000	200	0	11.2	11.2	1,000	200	0	6.8	6.8
12	$\hat{N}_R$	998	304	104	262.2	281.9	1, 000	215	15	26.9	31.0	1,000	208	8	12.7	15.2
	$\hat{N}_B$	1, 000	194	−6	17.5	18.4	1, 000	195	−5	11.6	12.8	1,000	195	−5	7.3	8.7
13	$\hat{N}_R$	997	389	189	4,293.5	4295.5	1, 000	197	−3	22.4	22.5	1,000	195	−5	11.5	12.5
	$\hat{N}_B$	1, 000	177	−23	14.3	27.2	1, 000	179	−21	10.0	23.5	1,000	182	−18	6.8	19.4
14	$\hat{N}_R$	1, 000	215	15	77.3	78.7	1, 000	183	−17	19.6	25.8	1,000	187	−13	12.3	17.8
	$\hat{N}_B$	1, 000	160	−40	13	42.2	1, 000	164	−36	9.7	37.0	1,000	171	−29	7.0	29.7
15	$\hat{N}_R$	1, 000	174	−26	47.1	54.0	1, 000	160	−40	15.8	42.8	1,000	170	−30	11	31.8
	$\hat{N}_B$	1, 000	134	−66	10.5	66.6	1, 000	141	−59	8.5	59.4	1,000	151	−49	6.9	49.0
16	$\hat{N}_R$	1, 000	256	56	77.2	95.5	1, 000	215	15	16.8	22.5	1,000	209	9	8.1	12.2
	$\hat{N}_B$	1, 000	199	−1	12.1	12.2	1, 000	199	−1	8.1	8.2	1,000	200	0	4.9	4.9
17	$\hat{N}_R$	1, 000	248	48	54.2	72.4	1, 000	211	11	15.4	18.7	1,000	206	6	7.5	9.6
	$\hat{N}_B$	1, 000	194	−6	11.0	12.4	1, 000	195	−5	7.3	8.9	1,000	196	−4	4.6	6.1
18	$\hat{N}_R$	1, 000	219	19	43.4	47.3	1, 000	195	−5	14.6	15.4	1,000	195	−5	8.2	9.6
	$\hat{N}_B$	1, 000	177	−23	11.6	25.6	1, 000	180	−20	8.4	21.7	1,000	184	−16	5.7	17.1
19	$\hat{N}_R$	1, 000	199	−1	32.6	32.6	1, 000	185	−15	13.7	20.2	1,000	189	−11	8.4	13.6
	$\hat{N}_B$	1, 000	162	−38	10.3	39.8	1, 000	167	−33	7.9	33.6	1,000	175	−15	5.7	25.9
20	$\hat{N}_R$	1, 000	144	−56	13.6	57.5	1, 000	139	−61	8.0	61.4	1,000	143	−57	6.5	57.2
	$\hat{N}_B$	1, 000	127	−73	6.7	73.0	1, 000	130	−70	5.9	69.9	1,000	135	−65	5.3	64.7

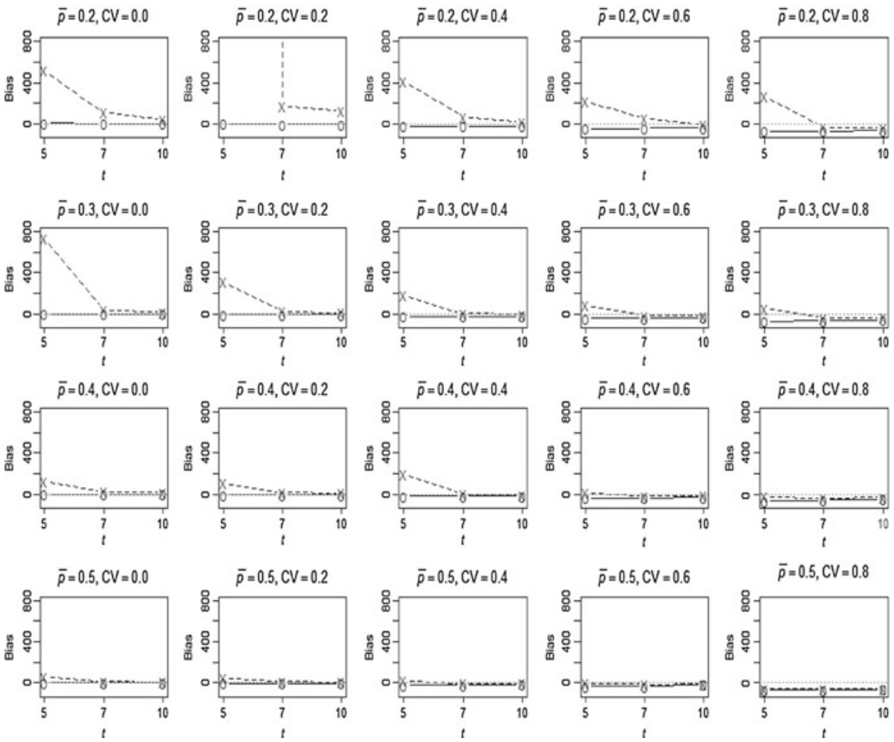

Fig. 1 Simulation results for the bias of $\hat{N}_R$ and $\hat{N}_B$ under the assumption that capture probabilities vary with individual dogs and sampling occasions. $N = 200$, and $[e_j, j = 1, \ldots, 10]$ = [0.4, 0.5, 0.45, 0.6, 0.5, 0.4, 0.5, 0.6, 0.55, 0.45]. *Dashed lines* with 'x':$\hat{N}_R$, *solid lines* with 'o':$\hat{N}_B$

As far as the bias is concerned, stability implies that biases associated with $\hat{N}_B$, if they exist, are real biases. Hence, even though $\hat{N}_B$ has a smaller standard deviation, it does not necessarily mean that $\hat{N}_B$ is a good estimator. Its overall performance depends upon the size of bias. When its bias is also small, $\hat{N}_B$ is no doubt a good estimator. Otherwise, it may not be a desirable estimator at all. The plots in the far left hand column of Fig. 1, in which CV = 0, indicate that $\hat{N}_B$ indeed performs very well with very small biases even with only five survey occasions, while $\hat{N}_R$ is not as good even if the number of survey occasions is as large as 10. This finding is not surprising since the design settings behind these four plots are similar to model M_0 except that we now allowed the capture probabilities to vary by survey occasions. Compared with Table 2, we can further infer that the time effect has little impact on $\hat{N}_B$ as long as individual dogs' capture probabilities stay the same for all dogs in each survey occasion. On the other hand, when the individual capture probabilities are not homogeneous so that CV is away from zero, the plots in the right four columns of Fig. 1 indicate that $\hat{N}_B$ tends to underestimate the true population size, and underestimation biases become more noticeable as CV grows. When CV is large enough, for example 0.4, so that heterogeneous capture probabilities become an issue, underestimation makes $\hat{N}_B$ no more a feasible estimator. And when CV reaches 0.8, it is severely biased. For a comparison

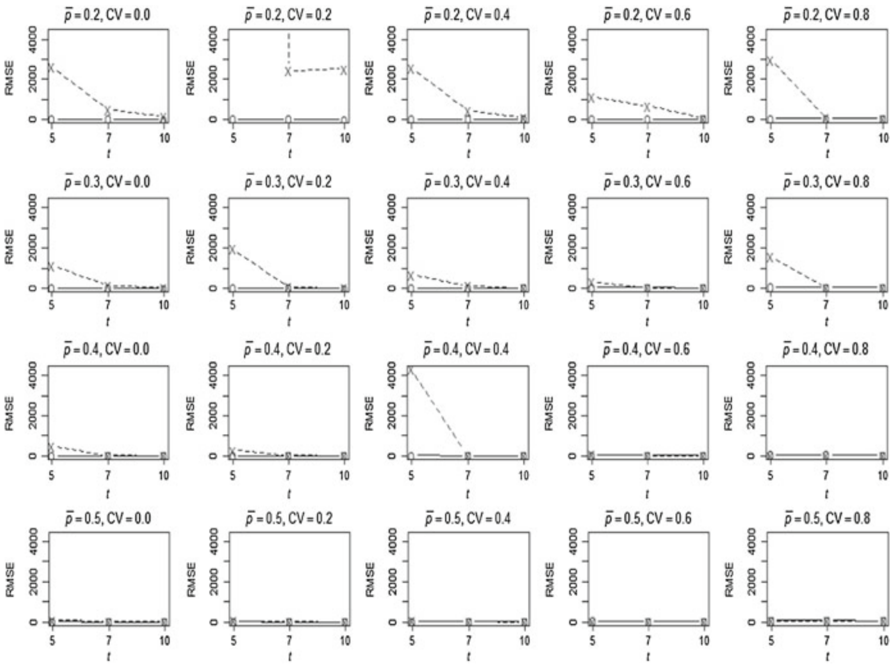

Fig. 2 Simulation results for the RMSE of $\hat{N}_R$ and $\hat{N}_B$ under the assumption that capture probabilities vary with individual dogs and sampling occasions. $N = 200$, and $[e_j, j = 1, \ldots, 10]$ = [0.4, 0.5, 0.45, 0.6, 0.5, 0.4, 0.5, 0.6, 0.55, 0.45]. *Dashed lines* with 'x':$\hat{N}_R$, *solid lines* with 'o':$\hat{N}_B$

purpose, it is interesting to note that $\hat{N}_R$ behaves differently as CV changes. It tends to overestimate the population size as CV is close to 0, and underestimates the size as CV is far away from 0. In addition, we can also find that$\hat{N}_R$ appears slightly less biased than $\hat{N}_B$ when $\bar{p}$ and CV are both greater than 0.4, as indicated by the four plots in the bottom right corner of Fig. 1. However, this does not necessarily mean that $\hat{N}_R$ might be preferable to $\hat{N}_B$ for certain cases. Although $\hat{N}_R$ is less biased here, its variability is still quite large relative to that of $\hat{N}_B$. Hence, it rules out the usefulness of $\hat{N}_R$.

The overall performances in terms of RMSE are shown in Fig. 2. From the plots, we can once again infer that there is no need to use $\hat{N}_R$. $\hat{N}_B$ appears to perform better in most situations. Even though it does not perform as good as $\hat{N}_R$ in certain cases, the differences appear slight. Hence, we prefer $\hat{N}_B$ to $\hat{N}_R$.

Although all the indications point to fact that $\hat{N}_B$ is a better estimator to use than $\hat{N}_R$, using $\hat{N}_B$ to deal with situations described by model M_{th} still requires caution. When $\bar{p}$ is not smaller than 0.4 and CV is not greater than 0.4, it appears that $\hat{N}_B$ can be safely used to provide a quick estimate of population size even if the time effect exists. Otherwise, use of $\hat{N}_B$ is not recommended, as serious underestimation bias would occur.

4 Discussion

Dogs are extremely beneficial to human beings as companions, rescue dogs, guides for the blind, and assistants in therapies. However, the well-being and survival of dogs are threatened when irresponsible owners abandon them. This not only causes social problems but also has a serious effect on rabies prevention programs. Therefore, to improve the welfare of dogs, it is imperative to implement a quantitative management plan for controlling dog population. This article explores the performances of estimators $\hat{N}_R$ (regression method) and $\hat{N}_B$ (Beck's method), two survey methods recommended by the WHO/WSPA (1990) guidelines and OIE's Terrestrial Animal Health Code (2010). Through simulation studies, we discussed the pros and cons of the methods, with a view to provide practitioners a better understanding of the estimators.

Although both estimators are recommended in the guidelines, their performances appear different. According to the simulation studies, we found that $\hat{N}_B$ outperforms $\hat{N}_R$ in the situations described by model M_0, a model both deemed appropriate. Hence, use of $\hat{N}_B$ in the situations satisfying the fundamental assumptions of model M_0 is recommended.

The superiority of $\hat{N}_B$ over $\hat{N}_R$ can also be observed in most situations described by model M_{th}, a model in which capture probabilities vary with individual dogs and survey occasions. However, caution should be exercised before its use in the situations described by M_{th}, as $\hat{N}_B$ tends to underestimate the population size, and underestimation worsens as CV increases (i.e., heterogeneity among individual capture probabilities becomes noticeable). Hence, unless CV is no greater than 0.4, in which $\hat{N}_B$ appears to still be able to provide decent estimates, use of $\hat{N}_B$ is also not recommended. Estimators specifically designed to deal with model M_{th} are necessary.

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