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ESTIMATING OF BIRTH WEIGHT USING PLACENTAL CHARACTERISTICS IN THE PRESENCE OF MULTICOLLINEARITY

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Abstract

In this study, it was aimed to compare the performance of proposed estimators in the presence of multicollinearity that will be used in regression analysis as an alternative to Least Squares. Birth weight was estimated by using placental features such as sex, placental efficiency, total cotyledon numbers, large cotyledon weight, medium cotyledon weight, small cotyledon weight, large cotyledon number, medium cotyledon number, small cotyledon number, large cotyledon width, medium cotyledon width, small cotyledon width, large cotyledon length, medium cotyledon length, small cotyledon length, large cotyledon depth, medium cotyledon depth, small cotyledon depth for Bafra sheep breed. In the presence of multicollinearity, more reliable models can be obtained by using some estimator. The performances of the Ridge and Liu estimators, which are suggested methods for this situation, were compared. MSE, RMSE, rRMSE, MAPE, R^2, and AIC were used as model comparison criteria. As a result of, in the presence of multicollinearity; Liu estimator is recommended as an alternative method to Least Squares.

Keywords: Least squares, Ridge estimator, Liu estimator, Multicollinearity, Placental characteristics

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1. Introduction

The main purpose of animal breeding is to genetically improve populations of livestock and thus produce more efficient production from future populations (Onder and Abaci, 2015; Sen et al., 2019). In general, newborn lambs with higher birth weight are considered as selection criteria that have higher birth weight are selected as breeding material for the future population (Sen et al., 2019).

Reproductive parameters have major effects in small ruminant breeding. In particular, the success of the gestation period effect the health of the newborn lamb (Brzozowska et al., 2020). Postnatal mortality of offspring in sheep breeding depends on placental features (Dwyer et al., 2005). Many studies showed that the placental features have positive and strong correlations between birth weight for newborn lambs (Echternkamp, 1993; Konyali et al., 2007; Alkass et al., 2013; Ozyurek, 2019; Osgerby et al., 2003; Dwyer et al., 2005; Sen et al., 2013; Sen and Onder, 2016). Placental features are more important indicators for the birth weight in sheep and goat breeding (Ozyurek and Turkyilmaz, 2020).

Morphometric parameters of the placenta affect fetal growth and thus, placental size play vital roles for the birth weight and detecting the postnatal viability (Sen et al., 2013; Brzozowska et al., 2020).

Placental features give much information for the birth weight, postnatal viability. Researches using many properties are the subject of multivariate statistics. One of the multivariate statistical methods used to reveal the relationships between placental morphological features and birth weight of animals is regression analysis. In multivariate statistical modeling, regression analysis is a process to estimate the relationship between explanatory variables and response variable (Ari and Önder, 2013). Many methods are used to estimate the response variable and the most common of which is the Least Squares (LS) method (Uckardes et al., 2012). LS method requires some assumptions to make an effective model estimation. When in the presence of multicollinearity between explanatory variables is provided from these assumptions, alternative methods such as Ridge estimator, Liu estimator are proposed (Hoerl and Kennard, 1970; Liu, 1993).

The aim of this study, to compare the performance of proposed estimators in the presence of multicollinearity that will be used in regression analysis as an alternative to Least Squares using some placental characteristics in Bafra sheep.

2. Material and Method

This study was carried out on 40 Bafra sheep kept on Ondokuz Mayis University research farm unit in Samsun Province of Turkey. For this aim, some placental measurements such as sex (S), placental efficiency (PE), total cotyledon numbers (TCN), large cotyledon weight (LCW), medium cotyledon weight (MCW), small cotyledon weight (SCW), large cotyledon number (LCN), medium cotyledon number (MCN), small cotyledon number (SCN), large cotyledon width (LCW_i), medium cotyledon width (MCW_i), small cotyledon width (SCW_i), large cotyledon length (LCL), medium cotyledon length (MCL), small cotyledon length (SCL), large cotyledon depth (LCD_e), medium cotyledon depth (MCD_e), small cotyledon depth (SCD_e) were used as explanatory variables. The birth weight of lamb is a response variable. All statistical analyses were performed using the RStudio software (R Core Team, 2020). The “stats”, “lmridge”, “liureg” packages were used to perform for LS method, Ridge estimator and Liu estimator, respectively (R Core Team, 2019; Imdad and Aslam, 2018a; Imdad and Aslam, 2018b). To perform the model selection criteria was used to “ehaGoF” package (Eyduran, 2019).

In the matrix form of multiple regression is:

$$Y = X\beta + \varepsilon$$

where; Y is a response variable, X is a matrix for the explanatory variables and β is a vector for regression coefficients and ε is an error term. The most common method used to estimate the model in regression analysis is the LS method. The main purpose of the LS minimizes the sum of squares of error terms (Kutner et al., 2004).

$$\hat{\beta}_{LS} = argmin \sum (y_i - \hat{y}_i)^2 \quad \mathrm{i} = 1,2, \dots, \mathrm{n}$$

Some assumptions need to be provided to estimate the optimum model with LS. The first assumption is that the regression model must be linear. The second assumption is that the value of the expected error for the regression model must be zero. Further, the variance of the errors must be constant and the errors must be independent (Sarstedt and Mooi, 2014). Besides these assumptions, there should not be a linear relationship (multicollinearity) between the explanatory variables (Tirink et al., 2020). In the presence of multicollinearity, the results of the model to be obtained will not reliable (Cankaya et al. 2019).

There are many methods for determining multicollineartiy. One of them is the determination of multicollinearity with Variance Inflation Factor (VIF) value. When the VIF value is greater than 10, it can be mentioned that there is multicollinearity between the explanatory variables (Albayrak, 2005; Topal et al., 2010).

$$VIF = c_{ij} = \frac{1}{1 - R_j^2}$$

2.1. Ridge Estimator

The ridge estimator, whose main purpose is to obtain more reliable models by eliminating the multicollinearity between the explanatory variables, was proposed by Hoerl and Kennard (1970). In the case of multicollinearity between the explanatory variables, variance and covariances will increase in the X'X matrix. (Vupa and Gurunlu Alma, 2008; Uckardes et al., 2012). To reduce the variance and covariances in the X'X matrix, the bias coefficient k is added to the diagonal elements of the matrix (Tirink et al., 2020). k should be between 0 and 1. If the bias coefficient of k is zero, regression parameter estimation is the same as LS (Uckardes et al., 2012). Regression parameter estimation as a matrix notation is given below with the ridge estimator.

$$\hat{\beta}_{Ridge} = (X'X + kI)^{-1} X'Y$$

It is important to calculate optimum k value. Many researchers suggested a lot of method for calculating the optimum k value. The equation is given below that proposed by Kurtulus (2001) for calculating the optimum bias coefficient of k value based on eigenvalue:

$$k \leq \frac{\lambda_{max} - 100\lambda_{min}}{99}, k \neq 0$$

2.2. Liu Estimator

The Liu estimator, whose main purpose is to eliminate the multicollinearity between explanatory variables. Liu estimator was proposed by Liu (1993). To eliminate the multicollinearity, the Liu estimator was proposed by combining Stein and Ridge estimator (Alpu and Samkar, 2010). Regression parameter estimation as a matrix notation is given below with the Liu estimator.

$$\hat{\beta}_{Liu} = (X'X + I)^{-1}(X'X + dI)\hat{\beta}_{LS}$$

d is a biasing parameter used to overcome the multicollinearity. d parameter should be between 0 and 1. $\hat{\beta}_{Liu}$ is a linear function of biasing parameter of d so that to calculate d is easier than k (Alpu and Samkar, 2010). The equation is given below that for calculating the optimum biasing parameter of d based on the matrix of eigenvectors (Q) (Alpu and Samkar, 2010):

$$\hat{d} = 1 - \hat{\sigma}^2 \left[\frac{\sum_{i=1}^{p} \frac{1}{\lambda_i(\lambda_i + 1)}}{\sum_{i=1}^{p} \frac{\hat{\alpha}_i^2}{(\lambda_i + 1)^2}} \right], \qquad \hat{\alpha} = Q'\hat{\beta}_{LS}$$

2.3. Model Selection Criteria

Mean square error (MSE), root mean square error (RMSE), relative root mean square error (rRMSE), mean absolute percentage error (MAPE), determination of coefficient (R^2) and Akaike information criteria (AIC) were used as a model selection criteria as To measure the model accuracy of estimators used model comparison criteria as given below.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2}$$

$$rRMSE = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2}}{\bar{y}} * 100$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| * 100$$

$$R^2 = \left[1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}\right]$$

$$AIC = n * \ln\left[\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2\right] + 2p$$

Within the scope of model selection criteria, the lowest RMSE, MAPE, AIC values and the highest R^2 values were considered for the criteria used in the selection of the best model. (Tatliyer, 2020).

2.4. Ethical Consideration

The experiment design was approved by the Local Animal Care and Ethics Committee of Ondokuz Mayis University with an approval number of 2018-31.

3. Results and Discussion

In this study, different estimators that are in the presence of multicollinearity were used to estimate the birth weight of Bafra sheep. Descriptive statistics for response and explanatory variables are in Table 1 and Table 2 and correlations among them was given in Figure 1.

3.1. Results of Least Squares

Regression coefficients, its standard error, test statistics and significance level obtained from the LS method are given in Table 3. According to the Table 3, intercept, S, SCW, MCL and LCDe were determined to be statistically significant ($p<0.05$).

3.2. Results of Ridge Estimator

VIF values for each biasing parameter of k were given in Table 5. In Table 5, the optimum k value was determined as 0.013. Regression coefficients, its standard error, test statistics and significance level obtained from the ridge estimator were given in Table 4. According to the Table 4, S and SCW were determined to be statistically significant ($p<0.05$).

3.3. Results of Liu Estimator

Regression coefficients, its standard error, test statistics and significance level obtained from the ridge estimator were given in Table 6. According to the Table 6, S, SCW and LCDe were determined to be statistically significant ($p<0.05$).

Table 1. Descriptive statistics for explanatory variables

		n	Median	Minimum	Maximum
Male	LCN	22	9	1	39
	MCN		22	5	38
	SCN		18	4	66
Female	LCN	18	8	18	21.50
	MCN		0	2	1
	SCN		26	51	36

Table 2. Descriptive statistics for response and explanatory variables

		n	Mean±Standard Deviation	Minimum	Maximum
Male	BW	22	5.19 ± 0.72	3.50	6.53
	PE		240.99 ± 104.24	2.32	505.71
	TCN		53.55 ± 17.79	26.00	89.00
	LCW		28.36 ± 23.01	6.94	100.00
	MCW		30.57 ± 12.38	10.19	59.00
	SCW		15.43 ± 9.79	1.00	34.00
	LCW_i		28.18 ± 7.75	15.20	47.08
	MCW_i		21.9 ± 4.16	16.40	30.22
	SCW_i		15.01 ± 3.89	9.40	23.36
	LCL		39.34 ± 9.04	26.60	61.24
	MCL		28.4 ± 4.86	21.00	37.20
	SCL		19.44 ± 3.58	14.80	27.56
	LCD_e		5.34 ± 1.51	3.00	9.88
	MCD_e		4.85 ± 1.61	3.00	9.81
	SCD_e		3.58 ± 1.25	2.10	6.74
Female	BW	18	4.23 ± 0.57	3.00	5.25
	PE		249.82 ± 93.07	3.25	418.12
	TCN		49.94 ± 20.52	15.00	74.00
	LCW		28.64 ± 16.52	0.00	64.26
	MCW		28.76 ± 12.16	7.34	49.00
	SCW		20.68 ± 15.54	4.00	70.13
	LCW_i		26.84 ± 7.93	0.00	37.06
	MCW_i		22.81 ± 4.34	16.57	31.44
	SCW_i		16.06 ± 3.39	10.30	22.78
	LCL		36.41 ± 11.67	0.00	55.68
	MCL		28.87 ± 5.15	22.72	36.87
	SCL		20.84 ± 3.89	15.19	26.10
	LCD_e		5.01 ± 1.79	0.00	7.71
	MCD_e		5.04 ± 1.73	2.75	9.85
	SCD_e		4.43 ± 1.76	2.18	8.60

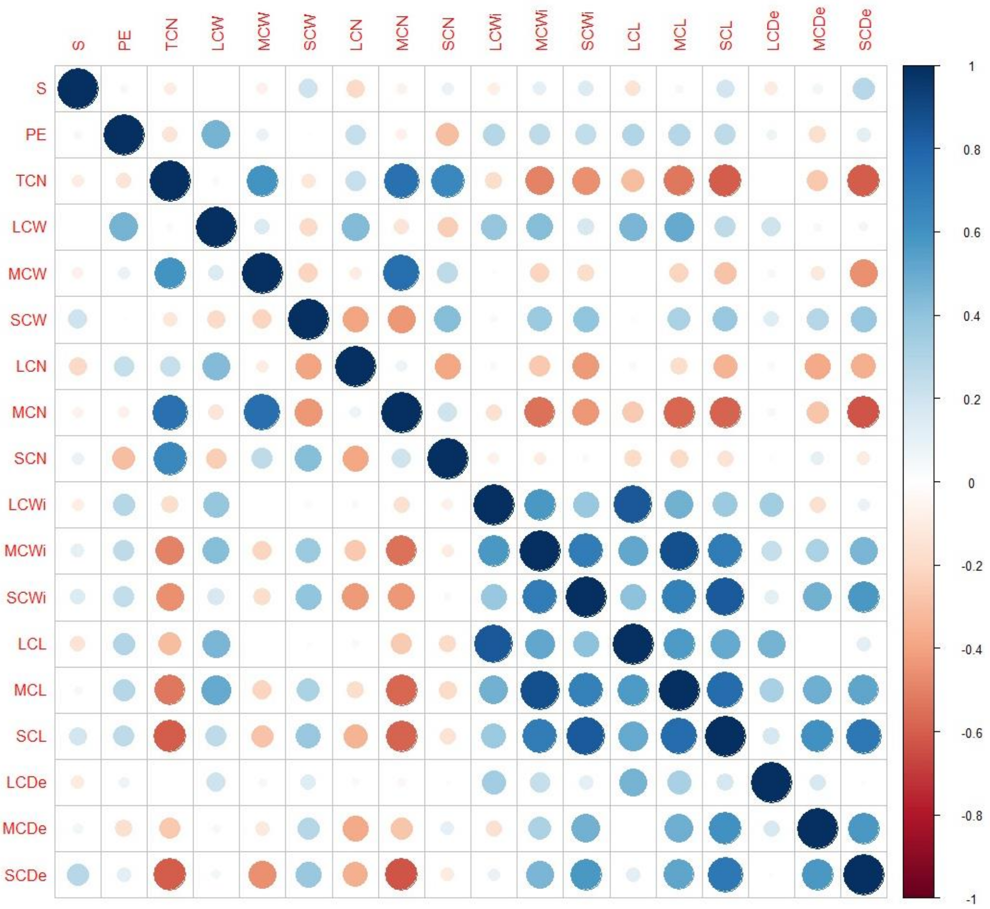

Figure 1. Correlation coefficients for explanatory variables.

Table 3. Results of LS method

	Estimate	Standard Error	*t*-value	p-value
(Intercept)	7.16	1.57	4.56	0.00
S	-0.98	0.24	-4.14	0.00
PE	0.00	0.00	-1.28	0.21
CN	0.06	0.04	1.50	0.15
LCW	0.02	0.01	1.75	0.09
MCW	-0.01	0.02	-0.80	0.43
SCW	0.03	0.01	2.43	0.02
LCN	-0.06	0.05	-1.18	0.25
MCN	-0.02	0.04	-0.61	0.55
SCN	-0.08	0.05	-1.63	0.12
LCW_i	0.00	0.04	-0.01	0.99
MCW_i	0.06	0.07	0.84	0.41
SCW_i	0.01	0.06	0.17	0.86
LCL	0.02	0.03	0.60	0.55
MCL	-0.12	0.06	-1.89	0.07
SCL	0.00	0.09	-0.02	0.98
LCD_e	-0.18	0.08	-2.19	0.04
MCD_e	0.10	0.13	0.81	0.43
SCD_e	-0.03	0.13	-0.19	0.85

Table 4. Results of Ridge estimator

	Estimate	Standard Error	*t*-value	p-value
Intercept	7.100	249.908	0.486	0.632
S	-0.985	0.698	-4.439	0.000
PE	-0.002	0.795	-1.307	0.204
CN	0.025	1.941	1.547	0.136
LCW	0.015	1.129	1.718	0.100
MCW	-0.008	1.173	-0.503	0.620
SCW	0.027	0.946	2.312	0.030
LCN	-0.016	1.265	-0.643	0.527
MCN	0.003	1.568	0.138	0.892
SCN	-0.032	1.492	-1.720	0.099
LCW_i	0.002	1.414	0.052	0.959
MCW_i	0.037	1.506	0.652	0.521
SCW_i	0.028	1.193	0.536	0.598
LCL	0.011	1.526	0.443	0.662
MCL	-0.094	1.625	-1.788	0.087
SCL	-0.008	1.642	-0.117	0.908
LCD_e	-0.151	0.752	-2.040	0.053
MCD_e	0.067	1.153	0.594	0.558
SCD_e	-0.033	1.124	-0.278	0.783

Table 5. Optimum k values according to the VIF values

	S	PE	CN	LCW	MCW	SCW	LCN	MCN	SCN	LCWi	MCWi	SCWi	LCL	MCL	SCL	LCDe	MCDe	SCDe
k=0	1.410	1.802	64.484	4.097	4.825	2.716	16.460	20.726	34.292	8.146	9.149	5.035	9.996	10.220	10.278	1.729	4.560	4.079
k=0.001	1.394	1.789	50.950	4.028	4.670	2.677	13.482	17.403	27.244	7.826	8.778	4.837	9.545	9.831	9.922	1.691	4.436	4.004
k=0.002	1.380	1.778	41.321	3.962	4.537	2.641	11.354	15.005	22.228	7.528	8.442	4.678	9.134	9.484	9.597	1.660	4.326	3.932
k=0.003	1.368	1.766	34.225	3.898	4.419	2.608	9.777	13.208	18.533	7.251	8.133	4.544	8.755	9.169	9.297	1.634	4.226	3.863
k=0.004	1.356	1.754	28.846	3.835	4.313	2.577	8.575	11.820	15.730	6.992	7.847	4.428	8.404	8.879	9.018	1.613	4.133	3.798
k=0.005	1.346	1.743	24.670	3.775	4.215	2.548	7.636	10.720	13.555	6.749	7.582	4.325	8.079	8.610	8.755	1.593	4.047	3.736
k=0.006	1.337	1.732	21.363	3.716	4.125	2.520	6.887	9.829	11.831	6.522	7.333	4.232	7.775	8.357	8.508	1.576	3.965	3.676
k=0.007	1.327	1.721	18.698	3.659	4.040	2.493	6.278	9.094	10.443	6.308	7.101	4.147	7.491	8.120	8.273	1.560	3.888	3.619
k=0.008	1.319	1.710	16.520	3.604	3.960	2.467	5.776	8.477	9.307	6.106	6.882	4.068	7.225	7.896	8.051	1.546	3.815	3.564
k=0.009	1.310	1.700	14.716	3.550	3.884	2.442	5.355	7.953	8.366	5.916	6.676	3.994	6.976	7.683	7.839	1.533	3.744	3.511
k=0.01	1.302	1.690	13.205	3.498	3.811	2.417	5.000	7.501	7.578	5.736	6.482	3.925	6.742	7.481	7.637	1.520	3.677	3.461
k=0.011	1.295	1.679	11.926	3.447	3.742	2.393	4.695	7.107	6.911	5.567	6.297	3.859	6.521	7.289	7.445	1.508	3.613	3.412
k=0.012	1.287	1.669	10.834	3.397	3.676	2.370	4.432	6.761	6.340	5.406	6.123	3.797	6.312	7.106	7.260	1.497	3.550	3.365
k=0.013	**1.280**	**1.660**	**9.895**	**3.349**	**3.612**	**2.348**	**4.203**	**6.454**	**5.849**	**5.253**	**5.957**	**3.737**	**6.115**	**6.931**	**7.084**	**1.486**	**3.490**	**3.319**
k=0.25	0.666	0.719	0.340	0.702	0.683	0.742	0.623	0.602	0.497	0.624	0.685	0.801	0.614	0.654	0.658	0.694	0.685	0.813
k=0.3	0.606	0.639	0.291	0.595	0.578	0.643	0.538	0.493	0.436	0.524	0.564	0.669	0.510	0.520	0.521	0.625	0.584	0.684
k=0.4	0.511	0.518	0.228	0.452	0.439	0.502	0.420	0.357	0.349	0.394	0.409	0.492	0.377	0.358	0.356	0.516	0.448	0.507
k=0.5	0.438	0.432	0.188	0.362	0.352	0.408	0.343	0.277	0.291	0.315	0.315	0.381	0.297	0.267	0.263	0.437	0.362	0.395
k=0.6	0.380	0.368	0.160	0.300	0.292	0.340	0.288	0.224	0.249	0.261	0.253	0.305	0.243	0.209	0.205	0.375	0.302	0.318
k=0.75	0.314	0.296	0.130	0.237	0.231	0.269	0.230	0.173	0.204	0.206	0.191	0.230	0.189	0.155	0.151	0.306	0.240	0.241
k=1	0.237	0.219	0.099	0.172	0.169	0.195	0.170	0.123	0.154	0.150	0.131	0.157	0.136	0.105	0.101	0.228	0.175	0.165

Table 6. Results of Liu estimator

	Estimate	Standard Error	t-value	p-value
Intercept	7.07E+00	4.37E+00	1.618	0.1056
S	-9.09E-01	2.14E-01	-4.252	2.12E-05
PE	-1.75E-03	1.33E-03	-1.309	0.1906
CN	6.46E-02	4.11E-02	1.575	0.1153
LCW	1.70E-02	9.81E-03	1.733	0.0831
MCW	-1.37E-02	1.76E-02	-0.775	0.4383
SCW	3.07E-02	1.26E-02	2.444	0.0145
LCN	-5.84E-02	4.82E-02	-1.211	0.2261
MCN	-2.58E-02	3.78E-02	-0.684	0.4942
SCN	-7.59E-02	4.46E-02	-1.701	0.0889
LCW_i	5.49E-05	3.56E-02	0.002	0.9988
MCW_i	5.88E-02	6.95E-02	0.846	0.3976
SCW_i	1.26E-02	5.93E-02	0.213	0.8314
LCL	1.94E-02	2.97E-02	0.653	0.5141
MCL	-1.21E-01	6.25E-02	-1.927	0.0539
SCL	-6.35E-03	8.22E-02	-0.077	0.9384
LCD_e	-1.76E-01	7.81E-02	-2.249	0.0245
MCD_e	1.09E-01	1.23E-01	0.889	0.374
SCD_e	-2.94E-02	1.25E-01	-0.236	0.8133

3.4. Comparison of the Estimators

If the assumptions are not provided in the model estimates made with LS, the reliability of the model estimation decreases. In this study, the Ridge and Liu estimator, which is one of the proposed estimators, was used as an alternative method to the LS in cases where the multicollinearity assumption, which is one of the assumptions, was not provided. MSE, RMSE, rRMSE, MAPE, R^2, and AIC were used as model comparison criteria. According to the model comparison criteria used in Table 7, it is possible to interpret the best model for the lowest MSE, RMSE, rRMSE, MAPE, R^2, and AIC and the highest R^2 value (Tatliyer, 2020). In table 7 examined, Liu estimator, used as an alternative estimator to LS, has the lowest MSE, RMSE, rRMSE, MAPE and AIC and the highest R^2 value. Tirink et al. (2019) were determined similar results.

Table 7. Model comparison criteria

Model Comparison Criteria	Least Squares	Ridge Estimator	Liu Estimator
Mean square error (MSE)	0.205	0.214	0.206
Root mean square error (RMSE)	0.453	0.463	0.454
Relative root mean square error (rRMSE)	9.51	9.726	9.53
Mean absolute percentage error (MAPE)	7.522	7.785	7.508
Coefficient of determination (R^2)	0.679	0.664	0.677
Akaike's information Criterion (AIC)	-59.398	-57.602	-59.236

4. Conclusion

In the evaluation of the data for agricultural studies according to cause and effect relationships, in the case of multicollinearity between the explanatory variables, Ridge and Liu estimators were used as an alternative to LS. For this purpose, it was aimed to estimate birth weight by using placental features in Bafra sheep. The results showed that Liu estimator is more reliable model estimation than LS and Ridge estimator. On account of in case of the multicollinearity, the Liu estimator is an alternative to LS.

Conflict of interest

The author declared that there is no conflict of interest.

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