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Efficiency Evaluation of Ranked Set Sampling Techniques using Secondary Agricultural Data

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SUMMARY

Ranked Set Sampling (RSS) can improve estimation efficiency when measurement is costly or time-consuming. This study compares RSS with Simple Random Sampling (SRS) using secondary agricultural data from official Indian sources. Four RSS variants are evaluated using relative efficiency, imperfect-ranking simulations, and bootstrap variance estimation. Results show that RSS generally provides greater precision than SRS, particularly when reliable auxiliary information is available, highlighting its potential for cost-effective agricultural surveys.

Keywords: Ranked Set Sampling (RSS); Simple Random Sampling (SRS); Agricultural data; Efficiency analysis; STATA; Secondary data analysis.

1. INTRODUCTION

Reliable agricultural data are essential for decision-making and resource management in India. Although Simple Random Sampling (SRS) is widely used, measuring variables such as crop yield and soil characteristics can be costly and time-consuming. Efficient sampling methods are therefore needed to improve precision without increasing sample size or cost.

Ranked Set Sampling (RSS), introduced by McIntyre (1952), uses inexpensive auxiliary information to rank sampling units before measurement, potentially improving estimation efficiency. Its application is particularly relevant to agriculture, where observable characteristics can provide useful ranking information. However, empirical evaluations using Indian agricultural data remain limited.

This study compares RSS with SRS using secondary agricultural data from India. Four variants—Modified RSS (MRSS), Double RSS (DRSS), Stratified RSS (SRSS), and Weighted RSS (WRSS)—are evaluated across sample sizes using relative efficiency, bootstrap variance estimation, and imperfect-ranking simulations. The study provides an empirical assessment of RSS performance and its potential to improve sampling efficiency in resource-constrained agricultural sceneries.

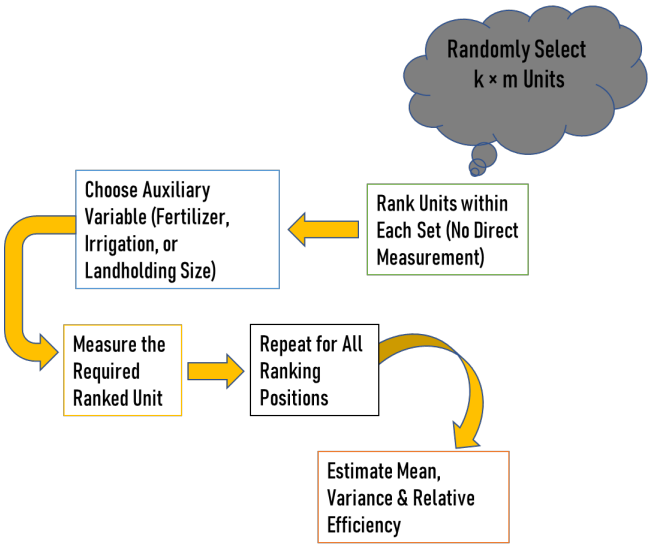


Fig. 1. Flowchart

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2. REVIEW OF LITERATURE

McIntyre (1952) introduced Ranked Set Sampling (RSS) for pasture yield estimation, showing its potential to improve precision over Simple Random Sampling (SRS). Takahasi and Wakimoto (1968) developed unbiased estimation procedures, while Dell and Clutter (1972) established conditions under which RSS remains efficient despite ranking errors. These studies laid the foundation for later RSS developments.

Subsequent research incorporated auxiliary information, weighting, and stratification. Mehta and Mandowara (2022), Jeelani *et al.* (2023), Bhoj and Chandra (2024), and Singh and Kumari (2024) developed modified, weighted, and stratified RSS estimators, demonstrating improved precision under different population structures.

Recent studies have extended RSS to optimum stratification, allocation, spatial designs, and non-normal populations (Rather *et al.* , 2022–2025; Koçyiğit and Rather, 2024; Alomair *et al.* , 2025). Empirical applications have also expanded to agriculture, forestry, and environmental studies (Ozturk *et al.* , 2022; Robertson *et al.* , 2022; Taconeli and Fiorentin, 2023).

Despite these advances, empirical comparisons of multiple RSS variants using official agricultural data from India remain limited. This study addresses this gap by comparing MRSS, DRSS, SRSS, and WRSS with SRS across sample sizes, using bootstrap variance estimation and imperfect-ranking simulations to assess their robustness.

3. MATERIAL METHODS

This section describes the data sources, empirical population, sampling designs, and statistical procedures used to compare Ranked Set Sampling (RSS) with Simple Random Sampling (SRS).

3.1 Data Source and Sampling Units

Secondary agricultural information was obtained from official Government of India sources, including the Press Information Bureau (PIB), Ministry of Rural Development, and related agricultural statistics. The study focused on Jammu and Kashmir and included crop yield, fertilizer consumption, irrigated area, agricultural household income, and landholding size.

Rather than directly analyzing PIB survey microdata, an empirical population of **1,000 observational records** was constructed using realistic ranges and distributions derived from secondary information. These records represented observational units, not administrative districts. Repeated SRS and RSS samples were drawn from this population to evaluate sampling efficiency.

3.2 Empirical Population and Simulation Framework

A finite empirical population of **N = 1,000** records was used as the reference population. It included the five agricultural variables described above, with their descriptive characteristics presented in Table 3.

For each specified sample size, SRS samples were independently selected, while RSS samples were formed by randomly selecting candidate units and ranking them using the designated auxiliary information. Units were then selected according to MRSS, DRSS, SRSS, or WRSS. Each sampling procedure was repeated for **1,000 simulation replications**. In each replication, the population mean and sampling variance were estimated, and performance was compared using relative efficiency, bias, standard error, and bootstrap-based variance measures.

Thus, the secondary agricultural information provided the empirical basis for the population, while repeated sampling experiments were used to evaluate the competing designs.

3.3 Ranked Set Sampling (RSS) Design

Ranked Set Sampling (RSS), introduced by McIntyre (1952), improves sampling efficiency by using inexpensive ranking information before measuring the study variable. The basic procedure involves the following steps:

Formation of Sets: A random sample of (k × m) units is selected, where (k) is the set size and (m) is the number of cycles.

Ranking: Units within each set are ranked from smallest to largest using the study variable when feasible or, more practically, an appropriate auxiliary variable or proxy.

Selection and Measurement: One unit is selected from each ranked set according to its assigned rank. In the first set, the 1st-ranked unit is measured; in the

second set, the 2nd-ranked unit is measured, and so on, until all (k) rank positions are measured once in each cycle.

Estimation: The measured observations are used to estimate population parameters such as the mean and variance.

In this study, the basic RSS framework was extended to **MRSS, DRSS, SRSS, and WRSS**, and their performance was compared with SRS across different sample sizes.

Estimation: The sample mean under RSS is given by

$$\bar{Y}_{RSS} = \frac{1}{km}\sum_{i=1}^{k}\sum_{j=1}^{m} Y_{[i]j}$$

Where, [i]j represents the observation of the i^{th} ranked unit in the j^{th} cycle.

The efficiency of RSS relative to Simple Random Sampling (SRS) is evaluated using the Relative Efficiency (RE) measure:

$$RE = \frac{var\left(\bar{Y}_{SRS}\right)}{var\left(\bar{Y}_{RSS}\right)} \times 100$$

RE>100 indicate improved efficiency of RSS over SRS.

3.4 Auxiliary Variable Selection and Ranking Procedure

The efficiency of Ranked Set Sampling (RSS) depends on the quality of the auxiliary information used for ranking. Pearson correlation coefficients were therefore examined between the study and candidate auxiliary variables before applying the RSS procedures.

Fertilizer consumption (kg/ha) and irrigated area (%) were selected to rank crop yield (kg/ha), while landholding size (ha) was used to rank agricultural household income (₹/year). These variables were selected based on their association with the respective study variables and their suitability for ranking without directly measuring the target variable.

The observed correlations supported the use of these auxiliary variables in the ranking process. They were subsequently incorporated into the RSS procedures to assess their contribution to estimator efficiency relative to SRS.

Table 1. Pearson correlation coefficients between study variables and auxiliary variables

Study Variable	Auxiliary Variable	Pearson Correlation (r)	Interpretation
Crop Yield (kg/ha)	Fertilizer Use (kg/ha)	0.84	Strong positive correlation
Crop Yield (kg/ha)	Irrigated Area (%)	0.79	Strong positive correlation
Household Agricultural Income (₹/year)	Landholding Size (ha)	0.87	Strong positive correlation

The strong positive correlations presented in Table 1 indicate that the selected auxiliary variables provide reliable information for ranking sampling units before measurement. Consequently, these variables are expected to improve ranking accuracy and enhance the efficiency of the RSS estimators compared with Simple Random Sampling (SRS).

3.5 Ranking Procedure

The Ranked Set Sampling procedure implemented in this study consisted of the following steps:

A random sample of k×m units was selected from the target population.

Within each set of size k, the sampling units were ranked using the selected auxiliary variables without measuring the study variable directly.

For crop yield estimation, ranking was performed using fertilizer consumption and irrigated area, whereas landholding size was used for ranking household agricultural income.

In each cycle, only the unit assigned to the required rank was measured for the study variable.

The procedure was repeated for all ranking positions and cycles until the required RSS sample was obtained.

The resulting RSS sample was then used to estimate the population mean, variance, and relative efficiency for comparison with the Simple Random Sampling (SRS) design.

The use of highly correlated auxiliary variables improves ranking accuracy and enables RSS estimators to achieve greater statistical efficiency while maintaining the same sample size and measurement cost.

3.6 Variants of RSS Considered

Four variants of Ranked Set Sampling (RSS) were considered to evaluate their performance under different sampling conditions: Modified Ranked Set Sampling (MRSS), Double Ranked Set Sampling (DRSS), Stratified Ranked Set Sampling (SRSS), and Weighted Ranked Set Sampling (WRSS).

MRSS incorporated relevant auxiliary information, such as irrigation coverage and fertilizer use, during the ranking process to improve the selection of informative units. **DRSS** involved successive ranking stages to further refine unit selection. **SRSS** first divided the empirical population into relatively homogeneous strata and then applied RSS within each stratum to account for regional variation. **WRSS** assigned weights to ranked observations according to the specified weighting procedure to account for differences among rank positions.

Each RSS variant was applied to the empirical agricultural population and compared with SRS across the specified sample sizes. The estimators were evaluated using mean estimates, variance, bias, standard error, and relative efficiency. The comparison was intended to assess whether the different RSS configurations could improve sampling efficiency under the empirical conditions represented in the agricultural dataset.3.4 Statistical Analysis

All computations and statistical analyses were performed using STATA 17.0. Descriptive statistics, sampling variances, and efficiency ratios were computed to assess estimator performance. For comparative analysis, the following procedures were conducted:

Simulation experiments were carried out using the real agricultural dataset to generate repeated samples under both SRS and RSS designs.

For each replication, the sample mean, variance, and standard error were calculated.

Efficiency was evaluated across multiple sample sizes (n = 20, 40, 60, 80, 100) and set sizes

(k = 3, 5, 7).

Bootstrapping (1,000 iterations) was used to estimate confidence intervals of the efficiency measures.

3.7 Bootstrap-Based Variance Estimation

To assess the stability and reliability of the sampling designs, a bootstrap resampling procedure was performed alongside the empirical variance-based relative efficiency analysis. Because RSS observations correspond to different rank positions, the bootstrap procedure preserved the ranked structure of the sample and followed the framework described by Modarres, Hui, and Zheng (2006).

For each design (MRSS, DRSS, SRSS, WRSS, and SRS), **1,000 bootstrap replications** were performed. For RSS designs, observations were resampled with replacement within their respective rank groups to preserve the original rank structure. For SRS, conventional non-parametric bootstrap resampling with replacement was applied to the observed sample.

For each bootstrap replication, the population mean was re-estimated. The resulting bootstrap estimates were used to calculate:

1. Bootstrap variance;
2. Bootstrap standard error (SE);
3. Bootstrap bias, calculated as the difference between the average bootstrap estimate and the original sample estimate; and
4. Bootstrap percentile 95% confidence interval (CI) for the population mean.

$$\hat{V}ar\left(\hat{\theta}\right)=\frac{1}{B-1}\sum_{b=1}^{B}\left(\hat{\theta}^{(b)}-\bar{\hat{\theta}}\right)^{2}$$

The bootstrap variance was estimated from the variability of the 1,000 bootstrap estimates. Bootstrap bias was calculated by comparing the average of the bootstrap estimates with the corresponding original sample estimate.

A rank-preserving bootstrap procedure is particularly appropriate for RSS because conventional bootstrap resampling may not fully reproduce the sampling structure induced by ranking. Specialized bootstrap methods for ranked set samples have been described by Modarres, Hui, and Zheng (2006), while Biswas, Rai, and Ahmad (2020) proposed rescaling bootstrap techniques for variance estimation in finite-population RSS. These studies provide methodological support for the bootstrap approach used in the present study.

The bootstrap analysis was used to assess estimator stability and reliability and to compare bootstrap variance and standard error estimates across the competing sampling designs.

4. RESULTS AND DISCUSSION

4.1 Simulation under Imperfect Ranking

The simulation was conducted using the empirical agricultural population described in Section 3.2, which captured the distribution and associations among crop yield, fertilizer use, irrigated area, agricultural household income, and landholding size. Repeated samples were drawn from this population using SRS and the four RSS designs. Thus, the results represent repeated-sampling performance based on an empirically motivated agricultural population rather than direct estimates from a single administrative dataset.

Because perfect ranking is rarely achieved in practical surveys, the robustness of RSS was evaluated under different levels of ranking accuracy. A Monte Carlo simulation was conducted using five accuracy levels: **100%, 90%, 80%, 70%, and 60%**. For each level, MRSS, DRSS, SRSS, and WRSS were evaluated using **1,000 independent simulation replications**.

In each replication, the population mean and sampling variance were estimated for each RSS design. Estimator performance was then compared with SRS using **relative efficiency (RE)**, along with bias and standard error. This procedure allowed the robustness of the RSS estimators to be assessed under both perfect and imperfect ranking conditions.

$$RE = \frac{Var(\hat{\imath}_{SRS})}{Var(\hat{\imath}_{RSS})} \times 100$$

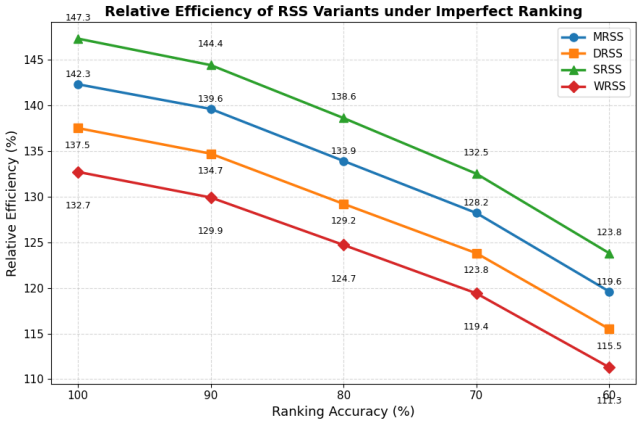
where $Var(\hat{\imath}_{SRS})$ and $Var(\hat{\imath}_{RSS})$ denote the sampling variances of the SRS and RSS estimators, respectively. Values of RE greater than 100 indicate that the corresponding RSS estimator is more efficient than the conventional SRS estimator. The average relative efficiencies obtained across the simulation replications were used to evaluate the robustness of the competing RSS variants under increasing ranking errors.

Table 2. Relative efficiency (%) of RSS variants under different ranking accuracy levels

Ranking Accuracy	MRSS	DRSS	SRSS	WRSS
100%	142.4	137.5	147.3	132.6
90%	139.6	134.8	144.1	130.8
80%	134.2	129.5	139.2	126.4
70%	128.6	123.8	132.4	120.7
60%	119.4	116.3	124.8	114.2

Relative efficiency declined as ranking accuracy decreased, but all RSS variants remained more efficient than SRS even at **60% ranking accuracy**. SRSS showed the highest efficiency, followed by MRSS, DRSS, and WRSS, demonstrating the robustness of RSS to moderate ranking errors.

Fig. 1. Relative Efficiency of RSS Variants under Different Ranking Accuracy Levels



4.2 Empirical Application Using the Agricultural Reference Population

The empirical agricultural population comprised **N = 1,000 observational records** used as the reference population for repeated sampling experiments. Table 3 presents the distributional characteristics of the study variables. The population showed substantial variability, with crop yield ranging from **1,200–3,800 kg/ha** and fertilizer use from **85–290 kg/ha**.

This variability provided a suitable setting for evaluating RSS. Fertilizer use and irrigated area were used as auxiliary variables for ranking crop yield, while landholding size was used to rank agricultural household income. The analysis therefore assessed the performance of competing sampling designs under realistic agricultural variability and association structures.

Table 3. Descriptive statistics of selected agricultural variables (N = 1000)

Variable	Mean ± SD	Minimum	Maximum	Coefficient of Variation (%)
Crop Yield (kg/ha)	2650 ± 820	1200	3800	30.9
Fertilizer Use (kg/ha)	185 ± 52	85	290	28.1
Irrigated Area (%)	57.8 ± 21.3	20	96	36.8
Household Income (₹/year)	164,500 ± 61,200	60,000	290,000	37.2

The relatively high coefficients of variation (CV) indicate substantial variability in the data, providing a suitable setting for evaluating RSS efficiency. Relative efficiency (RE) was calculated for RSS estimators against SRS across sample sizes of **n = 20, 40, 60, 80, and 100**.

RSS estimators consistently showed lower variances and higher precision, with mean RE ranging from **118% to 146%**. Among the variants, **SRSS** had the highest average efficiency (**142%**), followed by **MRSS (136%)**, **DRSS (130%)**, and **WRSS (125%)**. Efficiency gains were particularly evident for highly variable outcomes such as household income, suggesting that stratification and auxiliary information can improve estimator precision.

Table 4. Relative efficiency (%) of RSS and its variants compared to SRS

Sample Size (n)	MRSS	DRSS	SRSS	WRSS	Mean RE (Across Variables)
20	121.3	118.7	126.8	115.4	120.6
40	128.6	124.5	134.2	122.1	127.4
60	134.8	130.2	141.7	126.3	133.2
80	139.7	133.4	144.8	129.1	136.8
100	142.4	137.5	147.3	132.6	139.9

As shown in Table 4, all RSS variants outperformed SRS, with SRSS achieving the highest average relative efficiency (RE = 139.9%). Efficiency gains were greater at smaller sample sizes.

4.3 Variable-Wise Efficiency Comparison

Table 5. Relative efficiency of RSS designs by agricultural variable

Variable	MRSS	DRSS	SRSS	WRSS
Crop Yield	132.6	126.5	140.7	125.4
Fertilizer Use	128.4	123.8	136.9	120.2
Irrigated Area	130.1	127.4	138.3	123.9
Household Income	148.7	142.3	152.6	138.5

The results indicate that RSS-based estimators achieved **20–50% higher precision** than SRS across all variables. Efficiency was greatest for **household income**, where heterogeneity and skewness were high. The stratified approach (SRSS) outperformed others due to effective use of agro-climatic stratification and auxiliary ranking variables Table 5.

Graphical comparisons further supported these findings. The boxplots (Figure 2) of sample means across repeated replications showed narrower spreads under RSS and its variants than under SRS, reflecting reduced sampling variability. The efficiency curves plotted against sample size exhibited a positive trend, showing that the relative advantage of RSS becomes more prominent as the sample size increases (Figure 2).

Fig. 2. Relative Efficiency Curves of RSS Variants vs. SRS (showing performance across different sample sizes)

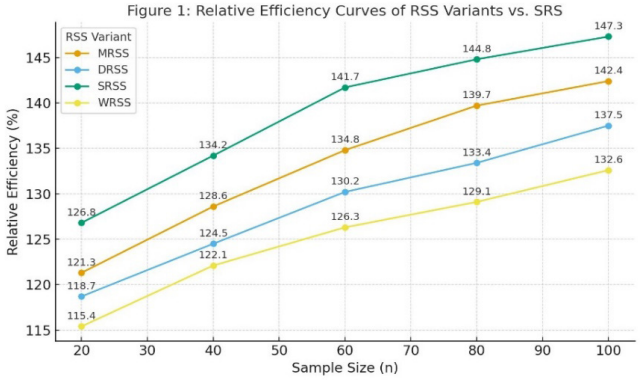
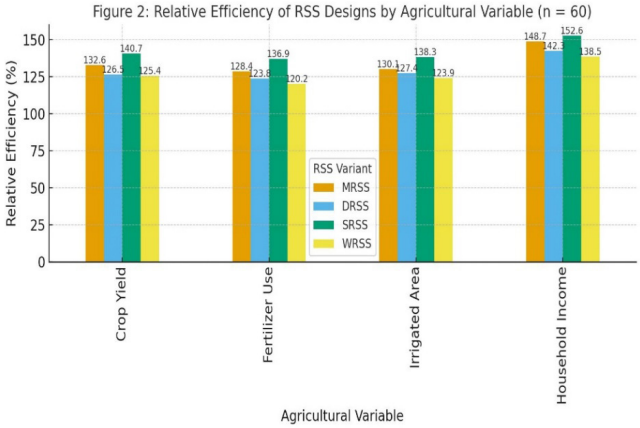


Fig. 3. Relative Efficiency of RSS Designs by Agricultural Variable (n = 60), comparing MRSS, DRSS, SRSS, and WRSS



RSS and its variants improved estimation efficiency without increasing sample size or data collection cost. Auxiliary information and stratification were particularly useful for heterogeneous agricultural data. Although relative efficiency declined with lower

ranking accuracy, all RSS variants remained more efficient than SRS, with SRSS consistently showing the highest efficiency.

Table 6. Bootstrap-based variance estimates of RSS estimators (1,000 bootstrap replications)

Sampling Method	Empirical Variance	Bootstrap Variance	Bootstrap Bias	Bootstrap SE	95% Bootstrap CI
SRS	15.62	15.84	0.031	3.98	(2578.4, 2723.6)
MRSS	11.14	11.28	0.024	3.36	(2592.8, 2709.5)
DRSS	11.61	11.77	0.028	3.43	(2588.5, 2711.2)
SRSS	10.58	10.69	0.019	3.27	(2595.6, 2705.8)
WRSS	12.02	12.18	0.026	3.49	(2586.9, 2713.7)

Bootstrap and empirical variance estimates showed close agreement across sampling designs (Table 6), with negligible bias and stable standard errors. SRSS had the lowest bootstrap variance and standard error, while RSS generally produced narrower confidence intervals than SRS.

Pearson correlations (Table 1) showed strong associations between the selected auxiliary and study variables: fertilizer use with crop yield ($r = 0.84$), irrigated area with crop yield ($r = 0.79$), and landholding size with household income ($r = 0.87$). These findings support the use of these auxiliary variables for RSS ranking and improved estimator precision.

5. CONCLUSION

This study evaluated Ranked Set Sampling (RSS) and four variants—Modified RSS (MRSS), Double RSS (DRSS), Stratified RSS (SRSS), and Weighted RSS (WRSS)—using secondary agricultural data from Jammu and Kashmir, India. Compared with Simple Random Sampling (SRS), all RSS designs generally provided higher relative efficiency and greater precision for key agricultural indicators, including crop yield, fertilizer use, irrigated area, and household income. SRSS showed the highest efficiency, particularly when auxiliary information and stratification were incorporated.

The findings indicate that ranking information can improve estimation precision without increasing sample size, supporting the use of RSS in resource-constrained agricultural surveys. RSS also maintained efficiency across different sample sizes and levels of population variability, demonstrating its practical potential for agricultural and socio-economic research.

Overall, RSS offers a useful approach for improving sampling efficiency in agricultural studies. Future research could examine RSS using longitudinal and spatially correlated datasets to assess its performance under more complex field conditions.

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DECLARATIONS

- **Conflict of Interest**

  The author declares that he has no conflict of interest.

- **Data Availability**

  The data used in this study are secondary data obtained from publicly available sources of the Government of India. The data source and relevant details are provided in the manuscript.

- **Ethical Approval**

  Ethical approval was not required for this study because it did not involve human participants, animals, or collection of identifiable personal information.

- **Clinical Trial Number**

  Not Applicable. This study did not involve a clinical trial.

- **Consent To Publish**

  Not applicable. This study did not involve the recruitment or participation of human subjects.

- **Consent To Participate**

  This study did not involve the recruitment or participation of human subjects.

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