CAPTURE-RECAPTURE TYPE MODEL FOR ESTIMATING ELUSIVE EVENTS WITH TAG LOSS

Supported by tetfund TERTIARY EDUCATION TRUST FUND

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Received: July 04, 2016 **Accepted:** September 13, 2016

Abstract: In capture-recapture experiments, if individuals lost their tags, the observed recaptures will be smaller than expected. This phenomenon results in overestimation of the population under consideration. Drugs addicts are usually referred for treatment or/and rehabilitation, on the process of these, they are likely to change their identity hence losing their tags. Tags loss method was therefore incorporated in the estimation of the size of elusive population. The simulation studies revealed that the proposed coverage probability tag loss model (CPTLM) is statistically consistent with small and large population sizes. The proposed model was applied to addicts' data collected from Northeast, Nigeria.

Keywords: Capture-recapture, tag-loss, overestimation, drug addicts

Introduction

Capture-recapture (C-R) methods were originally applied to animal populations in which sequence of samples were taken from a well-defined population; animals found without a tag in a particular sample were given a unique tag before returning that sample to the population. In that way, estimate of the population size and other relevant parameters are obtained. These methods have now been applied extensively to epidemiological and public health events with the aim of estimating the incidence and prevalence of such events (Seber *et al.*, 2000). The technique has also been adopted for other areas such as; the evaluation of census undercount (Ericksen and Kandame, 1985; Darroch *et al.*, 1993), software testing and reliability (Wohlin *et al.*, 1995; Ebrahimi, 1997; Briand *et al.*, 2000; Yip *et al.*, 2003), to mention a few. When there are only two samples, the method is called the Petersen method (or the Lincoln index), Jibasen (2011).

This work is concerned with estimating the number of drugs addicts within a given location; a case study of North eastern states of Nigeria, consisting of six states namely; Adamawa, Bauchi, Borno, Gombe, Taraba and Yobe States. The primary sources of data on drugs addicts in these States are from the National Drug Law Enforcement Agency (NDLEA) State command headquarters and the Psychiatric centres of the Specialists Hospital in these States. Patients are taking to the Centres for treatment and are also to the NDLEA for rehabilitation. NDLEA also makes direct arrest of barons and drugs users.

In practice, C-R methods can be applied to any situation in which records of individuals from the same population are kept in at least two different but incomplete lists. Thus "being on list i" can be equated to "being on sample i". The problem is to estimate those missing from both lists. These lists can come from different units or departments of the same agency (e.g. Doctors' and Pharmacists' record), or different agencies (e.g. The Police Force and the Prison Services' records). When applied to list, the Petersen method is known by the nomenclature; Dual System Methods (DSM); Dual System Estimation (DSE) or Dual Record Systems (DRS) (IWGDMF, 1995; El-khorazaty *et al.*, 1976; Ericksen and Kadane, 1985).

The assumptions required for this estimate to be valid can be spelt out in a number of ways. However, the key ingredients are: (1) the population is closed, that is, the population has a constant size for the entire period of the study, (2) the lists are independent, (3) each member of the population has the same chance of being on a given list, and (4) individuals are matched correctly, that is, individuals will not change their identity, in the terminology of C-R, no tags loss. Assumption (1) holds if the experiment is conducted within a reasonably short period of time. For (2) the listing systems may not be independent, since addicts can be referred across systems for rehabilitation or treatment; the NDLEA usually refer addicts to Psychiatric centres for treatment, likewise, Psychiatric centres can also refer psychoactive patients to the NDLEA for rehabilitation. We assumed that addicts have similar behaviours, hence assumption (3) holds, that is, addicts have the same probability of being on a given list. Assumption (4) will completely be false; matching will depend on the quality of records, the truthfulness of the information and the uniqueness of the tags used. Addicted individuals are likely to give false information about their identity deliberately to avoid stigmatization or arrest, or even unconsciously under the effect of intoxicant. This leads to tag loss. According to Pollock (1991), the loss or overlooked of marks (tags) can be serious, he suggests that one way to estimate tag loss is to use double marks. Pollock *et al.* (1990) stated that, if tag loss is likely to occur, an attempt should be made to estimate rate of loss and that if individuals lose their tags, N will be overestimated; this situation is referred to as positive biased (IWGFDMF, 1995).

The paper is organized as follows: the tag loss method of Seber (1982) is presented in section 2, followed by the coverage probability model (CPM) for estimating elusive events of Jibasen (2011), where tag los was incorporated. In section (3), the incorporated tag loss method called, coverage probability tag loss model (CPTLM) was applied to a set of simulated data and compared to the Petersen method and the CPM. Finally, in section 4, the proposed CPTLM was applied to data set obtained from the NDLEA and Psychiatric centres in the north eastern States of Nigeria.

Materials and Methods

The Petersen estimator is well-known; if we assumed the proportion on list 1, ${}^{n_1}/_{N}$ for the whole population is roughly the same as it is on list 2, ${}^{m_2}/_{n_2}$, then,

$${}^{n_1}/_{N} = {}^{m_2}/_{n_2}$$

and, solving for N yields the Petersen estimator:

$$\hat{N} = \frac{n_1 n_2}{m_2} \quad (1)$$

where, N, m_2, n_1 and n_2 are the population size, the numbers of individuals on both lists, on list 1 and on list 2, respectively.

According to IWGDMF (1995), if we exploit the mathematical statistics result, (1) can be written as;

$$E\left(\hat{N}\right) = \frac{E(n_1)E(n_2)}{E(m_2)} = Np_1p_2/p_{12} = NR \qquad (2)$$

Where: N, m_2, n_1 and n_2 and as defined earlier, p_1, p_2 and p_{12} are probabilities of being on list 1, list 2, and both list 1and 2, respectively. **Where**, R >1, if being on list 1 tends to decrease the chance of being on list 2, N will be overestimated, this is negative dependence(or positive biased) which can be credited to the fact that, individuals 'elusified' by losing their tags. It is therefore evident that, with elusive events, tags loss is therefore apparent which leads to negative dependence between lists. In epidemiological studies, tag loss has received little attention (Seber *et al*., 2000).

This paper assumed that addicts are referred across agencies and that on reference, they are likely to change their information identification making it difficult for matching. This will thus imply that being on the first list will decrease the chance of being on the second, thus $\hat{N}$ will lead to over estimation of N.

Addicts on a list are considered as having an identifying string of information, these are; first name, surname, age, religion, address and type of substance abused. These information were group into two, forming two tags.Tag A consists of name, age, and religion; tag B consists of individuals'address and type of substance abuse.

Tag loss method of Seber (1982)

Each individual on a list has a string of identifying information subdivided into tag A and tag B. Tag A consists of name, age, and religion; these are items we assume individuals are likely to be truthful about. Tag B consist of address and type of substance abused; these are items addicts are likely to lie about. If either substring is correct the individual is identified uniquely. We assume further that these tags are independent. This assumptions and assertion are in line with Seber *et al.* (2000).

Let,

π_x= the probability that a tag x is lost on the second list (x = A, B)

π_{AB} = the probability that both tags are lost

m_x = number of tagged individuals on the second list, with tag x only (x = A, B)

m_{AB} = number of tagged individuals on the second list with both tags

m_2 = those on both lists

As earlier stated that, the tags are assumed to be independent, that is, $\pi_{AB} = \pi_A\pi_B$, according to Seber (1982), the joint probability function of m_A, m_B, m_{AB} and m_2 is given by;

$$f(m_A, m_B, m_{AB}, m_2 \mid n_1, n_2) = f(m_A, m_B, m_{AB} \mid m_2) f(m_2 \mid n_1, n_2) \qquad (3)$$

where

$$f(m_A, m_B, m_{AB} \mid m_2) = \frac{m_2!}{m_A!\, m_B!\, m_{AB}!\, m_{o!}}[(1-\pi_A)\pi_B]^{m_A}[\pi_A(1-\pi_B)]^{m_B} \times [(1-\pi_A)(1-\pi_B)]^{m_{AB}}[\pi_A\pi_A]^{m_o}$$

$$m_o = m_2 - m_A - m_B - m_{AB},$$

and,

$$f(m_2 \mid n_1, n_2) = \binom{n_1}{m_2}\binom{N-n_1}{n_2-m_2}\Big/\binom{N}{n_2}$$

While, maximum-likelihood estimates of N, m_2, π_A and π_B are given by

$$\hat{N} = \frac{N_1N_2}{\hat{m}_2}$$

$$m_A = \hat{m}_2(1-\hat{\pi}_A)\hat{\pi}_B$$

$$m_B = \hat{m}_2(1-\hat{\pi}_B)\hat{\pi}_A$$

$$m_{AB} = \hat{m}_2(1-\hat{\pi}_A)(1-\hat{\pi}_B)$$

With the solutions,

$$\hat{\pi}_A = m_B/(m_B + m_{AB})$$

$$\hat{\pi}_B = m_A/(m_A + m_{AB})$$

$$\hat{m}_2 = (m_A + m_{AB})(m_B + m_{AB})/m_{AB} \qquad (4)$$

Provided $m_x \neq 0$ for at least one x. If at least one $m_x = 0$, the model collapsed to the classical model.

M_c: Coverage probability model (CPM)

Huggins (1991) used a form of a Hurwitz- Thompson (H-T) method to model heterogeneity of individual animals, where animals were assigned probabilities, following this idea, Jibasen (2011) introduced a model for estimating elusive events for two lists (called, coverage probability model (CPM)) based on the H-T method; this model was discovered to give better results than the Petersen method, in the presence of low recaptures. The model is presented below incorporating the method of estimating tag loss (4).

The joint probability density function for the coverage probability model is given as;

$$L\ f(n_1, n_2, n_{11}) = \binom{r}{n_1}\binom{r-n_1}{n_2-n_{11}}\binom{n_1}{n_{11}} p^{n_1+n_2}(1-p)^{sr-n_1-n_2} \qquad (5)$$

(see Jibasen, 2011; Jibasen *et al.*, 2012)

The ML estimator of p is $\hat{p} = \frac{n}{sr}$

The two sample estimator for estimating elusive events is given in (6) as;

$$\hat{N}_c = \frac{r}{p} = \frac{sr^2}{n} \qquad (6)$$

Where, $r = n_1 + n_2 - \hat{m}_2$

where, n_{11} has been replaced by, $\hat{m}_2$.

Hence,

$$\hat{N}_{M2} = \frac{s(n_1 + n_2 - \hat{m}_2)^2}{n}$$

Thus, $s =$ the number of lists (samples) involved in the experiment, here, $s = 2$

Simulation studies

The simulated data was thus based on the hypergeometric settings, the marginal totals (n_1 and n_2) were fixed as well as the assumed population size N, while the recaptures n_{11} were randomly generated. The variates: m_A, m_B and m_{AB} were simulated from n_{11}, from where $\hat{m}_2$ was estimated to replace n_{11}. Series of simulations were carried out for $n_1 = 50$, $n_2 = 10$ and the assumed population size $N = 90$, as showed in Tables 1 to 5. Simulation for other values of n_1, n_2 and N are summarized in Tables 6 to7. The Petersen estimator $\hat{N}$, the coverage probability model (CPM) estimator $\hat{N}_c$, and the coverage probability tag loss model (CPTLM) estimator $\hat{N}_{m2}$, were compared using the Akaike information criterion (AIC), while mean absolute deviation (MAD) was used to checked for the overall model performance for each set of simulated data. All simulated data were from Jibasen (2011).

Table 1 shows no tag loss; $n_{11} = m_A + m_B + m_{AB}$ the analyses thus showed that the CPTLM performs well compared with the CPM, but both performs better compared to the Petersen method. This reveals that the CPTLM performs well even when there is no tag loss. Table 2 shows a situation where one individual losses one tag. The result in Table 2 shows that if an individual loss both tags the CPTLM performs better than both the Petersen and the CPM. But if up to two individuals lost both tags the CPM performs better.

Table1: Simulated data for n_1=50, n_2=10 and N =90

S/N	n_{11}	M_A	M_B	M_{AB}	$\hat{m}_2$	$\hat{N}$	AIC $(\hat{N})$	$\hat{N}_c$	AIC $(\hat{N}_c)$	$\hat{N}_{m2}$	AIC $(\hat{N}_{m2})$
1	7	1	3	3	8	63	4.366	94	4.272	90	4.010
2	7	2	1	4	8	67	4.366	94	4.272	92	4.140
3	6	2	1	3	7	75	3.490	97	4.543	95	4.361
4	8	2	1	5	8	60	5.112	90	4.010	89	4.092
5	8	2	3	3	10	50	5.112	90	4.010	83	4.490
6	8	1	2	5	8	60	5.112	90	4.010	89	4.092
7	10	3	3	4	12	41	-	83	4.490	76	5.025
8	7	1	4	2	9	56	4.366	94	4.272	87	4.244
9	8	2	2	4	9	56	5.112	90	4.010	87	4.244
10	5	0	1	4	5	100	3.759	101	4.824	101	4.824
MAD						29		4		5	

Table2: Simulated data for n_1= 50, n_2 =10 and $N = 90$ with one tag loss

S/N	n_{11}	M_A	M_B	M_{AB}	$\hat{M}_2$	$\hat{N}$	AIC $(\hat{N})$	$\hat{N}_c$	AIC $(\hat{N}_c)$	$\hat{N}_{m2}$	AIC $(\hat{N}_{m2})$
1	7	1	2	3	7	63	4.366	94	4.272	95	4.361
2	7	1	1	4	6	67	4.366	94	4.272	96	4.474
3	6	2	1	3	7	75	3.490	97	4.543	95	4.361
4	8	2	1	4	8	60	5.112	90	4.010	92	4.140
5	8	1	2	4	8	50	5.112	90	4.010	92	4.140
6	8	1	1	5	7	60	5.112	90	4.010	93	4.219
7	10	1	2	6	9	41	–	83	4.490	86	4.327
8	7	1	2	3	7	56	4.366	94	4.272	95	4.361
9	8	2	1	4	8	56	5.112	90	4.010	92	4.140
10	5	1	1	2	5	100	3.759	101	4.824	103	4.968
MAD						29		4		5	

When individuals loss 2 tags, one from each string, Table 3 shows that the CPM is better model. Table 4 shows tag loss by substring A, while Table 5 shows tag loss by substring B. Each shows that the CPTLM performs well but the CPM is better.

Table 3: Simulated data for n_1= 50, n_2 =10 and $N = 90$ with two tag loss

S/N	n_{11}	M_A	M_B	M_{AB}	$\hat{M}_2$	$\hat{N}$	AIC $(\hat{N})$	$\hat{N}_c$	AIC $(\hat{N}_c)$	$\hat{N}_{m2}$	AIC $(\hat{N}_{m2})$
1	7	1	2	2	6	63	4.366	94	4.272	97	4.543
2	7	1	1	3	5	67	4.366	94	4.272	100	4.729
3	6	2	0	3	5	75	3.490	97	4.543	101	4.824
4	8	2	1	3	7	60	5.112	90	4.010	95	4.361
5	8	1	2	3	7	50	5.112	90	4.010	95	4.361
6	8	0	1	5	6	60	5.112	90	4.010	97	4.543
7	10	1	2	5	8	41	-	83	4.490	89	4.092
8	7	0	2	3	5	56	4.366	94	4.272	101	4.824
9	8	2	1	3	7	56	5.112	90	4.010	95	4.361
10	5	1	1	1	4	100	3.759	101	4.824	105	5.115
MAD						29		4		8	

Table 4: Simulated data for n_1= 50, n_2 =10 and $N = 90$ with one tag loss from substring A

S/N	n_{11}	M_A	M_B	M_{AB}	$\hat{M}_2$	$\hat{N}$	AIC $(\hat{N})$	$\hat{N}_c$	AIC $(\hat{N}_c)$	$\hat{N}_{m2}$	AIC $(\hat{N}_{m2})$
1	7	0	3	3	6	63	4.366	94	4.272	95	4.361
2	7	1	1	4	6	67	4.366	94	4.272	97	4.543
3	6	1	1	3	5	75	3.490	97	4.543	101	4.824
4	8	1	1	5	7	60	5.112	90	4.010	94	4.272
5	8	1	3	3	8	50	5.112	90	4.010	89	4.076
6	8	0	2	5	7	60	5.112	90	4.010	93	4.219
7	10	2	3	4	11	41	-	83	4.490	82	4.611
8	7	0	4	2	6	56	4.366	94	4.272	92	4.140
9	8	1	2	4	8	56	5.112	90	4.010	92	4.140
10	5	0	1	4	5	100	3.759	101	4.824	105	5.115
MAD						29		4		6	

Table 5: Simulated data for n_1= 50, n_2 =10 and $N = 90$ with one tag loss from substring B

S/N	n_{11}	M_A	M_B	M_{AB}	$\hat{M}_2$	$\hat{N}$	AIC $(\hat{N})$	$\hat{N}_c$	AIC $(\hat{N}_c)$	$\hat{N}_{m2}$	AIC $(\hat{N}_{m2})$
1	7	1	2	3	7	63	4.366	94	4.272	95	4.361
2	7	2	0	4	6	67	4.366	94	4.272	97	4.543
3	6	2	0	3	5	75	3.490	97	4.543	101	4.824
4	8	2	0	5	7	60	5.112	90	4.010	94	4.272
5	8	2	2	3	8	50	5.112	90	4.010	89	4.076
6	8	1	1	5	7	60	5.112	90	4.010	93	4.219
7	10	3	2	4	11	41	-	83	4.490	82	4.611
8	7	1	3	2	8	56	4.366	94	4.272	92	4.140
9	8	2	1	4	8	56	5.112	90	4.010	92	4.140
10	5	0	0	4	4	100	3.759	101	4.824	105	5.115
MAD						29		4		6	

For lack of space, simulation for various values of n_1, n_2 and N are summarized in Tables 6 and 7. The simulated results in Table 6 revealed that the CPTLM performs well when the elusiveness is high, that is, when more individuals 'elusifies'. The results further show that, even when all the recaptures are lost CPTLM performs better than the Petersen but not the CPM. When the population size is large, Table 7 shows that CPTLM performs better with smaller number of the tag loss compare to the CPM and far better than the classical method, the Petersen.

Table 6: Simulated results for various values of n_1, n_2 and N

N	n_1	n_2	n_{11}	$\hat{N}_{m2}$ with 3 loss	$\hat{N}_{m2}$ with 10 loss	$\hat{N}_{m2}$ with10 loss	$\hat{N}_c$	$\hat{N}$
200	100	10	10	193	220	200	182	100
	100	10	8	200	220	208	189	125
	100	10	6	208	220	216	197	167
	MAD			5	20	8	11	69
				$\hat{N}_{m2}$ with 10 loss	**$\hat{N}_{m2}$ with 20 loss**	**$\hat{N}_{m2}$ with 25 loss**		
200	100	40	24	227	264	284	192	167
	100	40	25	223	260	280	189	160
	100	40	27	216	253	272	182	148
	MAD			22	59	79	12	42
				$\hat{N}_{m2}$ with 25 loss	**$\hat{N}_{m2}$ with 30 loss**	**$\hat{N}_{m2}$ with 40 loss**		
200	90	70	46	242	259	177	162	137
	90	70	43	252	270	186	171	147
	90	70	42	256	274	189	174	150
	MAD			50	68	16	31	56

Table 7: Simulated results for various values of n_1, n_2 with large values of N

N	n_1	n_2	n_{11}	$\hat{N}_{m2}$ with 1 loss	$\hat{N}_{m2}$ with 2 loss	$\hat{N}_{m2}$ with 5 loss	$\hat{N}_c$	$\hat{N}$
300	150	10	7	296	300	312	293	214
	150	10	6	300	304	316	296	250
	150	10	8	293	296	308	289	188
MAD				4	3	12	7	83
1000	500	80	57	947	950	961	943	702
	500	80	51	969	972	983	965	784
	500	80	49	976	980	991	972	816
MAD				36	33	22	40	233
2000	900	80	49	1773	1777	1788	1769	1469
	900	80	48	1777	1780	1792	1773	1500
	900	80	57	1742	1746	1758	1739	1263
MAD				236	232	221	240	589
N	n_1	n_2	n_{11}	$\hat{N}_{m2}$ with 100 loss	$\hat{N}_{m2}$ with 150 loss	$\hat{N}_{m2}$ with 5 loss	$\hat{N}_c$	$\hat{N}$
3000	1500	300	195	3230	3422	2880	2862	2308
	1500	300	207	3185	3376	2837	2820	2174
	1500	300	194	3234	3426	2884	2866	2320
MAD				216	408	133	151	733

Estimation of the number of addicts from Northeast Nigeria using CPTLM

The CPTLM was used to estimate the population of addicts in the north east alongside the CPM. A 95% Confidence intervals based on the suggestion of Chao (1989) was constructed for $\hat{N}_{m2}$ with 5 tag loss, as shown in Table 8, the interval estimates shows that all the estimates of $\hat{N}_{m2}$ with 1 tag loss, 2 tag loss and for $\hat{N}_c$ falls within the acceptance region.

Table 8: Estimated populations of addicts of five Northeast States using CPTLM

State	Year	$\hat{N}_{m2}$ with 1 loss	$\hat{N}_{m2}$ with 2 loss	$\hat{N}_{m2}$ with 5 loss	LCL $\hat{N}_{m2}$ with 5 loss	UCL $\hat{N}_{m2}$ with 5 loss	$\hat{N}_c$
Adamawa	2006	239	243	244	150.0758	694.0903	235
	2007	172	176	178	99.56733	679.4685	168
	2006	170	174	176	101.8159	622.2887	166
	2007	206	210	212	134.5086	566.4152	203
	2008	283	287	289	188.6322	649.4115	280
Taraba	2006	197	200	202	122.1806	617.8411	193
	2007	179	183	185	111.1938	590.6701	175
	2006	224	228	230	146.0445	603.8456	221
	2007	218	222	224	132.0206	700.2673	214
	2008	233	237	239	149.9038	633.1515	229
Gombe	2006	386	390	392	250.1097	921.735	382
	2007	413	417	419	272.5436	928.3745	409
	2006	357	360	362	230.3457	870.088	353
	2007	320	324	326	216.1508	715.0046	317
	2008	313	317	319	213.2949	685.7079	309
Bauchi	2006	364	367	369	265.3076	688.6959	360
	2006	224	227	229	159.4315	486.0392	220
	2007	207	210	212	152.8454	409.0217	204
	2006	208	211	213	172.1324	323.4389	206
	2007	251	253	255	205.3606	388.0259	248
	2008	231	233	234	203.7887	303.1091	228
Borno	2006	553	557	558	386.1228	1056.389	549
	2007	593	597	599	432.5211	1032.522	590
	2006	678	682	684	477.3404	1240.633	674
	2007	506	510	512	366.2576	901.735	503
	2008	536	540	542	375.8013	1003.603	532
Total		8260	8354	8401	5715.297	18311.57	8167

Source: Jibasen (2011)

Tag loss is inevitable when dealing with elusive events. The simulation studies revealed that the CPTLM performs competitively alongside the CPM, and that the CPTLM performs better when the population size is large, whereas CPM performs better with smaller population sizes. It was also discovered that CPTLM performs well when there is no tag loss and as the number of loss tags reduces CPTLM performs better. The proposed tag loss model was applied to addicts' data, where a 95% confidence interval shows that all the estimates fall within the acceptance region.

Conclusion

The robustness of CPM was established by Jibasen (2011), this is really, the first attempt at improving (or even disapproving) on the performance of CPM. With this work, it has been established that CPM is a robust method of estimating elusive events from two sources, even when tag loss is inevitable.

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