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Estimation Of Parameters Of Pearson Type I Family Of Distributions Using Ranked Set Sampling

N.K.Sajeevkumar¹ and A.R.Sumi²

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ABSTRACT

In this work the ranked set sampling technique has been applied to estimate the best linear unbiased estimator (BLUE) of the location parameter μ and scale parameter σ of Pearson type I family of distributions, when the shape parameters p and q are known. The values of coefficients of ranked set sample in the BLUEs of μ and σ for $p > q$ have been explicitly derived in terms of coefficients of ranked set sample involved in the BLUE of μ and σ for $p < q$. The efficiency comparison of the BLUE of μ and σ is also done using ranked set sample with that of using order statistics.

1. INTRODUCTION

The concept of ranked set sampling (RSS) was first introduce by McIntyre (1952) as a process of improving the precision of the sample mean as an estimator of the population mean. This technique of data collection was introduced for situations where taking the actual measurements on sample observations is difficult as compared to the judgment ranking of them (see, Chen et al. (2004).The ranked set sampling technique can be executed as follows:

• Step 1: Randomly draw n simple random samples each of size n from the population of interest.

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• Step 2: Within each of the *n* sets, the sampled items are ranked from lowest to largest according to the variable of interest based on the researcher's judgment or by any negligible cost method that does not require actual quantifications.

• Step 3: From the first set of n units, the unit ranked lowest is measured. From the second set of n units, the unit ranked second lowest is measured. The process is continued until the n^{th} ranked unit is measured from the n^{th} set. Note that n^2 units are sampled but only n of them are measured with respect to the variable of interest. The above 3 steps describe one cycle of the RSS technique. Then *N.K. Sajeevkumar¹ and A.R.Sumi*²
Step 2: Within each of the *n* sets, the sampled items are ranked from lowest to
argest according to the variable of interest based on the researcher's judgment or
y any negligible co $f_{11}, X_{(2)2},..., X_{(n)n}$ form a ranked set sample of size n (see Lam *et al.* (1994), page 724).

The appealing feature of RSS is that, since RSS provides more structured samples than SRS, improved estimation may result from the use of RSS design.

Takahasi and Wakimoto (1968) established a very important statistical foundation for the theory of RSS. They showed that the mean of the RSS is unbiased estimator for the population mean and has higher efficiency than the mean of SRS. Dell and Clutter (1972) studied the effect of ranking error on the procedure. Stokes (1977) studied RSS with concomitant variables. Stokes and Sager (1988) discussed the application of this method to estimate volumes of trees in a forest.RSS was initially introduced for the estimation of mean (see Patil et al.,1994) without making assumptions on the underlying model. However, a large number of articles research on parametric methods for RSS focused mainly on BLUE estimators of location and scale parameters (see Bhoj and Ahsanullah, (1996), Fei et al. (1994), Lam et al., (1994), and Lam et al. (1996). dure. Stokes (1977) studied RSS with concomitant variables. Stokes and

(1988) discussed the application of this method to estimate volumes of

(1988) discussed the application of this method to estimate volumes of

1994)

The RSS has many statistical applications in biological and environmental studies and reliability theory (e.g. Dell and Clutter (1972), Stokes (1977), Stokes (1980), Mode et al. (1999); and Barabesi and El-Sharaawi, 2001).

2. ESTIMATION OF LOCATION AND SCALE PARAMETERS OF A DISTRIBUTION USING RANKED SET SAMPLING

In this section we consider the family of all absolutely continuous distributions with location parameter μ and scale parameter σ . Then any distribution belonging to it has a pdf of the form

$$
f(x;\mu,\sigma) = \frac{1}{\sigma}g\left(\frac{x-\mu}{\sigma}\right), \text{ where } x \in R, \ \mu \in R, \ \sigma > 0 \,.
$$
 (2.1)

Estimation of parameters of Pearson type I family of distributions ...

Let $X_{(1)1}, X_{(2)2},..., X_{(n)n}$ be the ranked set sample drawn from (2.1).Clearly
 $X_{(1)1}, X_{(2)2},..., X_{(n)n}$ are independent. Let $\underline{X} = (X_{(1)1}, X_{(2)2},..., X$ $X_{(1)1}, X_{(2)2},..., X_{(n)n}$ be the ranked set sample drawn from (2.1). Clearly Estimation of parameters of Pearson type I family of distributions ...

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 $(X_{(1)1}, X_{(2)2},..., X_{(n)n}$ be the ranked set sample drawn from (2.1).Clearly
 $X_{(1)1}, X_{(2)2},..., X_{(n)n}$ are independent. Let $\underline{X} = (X_{(1)1}, X_{(2)2},..., X_{(n)n})'$ $\underline{X} = (X_{(1)1}, X_{(2)2},..., X_{(n)n})'$, and then define ation of parameters of Pearson type I family of distributions ...
 $X_{(1)1}, X_{(2)2},..., X_{(n)n}$ be the ranked set sample drawn from (2.1). Clearly
 $X_{(2)2},..., X_{(n)n}$ are independent. Let $\underline{X} = (X_{(1)1}, X_{(2)2},..., X_{(n)n})'$, and th $\underline{Y} = (Y_{(1)1}, Y_{(2)2},..., Y_{(n)n})'$ as a vector of corresponding RSS arising from $f(x; 0, 1)$. *Estimation of parameters of Pearson type I family of distributions* ...

Let $X_{(1)1}, X_{(2)2},..., X_{(n)n}$ be the ranked set sample drawn from (2.1).Clearly
 $X_{(1)1}, X_{(2)2},..., X_{(n)n}$ are independent. Let $\underline{X} = (X_{(1)1}, X_{(2)2},$ Let $\alpha = (\alpha_{1:n}, \alpha_{2:n}, ..., \alpha_{n:n})'$ and $V = ((V_{i,j:n}))$ be the vector of means and dispersion matrix of \underline{Y} . Clearly, $V = dig (V_{1:n}, V_{2:n},..., V_{nn})$, where $V_{i:n} = V_{i,in}$. Then the best linear unbiased estimator of μ based on ranked set sampling is given by Lam et al., (1994, P.726), are independent. Let $\underline{X} = (X_{(1)}, X_{(2)},..., X_{(n)})$, and then define
 $\sum_{n} X_{(2)}, ..., X_{(n)}$ and $V = ((V_{i,j}, n))$ be the vector of means and dispersion
 $\sum_{n} \alpha_{nn} y'$ and $V = ((V_{i,j}, n))$ be the vector of means and dispersion

learly, ons ...

ble drawn from (2.1).Clearly
 $K_{(2)2},..., K_{(n)n}$, and then define

g RSS arising from $f(x; 0, 1)$.

wector of means and dispersion

,), where $V_{i,n} = V_{i,in}$. Then the

hked set sampling is given by

((1)

$$
\hat{\mu} = \frac{\alpha' V^{-1} (1 \alpha' - \alpha' 1') V^{-1}}{\Delta}
$$
\n
$$
= \frac{\sum_{i=1}^{n} \frac{X_{(i)i}}{V_{i:n}} \sum_{i=1}^{n} \frac{\alpha_{i:n}}{V_{i:n}} - \sum_{i=1}^{n} \frac{\alpha_{i:n}}{V_{i:n}} \sum_{i=1}^{n} \frac{\alpha_{i:n}}{V_{i:n}} X_{(i)i}}{\sum_{i=1}^{n} \frac{1}{V_{i:n}} \sum_{i=1}^{n} \frac{\alpha_{i:n}^2}{V_{i:n}} - \left(\sum_{i=1}^{n} \frac{\alpha_{i:n}}{V_{i:n}}\right)^2}
$$
\n
$$
(2.2)
$$

and its variance is

$$
V(\widehat{\mu}) = \frac{(\alpha' V^{-1} \alpha) \sigma^2}{\Delta}
$$

=
$$
\frac{\sum_{i=1}^n \frac{\alpha_{i:n}^2}{V_{i:n}}}{\sum_{i=1}^n \frac{1}{V_{i:n}} \sum_{i=1}^n \frac{\alpha_{i:1}^2}{V_{i:n}} - (\sum_{i=1}^n \frac{\alpha_{i:n}}{V_{i:n}})^2} \sigma^2.
$$

(2.3)

Also the BLUE of σ using RSS is

$$
= \frac{\frac{1}{i-1} \frac{V_{i,n}}{V_{i,n}} \frac{V_{i,n}}{i-1} \frac{V_{i,n}}{V_{i,n}} \frac{V_{i,n}}{i-1} \frac{V_{i,n}}{V_{i,n}} \frac{V_{i,n}}{i-1} \frac{V_{i,n}}{V_{i,n}} \frac{V_{i,n}}{i} \frac{V_{i,n}}{V_{i,n}} - \left(\sum_{i=1}^{n} \frac{\alpha_{i,n}}{V_{i,n}}\right)^2}{V(\bar{\mu}) = \frac{(\alpha' V^{-1} \alpha) \sigma^2}{\Delta}}
$$
\nand its variance is\n
$$
V(\bar{\mu}) = \frac{(\alpha' V^{-1} \alpha) \sigma^2}{\Delta}
$$
\n
$$
= \frac{\sum_{i=1}^{n} \frac{\alpha_{i,n}^2}{V_{i,n}}}{V_{i,n}} \frac{V_{i,n}}{V_{i,n}} \left(\sum_{i=1}^{n} \frac{\alpha_{i,n}}{V_{i,n}}\right)^2} \sigma^2.
$$
\nAlso the BLUE of σ using RSS is\n
$$
\hat{\sigma} = \frac{1'V^{-1}(1\alpha' - \alpha 1')V^{-1} \times \Delta}{\Delta}
$$
\n
$$
= \frac{\sum_{i=1}^{n} \frac{X(i)i}{V_{i,n}} \alpha_{i,n} \sum_{i=1}^{n} \frac{1}{V_{i,n}} - \sum_{i=1}^{n} \frac{\alpha_{i,n}}{V_{i,n}} \sum_{i=1}^{n} \frac{X(i)i}{V_{i,n}}}{V_{i,n}} - \sum_{i=1}^{n} \frac{\alpha_{i,n}}{V_{i,n}} \sum_{i=1}^{n} \frac{V_{i,n}}{V_{i,n}} \frac{V_{i,n}}{V_{i,n}}}
$$
\n
$$
= \frac{\sum_{i=1}^{n} \frac{X(i)i}{V_{i,n}} \alpha_{i,n} \sum_{i=1}^{n} \frac{\alpha_{i,n}^2}{V_{i,n}} - \left(\sum_{i=1}^{n} \frac{\alpha_{i,n}}{V_{i,n}}\right)^2}{V_{i,n}}
$$
\n(2.3)

(2.4)

and its variance

and its variance
\n
$$
V(\hat{\sigma}) = \frac{(1'V^{-1}1)\sigma^2}{\Delta}
$$
\n
$$
= \frac{\sum_{i=1}^{n} \frac{1}{V_{i:n}}}{\sum_{i=1}^{n} \frac{1}{V_{i:n}} \sum_{i=1}^{n} \frac{\alpha_{i:n}^2}{V_{i:n}} - (\sum_{i=1}^{n} \frac{\alpha_{i:n}}{V_{i:n}})^2} \sigma^2
$$
\nand
\n
$$
\text{cov}(\hat{\mu}, \hat{\sigma}) = -\frac{(\alpha'V^{-1}1)}{\Delta} \sigma^2
$$
\n
$$
= -\frac{\sum_{i=1}^{n} \frac{\alpha_{i:n}}{V_{i:n}}}{\sum_{i=1}^{n} \frac{\alpha_{i:n}}{V_{i:n}}} = -\frac{\sum_{i=1}^{n} \frac{\alpha_{i:n}}{V_{i:n}}}{\sum_{i=1}^{n} \frac{\alpha_{i:n}}{V_{i:n}}} \sigma^2,
$$

and

and its variance
\n
$$
(\bar{\sigma}) = \frac{\left(1'V^{-1}1\right)\sigma^2}{\Delta}
$$
\n
$$
= \frac{\sum_{i=1}^{n} \frac{1}{V_{i:n}}}{V_{i:n}} \sum_{i=1}^{n} \frac{\alpha_{i:n}}{V_{i:n}} - \left(\sum_{i=1}^{n} \frac{\alpha_{i:n}}{V_{i:n}}\right)^2 \sigma^2
$$
\n
$$
= -\frac{\sum_{i=1}^{n} \frac{1}{V_{i:n}}}{V_{i:n}} \sigma^2
$$
\n(2.5)
\nand
\n
$$
\text{cov}(\hat{\mu}, \hat{\sigma}) = -\frac{\left(\alpha'V^{-1}1\right)}{\Delta} \sigma^2
$$
\n
$$
= -\frac{\sum_{i=1}^{n} \frac{1}{V_{i:n}}}{V_{i:n}} \sum_{i=1}^{n} \frac{\alpha_{i:n}}{V_{i:n}} - \left(\sum_{i=1}^{n} \frac{\alpha_{i:n}}{V_{i:n}}\right)^2 \sigma^2,
$$
\nwhere $\Delta = \left(\alpha'V^{-1}\alpha\right)\left((V^{-1}1) - \left(\alpha'V^{-1}1\right)^2\right)$.
\n3. ESTIMATION OF LOCATION AND SCALE PARAMETERS OF
\nEARSON TYPE IFAMILY OF DISTRIBUTIONS USING RANKED SET
\nSAMPLING.
\nne family of distributions with probability density function (pdf) of the form
\n
$$
(x \beta, \beta, \beta) = \frac{1}{\sigma \beta(\beta, \beta)} \left[\frac{x-\mu}{\sigma}\right]^{\beta-1} \left[1 - \left(\frac{x-\mu}{\sigma}\right)^{\beta-1}\right], \mu < x < \mu + \sigma
$$
\n(3.1)

 (2.6)

3. ESTIMATION OF LOCATION AND SCALE PARAMETERS OF PEARSON TYPE I FAMILY OF DISTRIBUTIONS USING RANKED SET SAMPLING.

The family of distributions with probability density function (pdf) of the form $= 0$, otherwise, $1 - \frac{\lambda}{\epsilon}$, (p, q) $\langle p,q,\mu,\sigma\rangle = \frac{1}{\sqrt{1-\sigma^2}}$ $1 \qquad \qquad$ $q-1$ $\int_0^{\infty} \left(\frac{x-\mu}{\sigma} \right)^{\mu-1} \left[1 - \left(\frac{x-\mu}{\sigma} \right)^{\mu-1} \right], \mu < x$
otherwise, $p,q)$ $f(x, p, q,$ $p-1$ $($ \vee $\langle x \rangle \mu + c$ $\overline{}$ $\overline{}$ J $\overline{}$ L \vert 1 L L \downarrow J $\left(\frac{x-\mu}{\sigma}\right)^{n}$ L $\int_{0}^{p-1} |1 - (x - y)|^2 dx$ J $\left(\frac{x-\mu}{\mu}\right)^{\mu}$ L $=$ $\frac{1}{2} \left(\frac{x-1}{2} \right)$ -1 $($ \vee \vee $q-1$ σ | $\left| \frac{\mu}{x} \right| \leq \mu + \sigma$ μ σ μ $(\mu, \sigma) = \frac{\sigma}{\sigma \beta}$ (3.1)

where $\mu \in R, \sigma > 0, p > 0, q > 0$ and $\beta(p,q)$ is the usual complete beta function is called Pearson Type I family of distributions (see Johnson et al., 1995, p.210). A distribution defined by the pdf given in (3.1) is also called as generalized beta distribution. For convenience, we may write GBD (p, q, μ, σ) to denote the

distribution defined in (3.1). If we put $q = 1$ in (3.1), the obtained distribution is called Power function distribution.

If X has a distribution defined by (3.1), then $Y = \left| \frac{X - \mu}{\sigma} \right|$ J $\left(\frac{X-\mu}{\mu}\right)$ L $=\left(\frac{X-\sigma}{\sigma}\right)$ $Y = \left(\frac{X-\mu}{\sigma}\right)$ follows the wellknown standard beta distribution with pdf given by *Estimation of parameters of Pearson type I family of distributions ...*

distribution defined in (3.1). If we put $q = 1$ in (3.1), the obtained distribution is

fix has a distribution defined by (3.1), then $Y = \left(\frac{X - \mu}{$

$$
g(y; p, q) = \frac{1}{\beta(p, q)} y^{p-1} (1 - y)^{q-1}, 0 < y < 1
$$

= 0, otherwise. (3.2)

For convenience, we may write BD (p, q) to denote the distribution defined in (3.2). Extensive applications of beta distribution are seen in the available literature. For example see, Harrop - Williams (1989), Kopper and Grover (1992). Though the problem of estimating the parameters in (3.1) is discussed extensively in Johnson et al., (1995), one may not get explicit solution for maximum likelihood estimators from likelihood equation (3.1).Moreover the procedure involved in obtaining estimators by the method of moments is cumbersome (see, Elderton and Johnson (1969). In most of the real life situations only small samples could be reliable from a population and in such situations one cannot say much on reliability of estimators obtained by the method of moments or maximum likelihood procedure. These estimators are not even unbiased. In the available literature not any good finite sample estimators are seen, derived and their properties analyzed for the parameters involved in (3.1).However, Sajeevkumar et al., (2007) derived the BLUE of μ and σ involved in (3.1) using order statistics. Hence, there is necessity to derive reasonably good finite sample estimators of the parameters involved in (3.1) using ranked set sampling. In this work our aim is to derive the BLUEs of μ and σ involved in (3.1) using ranked set sampling technique. Let $X_{(1)1}, X_{(2)2},..., X_{(n)n}$ are the ranked set sample arising from (3.1) and let $Y_{(1)1}, Y_{(2)2},..., Y_{(n)n}$ are the ranked set sample from (3.2). Define $\underline{Y} = (Y_{(1)1}, Y_{(2)2},..., Y_{(n)n})'$ as a vector of corresponding observations in an extensively in Johnson *et al.*, (1995), one may not get explicit solution for
maximum likelihood estimators from likelihood equation (3.1).Moreover the
procedure involved in obtaining estimators by the method of moments RSS arising from (3.2). Let $\alpha = (\alpha_{1n}, \alpha_{2n}, ..., \alpha_{nn})'$ and $V = ((V_{i,j:n}))$ be the vector of means and dispersion matrix of Y. Clearly $V = dig(V_{1:n}, V_{2:n}, ..., V_{n:n})$, where $V_{in} = V_{i,in}$. Then the BLUEs of μ and σ based on ranked set sampling are given in (2.2) to (2.5). We have evaluated the BLUE of μ and σ of GBD (p, q, μ , σ)

using RSS for $n = 5(5)10$, $p = 2(0.5)4$, $q = 2(0.5)4$ with $p \le q$ are given in the Table 1 and Table 2.

It may be noted that the required estimators $\hat{\mu}$ and $\hat{\sigma}$ for $p > q$ can be obtained from Table 1 and Table 2 itself. The way in which the coefficients of the order statistics in $\hat{\mu}$ and $\hat{\sigma}$ for $p > q$ can be determined from those in Table 1 and Table 2 becomes clear from the results that we prove in the next Section. All the computational works involved in this paper were done using 'Mathcad '. *N.K. Sajeevkumar¹ and A.R.Sumi*

M.K. Sajeevkumar¹ and A.R.Sumi²

Table 1 and Table 2.

It may be noted that the required estimators $\hat{\mu}$ and $\hat{\sigma}$ for $p > q$ can be obtained

from Table 1 and Table 2 itself. T

4. RELATIONSHIP BETWEEN THE COEFFICIENTS OF RSS IN THE BLUES $\hat{\mu}$ AND $\hat{\sigma}$ OF GBD (P, Q, μ , σ) FOR $p > q$ WITH THOSE OF $p < q$

 $X_{(1)1}, X_{(2)2},..., X_{(n)n}$ be the ranked set sampling arising from (3.1) and let *N.K Sajeevkumar¹ and A.R.Sumi*²

M.K Sajeevkumar¹ and A.R.Sumi²

Table 1 and Table 2.

It may be noted that the required estimators $\hat{\mu}$ and $\hat{\sigma}$ for $p > q$ can be obtained

from Table 1 and Table 2 itself. $Y_{(1)1}, Y_{(2)2},..., Y_{(n)2}$ be the ranked set sampling arising from (3.2). Let *N.K Sajeevkumar¹ and A.R.Sumi*²

g RSS for $n = 5(5)10$, $p = 2(0.5)4$, $q = 2(0.5)4$ with $p \le q$ are given in the

e 1 and Table 2.

y be noted that the required estimators $\hat{\mu}$ and $\hat{\sigma}$ for $p > q$ can be obtained $\underline{X} = (X_{(1)1}, X_{(2)2},...,X_{(n)n})'$, and then define $\underline{Y} = (Y_{(1)1}, Y_{(2)2},...,Y_{(n)n})'$ as a vector of *N.K Sajeevkumar' and A.R.Sumi*
 $p = 2(0.5)4$, $q = 2(0.5)4$ with $p \le q$ are given in the

required estimators $\hat{\mu}$ and $\hat{\sigma}$ for $p > q$ can be obtained

2 itself. The way in which the coefficients of the order
 $p > q$ corresponding observations from RSS arising from (3.2). Let using RSS for $n = 5(5)10$, $p = 2(0.5)4$, $q = 2(0.5)4$ with $p \le q$ are given in the

Table 1 and Table 2.

It may be noted that the required estimators $\hat{\mu}$ and $\hat{\sigma}$ for $p > q$ can be obtained

from Table 1 and Table $\alpha = (\alpha_{1:n}, \alpha_{2:n}, ..., \alpha_{n:n})'$ and $V = ((V_{i,j:n}))$ be the vector of means and dispersion matrix of Y. Clearly, $V = dig(V_{1n}, V_{2n},...,V_{n n})$, where $V_{i n} = V_{i,i:n}$. For It may be noted that the required estimators $\hat{\mu}$ and $\hat{\sigma}$ for $p > q$ can be obtained
from Table 1 and Table 2 itself. The way in which the coefficients of the order
statistics in $\hat{\mu}$ and $\hat{\sigma}$ for $p > q$ can be convenience we write $\hat{\mu}_{(p,q)}$ and $\hat{\sigma}_{(p,q)}$ to denote the BLUE of μ and σ involved in (3.1).Then we have able 2 becomes clear from the results that we prove in the next Section. All the mputational works involved in this paper were done using 'Mathcad'.

4. **RELATIONSHIP BETWEEN THE COEFFICIENTS OF RSS IT THE BLUES** $\hat{\mu}$ **A** 4. RELATIONSHIP BETWEEN THE COEFFICIENTS OF RSS IN

THE BLUES $\hat{\mu}$ AND $\hat{\sigma}$ OF GBD (P, Q, μ , σ) FOR $p > q$

WITH THOSE OF $p < q$

Let $X_{(1)1}, X_{(2)2},..., X_{(n)n}$ be the ranked set sampling arising from (3.1) and le
 $K_{(1)i}, X_{(22)},..., X_{(n)n}$ be the ranked set sampling arising from (3.1) and let
 $K_{(22)},..., X_{(n)n}$ be the ranked set sampling arising from (3.1) and let
 $K_{(1)}, X_{(22)},..., X_{(n)n}$, and then define $\underline{Y} = (Y_{(1)}, Y_{(22)},..., Y_{(n)n})$ as a v $Y_{(1)i}, X_{(2)2},..., X_{(n)n})'$, and then define $Y = (Y_{(1)i}, Y_{(2)2},..., Y_{(n)n})'$ as a vector of
ponotions from RSS arising from (3.2). Let
 $y_n, \alpha_{2n}, ..., \alpha_{nn}$ and $V = ((V_{i,j:n}))$ be the vector of means and dispersion
c of Y. Clearly, $V = dig(V_{$

$$
\hat{\mu}_{(p,q)} = -\frac{\alpha' V^{-1} (\alpha' - \alpha I') V^{-1}}{\Delta} \underline{X},
$$
\n(4.1)

$$
\hat{\sigma}_{(p,q)} = -\frac{\Gamma V^{-1}(\alpha - \alpha \Gamma)V^{-1}}{\Delta} \underline{X} \,, \tag{4.2}
$$

$$
Var(\hat{\mu}_{(p,q)}) = \frac{(\alpha' V^{-1} \alpha) \sigma^2}{\Delta},
$$
\n(4.3)

$$
Var(\hat{\sigma}_{(p,q)}) = \frac{(\mathbf{1}'V^{-1}\mathbf{1})\sigma^2}{\Delta} \tag{4.4}
$$

and

$$
cov(\hat{\mu}_{(p,q)}, \hat{\sigma}_{(p,q)}) = -\frac{(\alpha'V^{-1})\sigma^2}{\Delta}
$$
\n(4.5)

mation of parameters of Pearson type I family of distributions ...
 $(\hat{\mu}_{(p,q)}, \hat{\sigma}_{(p,q)}) = -\frac{(\alpha'V^{-1}1)\sigma^2}{\Delta}$ (4.5)

Set $\Delta = (\alpha'V^{-1}\alpha)(V^{-1}1) - (\alpha'V^{-1}1) - (\alpha'V^{-1}1)^2$ and 1 is a column vector of *n* ones.
 $Z_{(1)1}, Z_{(2)2}, ..., Z_{($ where $\Delta = (\alpha'V^{-1}\alpha)(\alpha'V^{-1}\alpha)(\alpha'V^{-1}\alpha') - (\alpha'V^{-1}\alpha)\alpha'$ and 1 is a column vector of *n* ones. Estimation of parameters of Pearson type I family of distributions ...
 $\text{cov}(\hat{\mu}_{(p,q)}, \hat{\sigma}_{(p,q)}) = -\frac{(\alpha V^{-1}1)\sigma^2}{\Delta}$ (4.5)

where $\Delta = (\alpha'V^{-1}\alpha)(l'V^{-1}1) - (\alpha'V^{-1}1)^2$ and 1 is a column vector of *n* ones.

Let $Z_{(1)}, Z_{(2)2},$ $\{a_{11}, \ldots, a_{(n)n}\}$ be the RSS random sample of size *n* arising from $f(x;q,p,\mu,\sigma)$, where $f(x;q,p,\mu,\sigma)$ is obtained by inter changing p and q in (3.1) *Estimation of parameters of Pearson type I family of distributions* ...
 $\text{cov}(\hat{\mu}_{(p,q)}, \hat{\sigma}_{(p,q)}) = -\frac{(\alpha V^{-1}1)\sigma^2}{\Delta}$ (4.5)

where $\Delta = (\alpha V^{-1}\alpha)(V^{-1}1) - (\alpha'V^{-1}1)^2 - (\alpha'V^{-1}1)^2$ and 1 is a column vector of *n* ones.

Let $Z_{$ I J Ι I V $\left(\left(\frac{Z_{(1)1}-\mu}{\sigma}\right), \left(\frac{Z_{(2)2}-\mu}{\sigma}\right), \left(\frac{Z_{(3)3}-\mu}{\sigma}\right), \cdots, \left(\frac{Z_{(n)n}-\mu}{\sigma}\right)\right)$ $\left(\frac{Z_{(n)n}-\mu}{\sigma}\right)$ $\bigg), \ldots, \left(\frac{Z_{(n)n} - \sigma}{\sigma} \right)$ $\left(\frac{Z_{(3)3-\mu}}{\sigma}\right)$ $\bigg) \bigg($ $\left(\frac{Z_{(2)2}-\mu}{\sigma}\right)$ $\int_{2}^{2} \frac{Z_{(2)2} - Z_{(2)2}}{\sigma}$ $\left(\frac{Z_{(1)1}-\mu}{\sigma}\right)$ $\left(\frac{Z_{(1)1}-\mu}{\sigma}\right), \left(\frac{Z_{(2)2}-\mu}{\sigma}\right), \left(\frac{Z_{(3)3}-\mu}{\sigma}\right), \cdots, \left(\frac{Z_{(n)n}}{\sigma}\right)$ μ σ μ σ $_{\mu}$ $\frac{Z_{(0)} - \mu}{\sigma}$ $\left| \frac{Z_{(2)2} - \mu}{\sigma} \right| \left| \frac{Z_{(3)3} - \mu}{\sigma} \right|$ \ldots $\left| \frac{Z_{(n)n} - \mu}{\sigma} \right|$ distributed identically as Estimation of parameters of Pearson type I family of distributions...
 $\text{cov}(\hat{\mu}_{(p,q)}, \hat{\sigma}_{(p,q)}) = -\frac{(\alpha'V^{-1}1)\sigma^2}{\Delta}$ (4.5)

where $\Delta = (\alpha'V^{-1}\alpha)[V^{-1}1] - (\alpha'V^{-1}1)^2$ and 1 is a column vector of n ones.

Let $Z_{(1)1}, Z_{(2)2},..., Z$ $((1 - Y_{(n)n}), (1 - Y_{(n-1)n}), \cdots, (1 - Y_{(1)n})).$ Consequently we have
 $E(Z_{(r)n}) = \sigma(1 - \alpha_{(n-r+1)n}) + \mu$ Estimation of parameters of Pearson type I family of distributions ...
 $\operatorname{cov}(\hat{\mu}_{(p,q)}, \hat{\sigma}_{(p,q)}) = -\frac{(a'V^{-1}1)e^2}{\Delta}$ (4.5)

where $\Delta = [\alpha'V^{-1}\alpha](V^{-1}1) - [\alpha'V^{-1}1] - [\alpha'V^{-1}]^2$ and 1 is a column vector of *n* ones.

Let $Z_{(1)$ and
 $Var(Z_{(r)n}) = Var(Y_{(n-r+1)n}).$ *Estimation of parameters of Pearson type I family of distributions* ...
 $\operatorname{cov}(\hat{\mu}_{[p,q)}, \hat{\sigma}_{[p,q]}) = -\frac{(a^r V^{-1} V)^2}{\Delta}$ (4.5)

where $\Delta = [\alpha' V^{-1} \alpha] (V^{-1} V^{-1}] - (\alpha' V^{-1} V)^2$ and 1 is a column vector of *n* ones.

Let $Z_{(1)}, Z_{$ Estimation of parameters of Pearson type I family of distributions...
 $\cot(\hat{\mu}_{(p,q)}, \hat{\sigma}_{(p,q)}) = -\frac{(\alpha V^{-1}1)\sigma^2}{\Delta}$ (4.5)

where $\Delta = (\alpha'V^{-1}\alpha)(V^{-1}1) - (\alpha'V^{-1}1)^2$ and 1 is a column vector of *n* ones.

Let $Z_{(1)1}, Z_{(2)2},..., Z_{($ Let $Z = (Z_{(1)1}, Z_{(2)2}, \cdots, Z_{(n)n})$, then $E(Z) = \sigma(1 - J\alpha) + 1\mu$, where J is the $n \times n$ matrix given by . $1 \quad 0 \quad \cdots \quad 0 \quad 0$ $0 \quad 0 \quad \cdots \quad 1 \quad 0$ $\begin{bmatrix} 0 & 0 & \cdots & 0 & 1 \end{bmatrix}$ \downarrow \downarrow \downarrow \downarrow L ľ Ι. L $=$ \cdots e e Suele $J = \begin{bmatrix} 0 & 0 & \cdots \\ \cdot & \cdot & \cdot \end{bmatrix}$ $f(x,q, p, \mu, \sigma)$, where $f(x,q, p, \mu, \sigma)$ is obtained by inter changing p and q in (3.1)
Clearly $\left[\frac{2(n-2r)}{\sigma}\right]\left[\frac{2(n-2r)}{\sigma}\right]-\left[\frac{2(n-2r)}{\sigma}\right]$ distributed identically as
 $\left(\left|1-\frac{Y_{(n)}|_p}{(1-\sigma)(p_n)}\right|,\dots,\left|1-Y_{(j)n}\right|\right)$.

C 1- $Y_{(n)n}$ $[(1 - Y_{(n-1)n})$, \cdots , $(1 - Y_{(1)n})$).

onsequently we have
 $(Z_{(r)n}) = \sigma(1 - \alpha_{(n-r+1)n}) + \mu$

ad
 $\alpha(Z_{(r)n}) = Var(Y_{(n-r+1)n})$.
 $\alpha(Z) = \sigma(1 - J\alpha) + 1\mu$, where *J* is the *n* × *n* matrix given by
 $(Z) = \sigma(1 - J\alpha) + 1\mu$, where $(1 - Y_{(n-1)n}) \cdots (1 - Y_{(1)n})$

antly we have
 $\sigma(1 - \alpha_{(n-r+1)n}) + \mu$
 $= \frac{Var(Y_{(n-r+1)n})}{\sum_{i=1}^n P(x_i - x_i)}$.
 $y(x_i) = \sum_{i=1}^n P(x_i - x_i) + \mu$, where *J* is the *n* × *n* matrix given by
 \cdots 0 1]
 \cdots 1 0 1
 \cdots 0 0 1
 \cdots 0 0 0 $Z_{(p|n)} = V \omega \sqrt{V_{(n-r+1|n)}}$.
\n
$$
Z_{(p|n)} = V \omega \sqrt{V_{(n-r+1|n)}}
$$
.
\n
$$
= \sigma (1 - J\alpha) + 1\mu
$$
, where *J* is the $n \times n$ matrix given by
\n
$$
0 \quad 0 \quad \cdots \quad 0 \quad 1
$$

\n
$$
0 \quad 0 \quad \cdots \quad 1 \quad 0
$$

\n
$$
0 \quad 0 \quad \cdots \quad 1 \quad 0
$$

\n
$$
0 \quad 0 \quad \
$$

Clearly we have $J = J^{-1} = J'$ and $J = 1$. If we write $D(X) = \sigma^2 V$, then $D(Z) = J V J \sigma^2$. If we write $\hat{\mu}_{(q,p)}$ and $\hat{\sigma}_{(q,p)}$ to denote the BLUEs of μ and σ involved in $f(x; q, p, \mu, \sigma)$, then

$$
\hat{\mu}_{(q,p)} = -\frac{(1 - J\alpha)'JV^{-1}J(1(1 - J\alpha)' - (1 - J\alpha)I')JV^{-1}J}{\Delta'}\underline{X}.
$$
\n(4.6)

Let
$$
Z = (Z_{(1)}, Z_{(2)}, ..., Z_{(n) n})
$$
, then
\n
$$
E(Z) = \sigma(1-J\alpha) + 1\mu
$$
, where J is the $n \times n$ matrix given by
\n
$$
J = \begin{bmatrix} 0 & 0 & \cdots & 0 & 1 \\ 0 & 0 & \cdots & 1 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 1 & 0 & \cdots & 0 & 0 \end{bmatrix}
$$
\nClearly we have $J = J^{-1} = J'$ and $J1 = 1$. If we write $D(X) = \sigma^2 V$, then
\n
$$
D(Z) = JVJ\sigma^2
$$
. If we write $\hat{\mu}_{(q,p)}$ and $\hat{\sigma}_{(q,p)}$ to denote the BLUEs of μ
\nand σ involved in $f(x; q, p, \mu, \sigma)$, then
\n
$$
\hat{\mu}_{(q,p)} = -\frac{(1-J\alpha)'JV^{-1}J((1-J\alpha)' - (1-J\alpha)')V^{-1}J}{\Delta'}
$$
\n
$$
\Delta' = (1-J\alpha)'(JV^{-1}J)(1-J\alpha)(1'JV^{-1}J) - ((1-J\alpha)'(JV^{-1}J))^2
$$
\n
$$
= (\Gamma V^{-1}J - \alpha'V^{-1}J)(1'J^{-1} - J\alpha'V^{-1}I) - ((1'V^{-1} - \alpha'V^{-1}I)^2)
$$
\n
$$
= (\Gamma V^{-1}J1'V^{-1} - \alpha'V^{-1}J1'V^{-1}I) - (\Gamma V^{-1}\alpha)(1'V^{-1}I) + (\alpha'V^{-1}\alpha)(1'V^{-1}I) - (\alpha'V^{-1}I)^2 + 2((V^{-1}I)(\alpha'V^{-1}I))
$$
\n
$$
= (\alpha'V^{-1}\alpha)(1'V^{-1}I)(\alpha V^{-1}I)^2
$$
\n(4.7)

Thus using (4.6) and (4.7) we have $\Delta' = \Delta$.

reduces to

Thus using (4.6) and (4.7) we have
$$
\Delta' = \Delta
$$
.

\nFurther simplifying the numerator of (4.6) using (4.7) the BLUE $\hat{\mu}_{(q,p)}$ reduces to

\n
$$
\hat{\mu}_{(q,p)} = \frac{1'V^{-1}(\alpha' - \alpha I')V^{-1}}{\Delta}(JZ) - \frac{\alpha'V^{-1}(\alpha' - \alpha I')V^{-1}}{\Delta}(JZ).
$$
\nThe BLUE of $\sigma_{(q,p)}^*$ of σ given by

\n
$$
\hat{\sigma}_{(q,p)} = \frac{1'(\mathcal{J}V\mathcal{J}^{-1})\left[1 - (1 - J\alpha)^1 - (1 - J\alpha)^1\right]\left(\mathcal{J}V\mathcal{J}\right)^{-1}}{\Delta}Z.
$$
\nThen on simplifying (4.9) we get

\n
$$
\hat{\sigma}_{(q,p)} = -\frac{1'V^{-1}(\alpha^1 - \alpha I')V^{-1}}{\Delta}(JZ),
$$
\n(4.10)

\n
$$
Var(\hat{\mu}_{(q,p)}) = \frac{(1 - J\alpha)\left(\mathcal{J}V^{-1}\mathcal{J}(1 - J\alpha)\right)}{\Delta}\sigma^2
$$

The BLUE of $\sigma_{(q,p)}^*$ of σ given by

$$
\hat{\sigma}_{(q,p)} = \frac{1! \left(J V J^{-1} \right) \left[1 - (1 - J \alpha)^1 - (1 - J \alpha) I' \right] J V J)^{-1}}{\Delta} Z \,.
$$
\n(4.9)

Then on simplifying (4.9) we get

$$
\hat{\sigma}_{(q,p)} = -\frac{1'V^{-1}(\alpha^1 - \alpha 1')V^{-1}}{\Delta}(JZ),
$$
\n(4.10)

Thus using (4.6) and (4.7) we have
$$
\Delta' = \Delta
$$
.
\nFurther simplifying the numerator of (4.6) using (4.7) the BLUE $\hat{\mu}_{(q,p)}$
\nreduces to
\n
$$
\hat{\mu}_{(q,p)} = \frac{1'V^{-1}(\lfloor \alpha' - \alpha 1' \rfloor V^{-1} \left(JZ \right) - \frac{\alpha'V^{-1}(\lfloor \alpha^1 - \alpha 1' \rfloor V^{-1} \left(JZ \right))}{\Delta} \left(JZ \right).
$$
\n(4.8)
\nThe BLUE of $\sigma_{(q,p)}^*$ of σ given by
\n
$$
\hat{\sigma}_{(q,p)} = \frac{1'(\lfloor JUJ^{-1} \rfloor \lfloor - (1 - J\alpha) \rfloor - (1 - J\alpha) \lfloor JU \rfloor \lfloor JUJ \rfloor^{-1} \rfloor}{\Delta} Z.
$$
\n(4.9)
\nThen on simplifying (4.9) we get
\n
$$
\hat{\sigma}_{(q,p)} = -\frac{1'V^{-1}(\lfloor \alpha^1 - \alpha 1' \rfloor V^{-1} \left(JZ \right))}{\Delta}.
$$
\n
$$
Var(\hat{\mu}_{(q,p)}) = \frac{(1 - J\alpha)'(\lfloor JV^{-1}J \rfloor \lfloor - J\alpha) \rfloor}{\Delta} \sigma^2
$$
\n
$$
= \frac{1V^{-1}1 - 2\alpha'V^{-1}1 + \alpha'V^{-1}\alpha}{\Delta} \sigma^2,
$$
\n(4.11)

$$
\mu_{(q,p)} = \Delta \qquad (4.8)
$$
\n
$$
\hat{\sigma}_{(q,p)} = \frac{1! (JVI^{-1}) [1 - (1 - J\alpha)^1 - (1 - J\alpha)^1] [JVI^{-1}]}{\Delta} Z.
$$
\n(4.9)
\n
$$
\hat{\sigma}_{(q,p)} = \frac{1! (JVI^{-1}) [1 - (1 - J\alpha)^1 - (1 - J\alpha)^1] [JVI^{-1}]}{\Delta} Z.
$$
\n(4.9)
\n
$$
\hat{\sigma}_{(q,p)} = -\frac{1! V^{-1} (1\alpha^1 - \alpha 1^1) V^{-1}}{\Delta} (JZ),
$$
\n
$$
Var(\hat{\mu}_{(q,p)}) = \frac{(1 - J\alpha)^1 (JV^{-1}J)(1 - J\alpha)}{\Delta} \sigma^2
$$
\n
$$
= \frac{1! V^{-1} (1 - 2\alpha V^{-1} + \alpha V^{-1} \alpha V^{-1} \sigma^2}{\Delta} \sigma^2 ,
$$
\n(4.11)
\n
$$
Var(\hat{\sigma}_{(q,p)}) = \frac{1! JV^{-1}J1}{\Delta} \sigma^2
$$
\n(4.12)
\n
$$
= \frac{1! V^{-1} (1 - 2\alpha V^{-1} + \alpha V^{-1} \alpha V^{-1} \sigma^2}{\Delta} \sigma^2 ,
$$
\n(4.13)
\n
$$
cov(\hat{\mu}_{(q,p)}, \hat{\sigma}_{(q,p)}) = \frac{(\alpha V^{-1} (1 - 1! V^{-1} I))^2}{\Delta} \sigma^2 ,
$$
\n(4.13)
\nwhere $\Delta = (\alpha V^{-1} \alpha)(l'V^{-1} I) - (\alpha V^{-1} I)^2$ and 1 being a column vector of n ones.
\nSince in (4.8), $J(Z) = (Z_{(p,p)}, Z_{(p-1)p-1}, ..., Z_{(p-1)})$, we note that the coefficients of

and

$$
\text{cov}(\hat{\mu}_{(q,p)}, \hat{\sigma}_{(q,p)}) = \frac{\left(\alpha' V^{-1} 1 - 1' V^{-1} 1\right)}{\Delta} \sigma^2,
$$
\n(4.13)

where $\Delta = (\alpha' V^{-1} \alpha)(\alpha' V^{-1} \alpha') - (\alpha' V^{-1} \alpha')^2$ and 1 being a column vector of n ones. $\sigma_{(q,p)} = -\frac{y - \sqrt{(a^2 - a^2)^2}}{\Lambda} (Jz),$ (4.10)
 $Var(\hat{\sigma}_{(q,p)}) = \frac{y - \sqrt{(a^2 - a^2)^2}}{\Lambda} \sigma^2$
 $= \frac{y - \sqrt{(a^2 - a^2)^2}}{\Lambda} \sigma^2$ (4.11)
 $Var(\hat{\sigma}_{(q,p)}) = \frac{y - \sqrt{(a^2 - a^2)^2}}{\Lambda} \sigma^2$ (4.12)
 $= \frac{y - \sqrt{(a^2 - a^2)^2}}{\Lambda} \sigma^2$ (4.12)

and
 $cov(\hat{\mu}_{(q$ $,Z_{(n-1)n-1},..., Z_{(1)1}$, we note that the coefficients of $Var(\hat{\mu}_{(q,p)}) = \frac{(1-J\alpha)\left((\gamma^{-1}J)(1-J\alpha)\sigma^2\right)}{\Delta} \sigma^2$
 $= \frac{|\gamma^{-1}1 - 2\alpha\gamma^{-1}1 + \alpha\gamma^{-1}\alpha}{\Delta} \sigma^2$,
 $Var(\hat{\sigma}_{(q,p)}) = \frac{1'J^{V-1}J1}{\Delta}\sigma^2$

and
 $cov(\hat{\mu}_{(q,p)}, \hat{\sigma}_{(q,p)}) = \frac{(\alpha\gamma^{-1}1 - 1'\gamma^{-1}1)}{\Delta}\sigma^2$,

where $\Delta = (\alpha'\gamma^{-1}\alpha)(|\gamma^{-1}1) - (\alpha'\gamma^{-1}1)^$ $Var(\hat{\mu}_{(q,p)}) = \frac{(1 - Ja)^{'}(V^{r-1}J)(1 - Ja)}{\Delta} \sigma^2$
 $= \frac{W^{-1}1 - 2\alpha'V^{-1} + \alpha'V^{-1}\alpha}{\Delta} \sigma^2$,
 $\frac{1}{(\alpha, p)} = \frac{1}{\Delta} \frac{V^{-1}1}{\Delta}$
 $= \frac{1}{\Delta} \frac{V^{-1}1}{\Delta}$
 $= \frac{(4V^{-1}a)(V^{-1}) - (a'V^{-1})^2}{\Delta} \sigma^2$,
 $= \frac{(4.13)}{\Delta}$
 $= (a'V^{-1}a)(V^{-1}) - (a'V^{-1$ (4.11)

(4.12)

(4.13)

of n ones.

efficients of

in $\hat{\mu}_{(p,q)}$ and

value of the

theorem. $Var(\hat{\sigma}_{(q,\rho)}) = \frac{(1-J\alpha)\left(\rho V^{-1}J\right)(1-J\alpha)}{\Delta}\sigma^2$
 $= \frac{|V^{-1}1 - 2\alpha V^{-1}1 + \alpha V^{-1}\alpha}{\Delta}\sigma^2$,
 $Var(\hat{\sigma}_{(q,\rho)}) = \frac{|(JV^{-1}J] \sigma^2}{\Delta}\sigma^2$ (4.11)

and
 $cov(\hat{\mu}_{(q,\rho)}, \hat{\sigma}_{(q,\rho)}) = \frac{(\alpha V^{-1}1 - IV^{-1}1)}{\Delta}\sigma^2$,

where $\Delta = (\alpha V^{-1}\alpha)(V^{-1}1) - (\alpha V^{-1})^2$ an $\frac{1- J\alpha \int (\sqrt{V^{-1}J})(1-J\alpha)}{\Delta} \sigma^2$
 $\frac{1V^{-1}1-2\alpha'V^{-1}1+\alpha'V^{-1}\alpha}{\Delta} \sigma^2$,

(4.11)

(4.12)

(4.12)

(4.13)

and 1 being a column vector of n ones.
 $\ldots, Z_{(1)\parallel}$, we note that the coefficients of

f the coefficients of $X_{$ $Var(\hat{\sigma}_{(q,p)}) = \frac{V J V^{-1} J}{\Delta} \sigma^2$
 $= \frac{V' J V^{-1} J}{\Delta} \sigma^2$ (4.11)

and
 $= \frac{V V^{-1} L}{\Delta} \sigma^2$ (4.12)

where $\Delta = (\alpha' V^{-1} \alpha)(V^{-1} I) - (\alpha' V^{-1} I)^2$ and 1 being a column vector of n ones.

Since in (4.8), $J(Z) = (Z_{(n,p)}, Z_{(q-1)h-1}, ..., Z_{(1$ $\frac{1}{2} = \frac{|V^{-1}1 - 2\alpha'V^{-1}1 + \alpha'V^{-1}\alpha}{\Delta} \sigma^2$,

(4.12)
 $\frac{1}{2}$ (4.12)
 $\frac{1}{2}$ (4.12)
 $\frac{1}{2}$ (4.12)

(4.13)
 $\frac{1}{2}$ (4.13)
 $\frac{1}{2}$ ($\frac{1}{2}$ and 1 being a column vector of n ones.
 $\frac{1}{2}$ ($\frac{1}{2}$),

Theorem 4.1

Estimation of parameters of Pearson type I family of distributions ...
 Theorem 4.1

Let $X_{(1)1}, X_{(2)2},...,X_{(n)n}$ be the ranked set sampling arising from $f(x; p, q, \mu, \sigma)$.

Let $Z_{(1)1}, Z_{(2)2},..., Z_{(n)n}$ be the RSS random sa $X_{(1)1}, X_{(2)2},..., X_{(n)n}$ be the ranked set sampling arising from $f(x; p, q, \mu, \sigma)$. Estimation of parameters of Pearson type I family of distributions ...
 Theorem 4.1

Let $X_{(1)1}, X_{(2)2},...,X_{(n)n}$ be the ranked set sampling arising from $f(x, p, q, \mu, \sigma)$.

Let $Z_{(1)1}, Z_{(2)2},..., Z_{(n)n}$ be the RSS random sa $Z_{(1)1}, Z_{(2)2},..., Z_{(n)n}$ be the RSS random sample of size *n* arising from Extimation of parameters of Pearson type I family of distributions ...
 Cheorem 4.1

Let $X_{(1)1}, X_{(2)2},..., X_{(n)n}$ be the ranked set sampling arising from $f(x, p, q, \mu, \sigma)$.

Let $Z_{(1)1}, Z_{(2)2},..., Z_{(n)n}$ be the RSS random sa $f(x;q,p,\mu,\sigma)$ then the coefficient of $Z_{(r)n}$ in the BLUE of

Estimation of parameters of Pearson type I family of distributions ...
 Theorem 4.1

Let $X_{(1)}, X_{(2)2},..., X_{(n)n}$ be the ranked set sampling arising from $f(x, p, q, \mu, \sigma)$.

Let $Z_{(1)}, Z_{(2)2},..., Z_{(n)n}$ be the RSS random sample *Estimation of parameters of Pearson type I family of distributions* ...
 Theorem 4.1

Let $X_{(1)i}, X_{(2)2},..., X_{(n)n}$ be the ranked set sampling arising from $f(x, p, q, \mu, \sigma)$.

Let $Z_{(1)i}, Z_{(2)2},..., Z_{(n)n}$ be the RSS random sa Estimation of parameters of Pearson type I family of distributions ...

Theorem 4.1

Let $X_{(1)1}, X_{(2)2},...,X_{(n)n}$ be the ranked set sampling arising from $f(x, p, q, \mu, \sigma)$.

Let $Z_{(1)1}, Z_{(2)2},..., Z_{(n)n}$ be the RSS random samp in the BLUE of $\hat{\sigma}_{(p,n)}$ in $f(x; p, q, \mu, \sigma)$.

be the ranked set sampling arising from $f(x; p, q, \mu, \sigma)$.

be the RSS random sample of size *n* arising from

oefficient of $Z_{(r)n}$ in the BLUE of
 (α, σ) is equal to the Estimation of parameters of Pearson type I family of distributions ...
 Theorem 4.1

Let $X_{(1)}, X_{(2)2},...,X_{(n)n}$ be the ranked set sampling arising from $f(x, p, q, \mu, \sigma)$.

Let $Z_{(1)}, Z_{(2)2},..., Z_{(n)n}$ be the RSS random sample in ^p,^q ^ˆ of involved in $f(x; p, q, \mu, \sigma)$. Further *Estimation of parameters of Pearson type I family of distributions* ...

Theorem 4.1

Let $X_{(i|k)}, X_{(2|2)},..., X_{(n|k)}$ be the ranked set sampling arising from $f(x, p, q, \mu, \sigma)$.

Let $Z_{(1|i)}, Z_{(2|2)},..., Z_{(n|k)}$ be the RSS random *Estimation of parameters of Pearson type I family of distributions* ...

Theorem 4.1

Let $X_{(0)}, X_{(2p)},..., X_{(p)}$ be the ranked set sampling arising from $f(x, p, q, \mu, \sigma)$.

Let $Z_{(1)}, Z_{(2p)},..., Z_{(p)}$ be the RSS random sample of

5. EFFICIENCY COMPARISON OF THE BLUE OF μ AND σ USING RANKED SET SAMPLE WITH THAT OF ORDER STATISTICS.

To compare our estimator defined in Section 3 using RSS we take the BLUE of μ and σ using order statistics derived by Sajeevkumar et al., (2007). Let $X_{1:n}, X_{2:n},..., X_{n:n}$ be the order statistics of size n taken from (3.1) and let $Y_{1:n}, Y_{2:n},..., Y_{n:n}$ be the order statistics of size n taken from (3.2). Also let n $\hat{\mu}_{(q,p)}$ and $\hat{\sigma}_{(q,p)}$ of the parameters of μ and σ involved in $f(x, p, q, \mu, \sigma)$ and

he coefficients of $Z_{(p,n)}$ in the BLUE of $\hat{\sigma}_{(q,p)}$ of σ in $f(x, p, q, \mu, \sigma)$ is equal to

he - ve values of the coeffi and $\hat{\sigma}_{(q,p)}$ of the parameters of μ and σ involved in $f(x, p, q, \mu, \sigma)$ and

cicints of $Z_{(r)_n}$ in the BLUE of $\hat{\sigma}_{(q,p)}$ of σ in $f(x, p, q, \mu, \sigma)$ is equal to

values of the coefficient of $X_{(n-r+1)n-r+1}$ in $\$ $X = (X_{1:n}, X_{2:n},..., X_{n:n})'$ and $Y = (Y_{1:n}, Y_{2:n},..., Y_{n:n})'$. Also let $\xi = (\xi_{1:n}, \xi_{2:n}, \dots, \xi_{n:n})$ and $B = ((b_{r,s:n}))$ be the vector of means and dispersion matrix of Y. Then the BLUE and its variance of μ and σ are given by see Sajeevkumar et al., (2007) are as follows ar $(\hat{\mu}_{(q,p)}) = Var(\hat{\mu}_{(p,q)}) + 2Cov(\mu_{(p,q)}, \hat{\sigma}_{(p,q)}) + Var(\hat{\sigma}_{(p,q)})$,
 $\arg(\hat{\sigma}_{(p,q)}) = Var(\hat{\sigma}_{(q,p)})$, $Cov(\hat{\mu}_{(q,p)}, \hat{\sigma}_{(q,p)}) = -Cov(\hat{\mu}_{(p,q)}, \hat{\sigma}_{(p,q)}) - Var(\hat{\sigma}_{(p,q)})$.

5. **EFFICIENCY COMPARISON OF THE BLUE OF** μ **AND** σ USING **RANKED SET SAM** 5. EFFICIENCY COMPARISON OF THE BLUE OF μ AND σ
USING RANKED SET SAMPLE WITH THAT OF ORDER
STATISTICS.

compare our estimator defined in Section 3 using RSS we take the BLUE

and σ using order statistics derived USING RANKED SET SAMPLE WITH THAT OF ORDER

STATISTICS.

STATISTICS.

mpare our estimator defined in Section 3 using RSS we take the BLUE of

d σ using order statistics derived by Sajeevkumar *et al.*, (2007). Let
 $x_{$

$$
\mu_{(p,q)}^* = \frac{\xi^{\prime} B^{-1} (1\xi^{\prime} - \xi 1^{\prime}) B^{-1}}{\Delta} X , \qquad (5.1)
$$

$$
\sigma_{(p,q)}^* = \frac{1'B^{-1}(1\zeta' - \zeta 1')B^{-1}}{\Delta} X,
$$
\n(5.2)

$$
Var(\mu_{(p,q)}^*) = \frac{\left(\xi' B^{-1} \xi \right) \sigma^2}{\Delta} \,,\tag{5.3}
$$

$$
31\quad
$$

$$
Var(\sigma_{(p,q)}^*) = \frac{(\mathbf{I}^T B^{-1} \mathbf{I}) \sigma^2}{\Delta},
$$

\nand
\n
$$
Cov(\mu_{(p,q)}^*, \sigma_{(p,q)}^*) = -\frac{(\xi^T B^{-1} \mathbf{I}) \sigma^2}{\Delta},
$$
\n(5.5)

and

$$
Cov(\mu_{(p,q)}^*, \sigma_{(p,q)}^*) = -\frac{\left(\xi' B^{-1} \mathbf{1}\right) \sigma^2}{\Delta},\tag{5.5}
$$

N.K Sajeevkumar¹ and A.R.Sumi²
 $(\sigma_{(p,q)}^*) = \frac{(1/B^{-1}1)\sigma^2}{\Delta}$,
 $(\mu_{(p,q)}^*, \sigma_{(p,q)}^*) = -\frac{(\xi'B^{-1}1)\sigma^2}{\Delta}$,
 $\text{re } \Delta = (\xi'B^{-1}\xi)(1'B^{-1}1) - (\xi'B^{-1}1)^2$ and 1 is a column vector of *n* ones.

ciency of our estimator using RSS where $\Delta = (\xi' B^{-1} \xi)(1' B^{-1} 1) - (\xi' B^{-1} 1)^2$ and 1 is a column vector of *n* ones. Efficiency of our estimator using RSS related to the BLUE of μ and σ using order statistics is also made and is given in Table 1 and Table 2. We have evaluated Var($\hat{\mu}$), Var($\hat{\sigma}$) and tabulated the values of $\frac{Var(\hat{\mu})}{\sigma^2}$ (μ^*) $\frac{Var(\mu^*)}{\sigma^2}, \frac{Var(c)}{\sigma^2}$ (σ^*) $\frac{Var(\sigma^*)}{\sigma^2}, \frac{Var(\sigma^*)}{\sigma^2}$ $(\hat{\mu})$ σ $\frac{Var(\hat{\mu})}{2}$, 2 $\hat{(\sigma)}$ $\frac{Var(\hat{\sigma})}{\sigma^2}$, and the efficiency $e_1(\hat{\mu}/\mu^*)$ of $\hat{\mu}$ relative to μ^* and the efficiency $e_1(\hat{\sigma}/\sigma^*)$ of $\hat{\sigma}$ relative to σ^* for $n=5$ (5)10, $p=2(0.5)4$, $q=2(0.5)4$ with $p \le q$ are given in the Table 1 and Table 2.

CONCLUSION

In this work we found that BLUE of μ and σ using ranked set sampling is much better than the BLUE of μ and σ using order statistics suggested by Sajeevkumar et al., (2007).

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$$
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$$

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