Journal of Statistics Applications & Probability Letters
An International Journal

http://dx.doi.org/10.18576/jsapl/090201

Transformed ratio type estimators under Adaptive Cluster Sampling: An application to COVID-19

Rajesh Singh[1] *and Rohan Mishra*[2,*]

Department of Statistics, Institute of Science, Banaras Hindu University, Varanasi-221005, U.P., India

Received: 2 Oct. 2021, Revised: 12 Nov. 2021, Accepted: 25 Dec. 2021
Published online: 1 May 2022

Abstract: The initial spread of COVID-19 is highly clustered or clumped. In such a case conventional sampling designs viz., Simple random sampling without replacement, Stratified random sampling or other non-adaptive designs cannot be used to estimate the average cases of COVID-19 as the sample drawn will not be a representative one. In this article, we have proposed four transformed ratio type estimators in Adaptive cluster sampling (ACS) to estimate the average of new COVID-19 cases. The expressions of bias and mean squared error (MSE) of the proposed estimators are derived up to first order of approximation and presented. The performance of the proposed estimators have been analyzed through a simulation study, on COVID-19 cases in the Indian state of Goa. The proposed estimators perform better than all the estimators presented in this article.

Keywords: COVID-19, Transformed estimator, Rare, Auxiliary information, Simulation, Adaptive cluster sampling

1 Introduction

The type of sampling design to be used depends on the population under study and when that population is rare or highly clustered, the conventional sampling designs cannot be used to estimate the population's parameter of interest as in such a case, most of the sampled units will provide a heavily biased estimate of the population's parameter of interest. This has been, one of the major issues in survey sampling theory. However, Thompson[1] proposed a sampling design that gives an edge to the researcher, allowing them to fix a criterion or a condition according to which the units will be selected in the sample. This sampling design is called Adaptive cluster sampling (ACS). Due to its need and flexibility, ACS designs have been used in various disciplines such as Ecological science (e.g.,[2,3]), Environmental science (e.g.,[4]), Epidemiological study [5].

As per WHO, COVID-19 is caused by the SARS-CoV-2 virus. The virus spreads in various ways, some of them include, spreading between people who are in close proximity with each other or in a poorly ventilated indoor setting or getting infected by touching a surface contaminated by the virus when touching their eye, nose or mouth without cleaning their hands [6].

As a result, localities followed by cities and then entire states become a hotspot of the virus putting an immense burden on the healthcare system of a country. At first, when the virus starts to spread, the cases are highly clustered or rare and at different places depending on the carrier of the virus, in such a situation using classical sampling designs to estimate the average number of cases would result in extremely biased estimates. To deal with this, adaptive cluster sampling becomes the only viable option.

Using known auxiliary information many ratio estimators ([7]-[10]) are proposed under SRS paradigm. In ACS, Dryver Chao [11] proposed ratio estimator. Singh R and Mishra Rohan[14] proposed a generalized ratio estimator, Chutiman [12] proposed some modified ratio estimators followed by Yadav et al.[13] proposing improved ratio estimators using known auxiliary information to estimate the unknown population mean of a finite population.

* Corresponding author e-mail: i.rohanskmishra@gmail.com

Application of ACS design in communicable diseases has been seldom done. In this article, we aim at applying ACS design to estimate the average COVID-19 cases in the Indian state of Goa by our proposed four transformed ratio type estimators.

In this article, we have proposed four transformed ratio type estimators to estimate the average of new cases of COVID-19, using known information of the auxiliary variable, viz., the population coefficient of variation, the population mean square of the auxiliary variable, the coefficient of skewness, kurtosis of the auxiliary variable and the coefficient of correlation between the study variable and the auxiliary variable.

The methodology of ACS design is presented in section 2. In section 3 some related estimators under ACS design are presented. The proposed transformed ratio type estimators along with their derivations of bias and MSE are presented in section 4. In section 5 a simulation study to estimate average new cases of COVID-19 in the Indian state of Goa[19] between 27^{th} of March 2020 to 4^{th} of July 2020 is conducted. A discussion on the results obtained is presented in section 6. The final concluding remarks of the article are presented in section 7.

2 Methodolgy of ACS design

ACS is an adaptive sampling design in which, the units in the final sample depends on all the units which have been observed during the survey. Initially, a sample of size n_1 is drawn from the population of size N using any conventional sampling design (usually SRSWOR) and if these selected units satisfy some researcher-specific condition C, then additional units are drawn from a pre-defined neighbourhood.
So, before conducting the survey, two things should be clearly defined:

- the neighbourhood of a unit (or observation)
- the researcher-specific condition (C)

This researcher-specific condition for selecting the observation on survey variable y is usually $y_i > 0$. In ACS, the used choice of neighbourhood is 4 unit first order in which, if any i^{th} unit selected in the initial sample is greater than 0, the units adjacent to this i^{th} unit in its East, West, North and South directions are also selected. This process of selecting the neighbourhood keeps on going until no further additional unit satisfies the condition C.

The units satisfying condition C form a network, and units not satisfying it are called edge units and are considered to be a network of size 1. The selection of any unit of a network leads to the selection of the entire network. These networks and edge units together form a cluster (Fig. 1).
The clusters are obviously not disjoint due to overlapping edge units but the units of a network are non-overlapping and thus the entire population can be partitioned as a set of networks and edge units.
Once there are no more additional units satisfying condition C, ACS terminates and the sample obtained consists of units selected in the initial sample and adaptively selected units.
Once the population is divided into networks and edge units, we make a transformed population by assigning the average value of a network to all the units of this network but edge units stay the same. Once the transformed population is obtained, and we consider averages of networks then ACS can be regarded as either SRSWOR or SRSWR.

3 Estimators in Adaptive Cluster Sampling

Let the population size be N and the sample size of initial sample selected using Simple Random Sampling Without Replacement be n. According to [11] when we consider the average of networks then Adaptive Cluster Sampling can be regarded as Simple Random Sampling.
An unbiased estimator for population mean under ACS was proposed in 1990 by [5]. This estimator was a modification of Hansen and Hurwitz [20]. Thompson's estimator is as follows:

$$\bar{y}_{ACS_1} = (\frac{1}{n})\sum_{i=1}^{n} wy_i$$

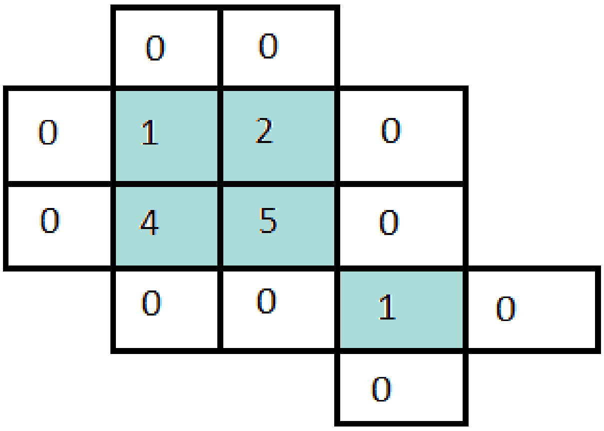

Fig. 1: An example of a hypothetical cluster with pre-defined condition (C) $y_i > 0$. The units having y-values 1, 2, 4, 5 and 1 form a network of size five. The edge units are the units with y values 0 and are adjacent to the y values greater than 0. Together they form a cluster.

where w_{yi} denote the network means of a network containing the i^{th} unit, so $w_{yi} = \sum_{j\varepsilon\Psi_i}(y_j)$, where ψ_i is the network containing unit i amd m_i be the number of units in the network ψ_i The variance of Thompson's estimator is

$$V(\bar{y}_{ACS_1}) = (\frac{1}{n} - \frac{1}{N})\bar{Y}^2 C_{wy}^2 = f\bar{Y}^2 C_{wy}^2$$

where $f = \frac{1}{n} - \frac{1}{N}$, $C_{wy}^2 = \frac{S_{wy}^2}{\bar{Y}^2}$ and $S_{wy}^2 = \frac{1}{N-1}\sum_{i=1}^{N}(w_{yi} - \bar{Y})^2$.
A modified ratio estimator was proposed by Dryver and Chao [11] as

$$\bar{y}_{ACS_2} = \frac{\sum_{i=1}^{n} w_{y_i}}{\sum_{i=1}^{n} w_{x_i}}\bar{X}$$

.
where w_{yi} and w_{xi} denote the network means of a network containing the i^{th} unit, so $w_{yi} = \sum_{j\varepsilon\Psi_i}(y_j)$ and $w_{xi} = \sum_{j\varepsilon\Psi_i}(x_j)$, where ψ_i is the network containing unit i and m_i be the number of units in the network ψ_i.
The Mean Square Error of Dryver and Chao up to first order of approximation is

$$MSE(y_{ACS_2}) = (\frac{1}{n} - \frac{1}{N})\bar{w}_y^2[C_{wy}^2 + C_{wx}^2 - 2\rho_{wxwy}C_{wx}C_{wy}]$$

Using the coefficient of variation C_{wx} and kurtosis $\beta_2(wx)$ on the network means of auxiliary variable w_x, Chutiman [12] proposed the following estimators

$$\bar{y}_{ACS_3} = \bar{wy}(\frac{\bar{X} + C_{wx}}{\bar{wx} + C_{wx}})$$

$$\bar{y}_{ACS_4} = \bar{wy}(\frac{\bar{X} + \beta_2(wx)}{\bar{wx} + \beta_2(wx)})$$

The Mean Squared Errors up to the first order of approximations are

$$MSE(\bar{y}_{ACS_3}) = (\frac{1}{n} - \frac{1}{N})\bar{Y}^2[C_{wy}^2 + \theta_{w3}^2 C_{wx}^2 - 2\theta_{w3}\rho_{wxwy}C_{wx}C_{wy}]$$

$$MSE(\bar{y}_{ACS_4}) = (\frac{1}{n} - \frac{1}{N})\bar{Y}^2[C_{wy}^2 + \theta_{w5}^2 C_{wx}^2 - 2\theta_{w5}\rho_{wxwy}C_{wx}C_{wy}]$$

where $\theta_{w3} = \frac{\bar{Y}}{\bar{Y}+C_{wx}}$, $\theta_{w4} = \frac{\bar{X}\beta_2(wx)}{\bar{X}\beta_2(wx)+C_{wx}}$ $\theta_{w5} = \frac{\bar{X}}{\bar{X}+\beta_2(wx)}$
Yadav et al. [13] proposed improved ratio estimators of population mean using known coefficient of variation, skewness and kurtosis of the network means of auxiliary variables. The estimators are

$$\bar{y}_{ACS_5} = \bar{w}_y(\frac{\beta_2(w_x)\bar{X} + \beta_1(w_x)}{\beta_2(w_x)\bar{w}_x + \beta_1(w_x)})$$

$$\bar{y}_{ACS_6} = \bar{w}_y(\frac{\beta_1(w_x)\bar{X} + \beta_2(w_x)}{\beta_1(w_x)\bar{w}_x + \beta_2(w_x)})$$

$$\bar{y}_{ACS_7} = \bar{w}_y(\frac{\bar{Y} + \rho_{wxwy}}{\bar{w}_x + \rho_{wxwy}})$$

The Mean Square Errors up to the first order of approximations are obtained as follows

$$MSE(\bar{y}_{ACS_5}) = (\frac{1}{n} - \frac{1}{N})[C_{wy}^2 + \theta_{w8}^2 C_{wx}^2 - 2\theta_{w8}\rho_{wxwy}C_{wx}C_{wy}]$$

$$MSE(\bar{y}_{ACS_6}) = (\frac{1}{n} - \frac{1}{N})[C_{wy}^2 + \theta_{w9}^2 C_{wx}^2 - 2\theta_{w9}\rho_{wxwy}C_{wx}C_{wy}]$$

$$MSE(\bar{y}_{ACS_7}) = (\frac{1}{n} - \frac{1}{N})[C_{wy}^2 + \theta_{w6}^2 C_{wx}^2 - 2\theta_{w6}\rho_{wxwy}C_{wx}C_{wy}]$$

where $\theta_{w6} = \frac{\bar{X}}{\bar{X}+\rho_{wxwy}}$, $\theta_{w8} = \frac{\bar{X}\beta_2(wx)}{\bar{X}\beta_2(wx)+\beta_1(wx)}$, $\theta_{w9} = \frac{\bar{X}\beta_1(wx)}{\bar{X}\beta_1(wx)+\beta_2(wx)}$

4 Proposed Estimators

The main objective of this article is to construct transformed ratio type estimators which can be used when the population under study is rare or clumped and results in least bias and MSE. Following the lines of [14,18], we propose following transformed ratio type estimators:

$$t_1 = \bar{w}_y[\frac{\rho_{wxwy}\bar{X} + \beta_1(w_x)}{\rho_{wxwy}\bar{w}_x + \beta_1(w_x)}]$$

$$t_2 = \bar{w}_y[\frac{\rho_{wxwy}\bar{X} + \beta_2(wx)}{\rho_{wxwy}\bar{w}_x + \beta_2(wx)}]$$

$$t_3 = \bar{w}_y[\frac{\beta_1(wx)\bar{X} + C_{wx}}{\beta_1(wx)\bar{w}_x + C_{wx}}]$$

$$t_4 = \bar{w}_y[\frac{\beta_1(wx)\bar{X} + S_{wx}}{\beta_1(wx)\bar{w}_x + S_{wx}}]$$

The Bias and Mean Squared Error for t_1 are:

$$t_1 = \bar{w}_y[\frac{\rho_{wxwy}\bar{X} + \beta_1(w_x)}{\rho_{wxwy}\bar{w}_x + \beta_1(w_x)}$$

Note that the sampling error in Adaptive cluster sampling for the study and auxiliary variable is as follows:

$$e_{\bar{wy}} = \frac{\bar{w_y}}{\bar{Y}} - 1 e_{\bar{wx}} = \frac{\bar{w_x}}{\bar{X}} - 1 E(e_{\bar{wy}}) = 0 E(e_{\bar{wx}}) = 0$$

and $E(e_{\bar{wy}}{}^2) = fC_{wy}^2$, $E(e_{\bar{wx}}{}^2) = fC_{wx}^2$Expanding t1 in terms of $e_{\bar{wy}}$ and $e_{\bar{wx}}$

$$\bar{Y}(e_{\bar{wy}} + 1)[(1 + \frac{\beta_1(wx)}{\rho_{wxwy}\bar{X}})][e_{\bar{wx}} + 1 + \frac{\beta_1(wx)}{\rho_{wxwy}\bar{X}}]^{-1}$$

taking

$$1 + \frac{\beta_1(wx)}{\rho_{wxwy}\bar{X}} = \lambda_1$$

.Now

$$t_1 = \bar{Y}(e_{\bar{wy}} + 1)\lambda_1[e_{\bar{wx}} + \lambda_1]^{-1}$$

Expanding $[e_{\bar{wx}} + \lambda_1]^{-1}$ using $[a+b]^{-1}$ and multiplying, we get

$$t_1 = \bar{Y} + \bar{Y}[\frac{-e_{\bar{wx}}}{\lambda_1} + \frac{e_{\bar{wx}}{}^2}{\lambda_1^2} + e_{\bar{wy}} - \frac{e_{\bar{wx}}e_{\bar{wy}}}{\lambda_1} + \delta]$$

where δ represents higher order of sampling error terms. Taking Expectation on both sides, we get Bias as:

$$Bias(t_1) = (\frac{1}{n} - \frac{1}{N})\bar{Y}[\frac{(C_{wx})^2}{\lambda_1^2} - \frac{\rho_{wxwy}C_{wx}C_{wy}}{\lambda_1}]$$

Expanding $(t_1 - \bar{Y})^2$ and taking expectation we get MSE as:

$$MSE(t_1) = (\frac{1}{n} - \frac{1}{N})\bar{Y}^2[C_{wy}^2 + \frac{C_{wx}^2}{\lambda_1^2} - \frac{2\rho_{wxwy}C_{wx}C_{wy}}{\lambda_1}]$$

The Bias and the Mean Squared Error up to first order approximations for $t2$, $t3$ and $t4$ are obtained in the same way, their expressions are:

$$Bias(t_2) = (\frac{1}{n} - \frac{1}{N})\bar{Y}[\frac{(C_{wx})^2}{\lambda_2^2} - \frac{\rho_{wxwy}C_{wx}C_{wy}}{\lambda_2}]$$

$$MSE(t_2) = (\frac{1}{n} - \frac{1}{N})\bar{Y}^2[C_{wy}^2 + \frac{C_{wx}^2}{\lambda_2^2} - \frac{2\rho_{wxwy}C_{wx}C_{wy}}{\lambda_2}]$$

$$Bias(t_3) = (\frac{1}{n} - \frac{1}{N})\bar{Y}[\frac{(C_{wx})^2}{\lambda_3^2} - \frac{\rho_{wxwy}C_{wx}C_{wy}}{\lambda_3}]$$

$$MSE(t_3) = (\frac{1}{n} - \frac{1}{N})\bar{Y}^2[C_{wy}^2 + \frac{C_{wx}^2}{\lambda_3^2} - \frac{2\rho_{wxwy}C_{wx}C_{wy}}{\lambda_3}]$$

$$Bias(t_4) = (\frac{1}{n} - \frac{1}{N})\bar{Y}[\frac{(C_{wx})^2}{\lambda_4^2} - \frac{\rho_{wxwy}C_{wx}C_{wy}}{\lambda_4}]$$

$$MSE(t_4) = (\frac{1}{n} - \frac{1}{N})\bar{Y}^2[C_{wy}^2 + \frac{C_{wx}^2}{\lambda_4^2} - \frac{2\rho_{wxwy}C_{wx}C_{wy}}{\lambda_4}]$$

where $\lambda_2 = 1 + \frac{\beta_2(wx)}{\rho_{wxwy}\bar{X}}$, $\lambda_3 = 1 + \frac{C_{wx}}{\beta_1(wx)\bar{X}}$,$\lambda_4 = 1 + \frac{S_{wx}}{\beta_1(wx)\bar{X}}$

5 Simulation study

In this section, we have conducted a simulation study on daily new cases of COVID-19 in the Indian state of Goa from 27^{th} of March 2020 to 4^{th} of July 2020 [19].
Average new cases of COVID-19 in this 100 days duration is estimated for the state of Goa, taking daily occurrences of new COVID-19 cases of Arunachal Pradesh as an auxiliary variable.

The rationale behind taking the daily occurrence of new cases of the virus of Arunachal Pradesh as an auxiliary variable for estimation of average cases of Goa is that the pattern of spread was to an extent the same. Moreover, the correlation coefficient of daily new cases of Arunachal Pradesh with that of Goa is greater than 0.7.

For simulation study, the MSE is,

$$MSE(t_*) = \frac{1}{10000} \sum_{i=1}^{10000} (t_* - \mu_y)^2, \tag{1}$$

where t_* represents all the estimators presented in this study respectively and 10000 is the number of replications or the number of repetitive samples drawn for sample of size 40, 45, 50 and 55.

Table 1: Bias of all the estimators

n	$\bar{y}_{ACS_1}$	$\bar{y}_{ACS_2}$	$\bar{y}_{ACS_3}$	$\bar{y}_{ACS_4}$	$\bar{y}_{ACS_5}$	$\bar{y}_{ACS_6}$	$\bar{y}_{ACS_7}$	t_1	t_2	t_3	t_4
40	-0.3242	-0.2959	-0.2969	-0.3503	-0.2964	-0.2987	-0.2967	-0.298	-0.3009	0.2967	-0.3473
45	-0.3334	-0.2931	-0.2942	-0.3478	-0.2936	-0.2961	-0.2939	-0.2953	-0.2985	-0.2939	-0.3501
50	-0.3477	-0.3264	-0.3274	-0.3807	-0.3269	-0.3292	-0.3727	-0.3284	-0.3313	-0.3272	-0.3754
55	-0.3012	-0.3096	-0.3101	-0.3623	-0.3098	-0.3111	-0.31	-0.3107	-0.3123	-0.31	-0.3335

Table 2: MSE of all the estimators

n	$\bar{y}_{ACS_1}$	$\bar{y}_{ACS_2}$	$\bar{y}_{ACS_3}$	$\bar{y}_{ACS_4}$	$\bar{y}_{ACS_5}$	$\bar{y}_{ACS_6}$	$\bar{y}_{ACS_7}$	t_1	t_2	t_3	t_4
40	4.1171	2.4837	2.4803	2.4887	2.4821	2.4745	2.481	2.4769	2.4681	2.481	2.6121
45	4.0572	2.452	2.4483	2.4558	0.4503	2.4419	2.449	2.4446	2.4348	2.4491	2.5619
50	4.0736	2.4735	2.4699	2.4809	2.4178	2.4636	2.4706	2.4663	2.4567	2.4706	2.5854
55	2.7765	1.6633	1.6608	1.6783	1.6621	1.6566	1.6613	1.6584	1.6519	1.6613	1.7412

6 Discussion

From the results of the simulation study, presented in Table 1, we see that the modified ratio estimator of ACS design $\bar{y}_{ACS_2}$ is having more bias as compared to the proposed transformed ratio type estimators t_1, t_2 and t_3 proving that the proposed transformed ratio type estimators are providing estimates more closer to the true value of average cases. From Table 2, we can see that the unbiased estimator of the population mean $\bar{y}_{ACS_1}$ gives nearly twice MSE as compared to all the proposed transformed ratio type estimators and proposed transformed ratio type estimators t_1, t_2 and t_3 result in lowest MSE as compared to all the estimators of this article. This proves that the proposed three estimators have a greater efficiency over all the estimators of this article.

7 Conclusion

When it comes to the cases where the population under study is rare or hidden clustered, non-adaptive research designs results in a highly biased estimates. An example of such a population is the initial spread of COVID-19 which has been

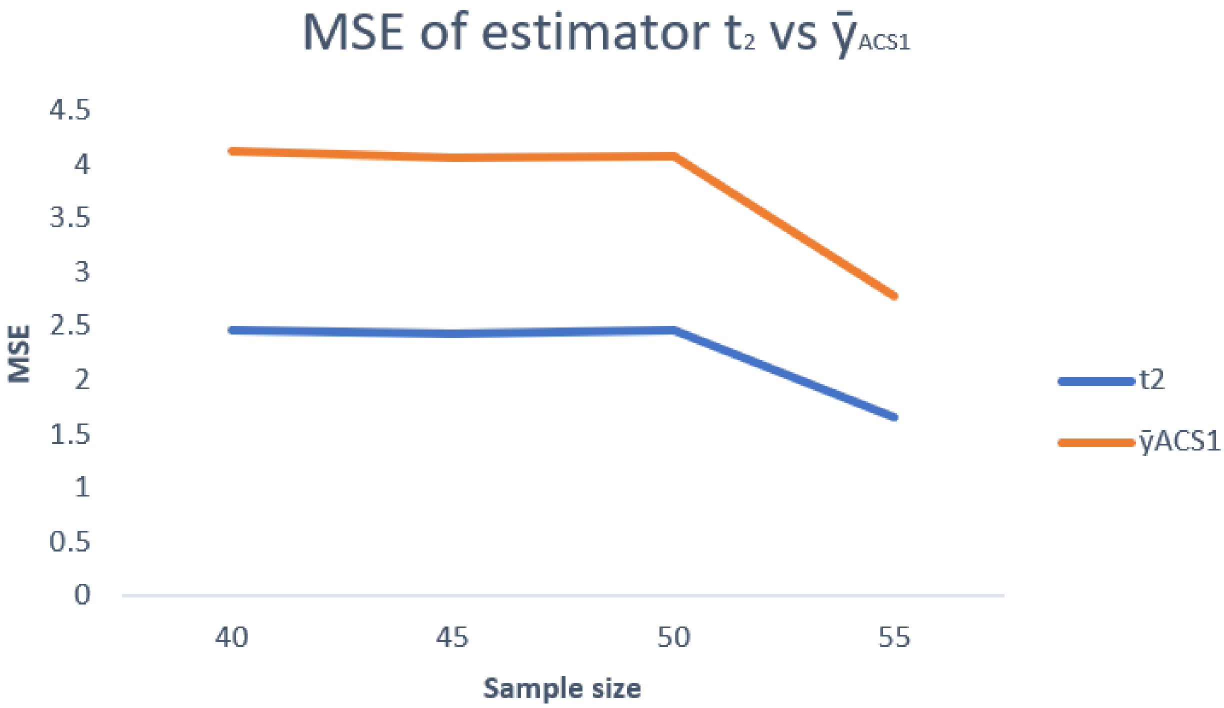

Fig. 2: MSE comparison of estimator $\bar{y}_{ACS1}$ and estimator t_2

considered in this article. We proposed 4 transformed ratio type estimators and compared them with existing estimators of the same family. Compared to the simple mean $\bar{y}_{ACS_1}$ and modified ratio estimator under ACS $\bar{y}_{ACS_2}$, the proposed estimators t_1, t_2 and t_3 performed much better in terms of MSE but the proposed transformed ratio type estimator t_2 resulted in minimum MSE amongst all the proposed and existing estimators as evident from Table 2. Thus, for estimating the unknown population mean of such a rare or highly clustered data, using the proposed estimator t_2 is advised.

Acknowledgement

The authors are grateful to the anonymous referee for a careful checking of the details and for helpful comments that improved this paper.

References

[1] Steven K Thompson , Adaptive cluster sampling, Journal of the American Statistical Association, Taylor & Francis Group **85(412)**, 1050-1059 (1990).
[2] B. Acharya, G. Bhattarai and A. De Gier, Stein, Systematic adaptive cluster sampling for the assessment of rare tree species in Nepal, Forest Ecology and Managemen, Elsevier **187**, 65-73 (2000).
[3] M. Elizabeth Conners and Steven J Schwager, The use of adaptive cluster sampling for hydroacoustic surveys, ICES Journal of Marine Science, Oxford University Press **59(6)**, 1314-1325 (2002).
[4] Raymond L Correll, The use of composite sampling in contaminated sites?a case study, Environmental and Ecological Statistics, Springer **8(3)**, 185-200 (2001).
[5] Steven K Thompson, NIDA Research Monograph **167**, 296-319 (1997).
[6] WHO, https://www.who.int/news-room/q-a-detail/coronavirus-disease-covid-19-how-is-it-transmitted, (2021).
[7] R. Singh, M. Kumar and H. P. Singh, On estimation of population mean using information on auxiliary attribute, Pakistan Journal of Statistics and Operation Research, 363-371 (2013).

[8] R. Singh and M. Kumar, A note on transformations on auxiliary variable in survey sampling, Model Assisted Statistics and Applications, IOS Press **6(1)**, 17-19 (2011).
[9] P. Sharma and R. Singh, Improved estimators for simple random sampling and stratified random sampling under second order of approximation, SIT _new series, **14(3)**, 379-390 (2013).
[10] R. Singh, and P. Sharma, Efficient estimators using auxiliary variable under second order approximation in simple random sampling and two phase sampling, Advances in Statistics (2014).
[11] A. L. Dryver, and C.T. Chao, Ratio estimators in adaptive cluster sampling, Environmetrics: The official journal of the International Environmetrics Society, Wiley Online Library **18(6)**, 607-620 (2007).
[12] N. Chutiman, Adaptive cluster sampling using auxiliary variable, Journal of Mathematics and Statistics **9(3)**, 249-255 (2013).
[13] S. K. Yadav, S. Misra, S. S. Mishra and N. Chutiman, Improved ratio estimators of population mean in adaptive cluster sampling, J Stat Appl Probab Lett **3(1)**, 1-6 (2016).
[14] R. Singh, and R. Mishra, Improved Exponential Ratio Estimators in Adaptive Cluster Sampling, J Stat Appl Probab Lett. **9(1)**, (2022).
[15] K. Vasudevan, A. Kumar and R. Chellam, Structure and composition of rainforest floor amphibian communities in Kalakad-Mundanthurai Tiger Reserve, Current Science, JSTOR, 406-412 (2001).
[16] W. G. Cochran, The journal of agricultural science, Cambridge University Press **30(2)**, 262-275 (1940).
[17] P. Singh, C. Bouza and R. Singh, Journal of Scientific Research **63(1&2)**, 273-280 (2019).
[18] S. K. Yadav, and C. Kadilar, Revista colombiana de Estadistica, Universidad Nacional de Colombia **36(1)**, 145-152 (2013).
[19] PRS INDIA, https://prsindia.org/covid-19/cases, (2021).
[20] M. H. Hansen, and W. N. Hurwitz, On the theory of sampling from finite populations, The Annals of Mathematical Statistics, JSTOR **14(4)**, 333-362 (1943).