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Use of ridge regression analysis in the multicollinearity in animal science

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Abstract

Ridge and basic investment are analysis methods used to guide regression analysis, to make very convenient regression analysis. Although the least squares estimates are unbiased when multicollinearity occurs, the variances of the estimates can be quite far from their true values. Ridge and principal components regression standard errors are reduced by allowing one-level biased regression estimates. Therefore, when multicollinearity is present, the ridge regression method can be used as an alternative to the least squares method. In this study, it was aimed to develop a model that predicts various egg quality criteria obtained from 238 Lohmann LSL-white commercial laying hens at 46 weeks of age. Due to the multicollinearity between egg quality criteria, ridge regression analysis methods, which are alternatives to least squares regression, were applied and these two methods were compared for the same data set. The coefficient of determination (R^2) and coefficient of variation were used as comparison criteria. According to these criteria, it was observed that the least squares (R^2=0.876), ridge (R^2=86.9) methods gave the best fit, respectively. As a result, it was concluded that it would be more accurate to use Ridge regression methods instead of using the least squares method in case of multicollinearity.

Keywords: Multicollinearity, Ridge regression, Least squares method

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1. Introduction

Agriculture is the most basic sector in meeting the nutritional needs of human beings and combining plant and animal production activities. In agriculturally developed countries, animal production comes before plant production. In Türkiye, 65% of the agricultural sector consists of crops, 25% of animal husbandry, 7% of aquaculture and 3% of forestry (Aydın Can, 2019). Despite selection studies, egg production is under the influence of many factors to achieve a good yield. Commercial egg production, it is directly affected by factors such as temperature, lighting, age, nutrition, genetic structure and disease. (Takma et al., 2017). One of the statistical methods used to reveal the cause-effect relationship of economic factors and productivity characteristics that change depending on many factors in the livestock sector is multiple regression analysis. By selecting a large number of independent variables and a dependent variable, regression coefficients that minimize the distance between the actual measurements of the dependent variable and the predictive measurements obtained from the independent variables are estimated by the Least Squares (LS) method. With the regression equation obtained from the sample, in addition to determining the cause-effect relationships between variables, predictions can be made more confidently (Akçay and Sarıözkan, 2015).

2. Material and Methods

2.1. Material

In our study, animal material was created by obtaining 238 Lohmann LSL-white commercial laying hens, aged 46 weeks, raised in the Poultry Unit of Atatürk University Food and Livestock Application and Research Center.

Statistical analysis of the data was done with SPSS and NCSS package programs.

2.2. Methods

In models where multicollinearity problems are identified, it is recommended to bias the regression coefficients without eliminating the variables in the model in order to reduce the negative effects of the multicollinearity problem (Örk Özel and Gezer, 2020).

In case of multicollinearity, it has been determined that using biased estimation methods is a more appropriate approach instead of LS. The first of the biased estimation methods consists of the Ridge Regression (RR) method, in which estimation variances are reduced by adding a small positive number to the diagonal elements of the Principal Component Regression (PCR) and correlation matrix instead of the real variables using orthogonal transformations (Arı and Önder, 2012).

2.2.1. Ridge regression

Ridge regression analysis, which is a method that reveals the cause-effect relationship between a dependent and one or more independent variables, allows prediction of the model. The matrix notation of the function for a multiple regression model with multiple independent variables is expressed as follows:

$$Y = \beta X + \varepsilon \tag{1}$$

In the above equation; Y: $n \times 1$ dimensional dependent variable vector, X: n × (p+1) dimensional independent variables matrix, β: (p+1) × 1 dimensional vector of coefficients, and ε: $n \times 1$ dimensional error vector (Yılmaz et al., 2020).

By making the necessary conversions from the regression prediction Equation 1;

$$\beta^* = (X'X)^{-1}X'Y \tag{2}$$

In the presence of multicollinearity, if there is a high relationship between independent variables, the variances of the X'X matrix will increase significantly. In this case, important parameter values will become unimportant as a result of the increase in variance. To eliminate the problem, the variance of this matrix is significantly reduced by adding a positive constant k to the diagonal elements of the X'X matrix in Equation 2 (Üçkardeşler et al., 2012).

By adding the k constant in Equation 2 for parameter estimation for the RR model;

$$\beta^* = (X'X\ kI)^{-1}X'Y \qquad 0 \leq k \leq 1$$

It is produced in the form (Üçkardeşler et al., 2012).

β^* in the equation is (p-1) × 1 dimensional RR coefficients vector, I is a (p-1) × (p-1) dimensional identity matrix, and k is a constant value and mostly between $0 \leq k \leq 1$. The k value, which is the ridge parameter, provides a lower mean square error than the LS method (Yağanoğlu et al., 2010).

2.2.2. Determining the ridge parameter (*k*)

In the Ridge regression, determining the k parameter in the model is based on eigenvalues. In the RR process, it is obtained by observing the Ridge trace graph or determining the value of the k parameter to determine which point becomes stationary or which point has the eigenvalue closest to 1 (Üçkardeşler et al., 2012). In the ridge trace graph, regression coefficients are expressed as a function of k, and the k value at which the coefficients remain constant is selected in the graph created by writing regression coefficients on the vertical axis and k values on the horizontal axis (Yağanoğlu et al., 2010). Many researchers have recommended different equations to determine the k value. By using the condition index in determining the k constant suggested which is based on the eigenvalue in the equations;

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

equation has been created. Using this equation, the point where the k parameter value approaches the VIF value of 1 is determined (Üçkardeşler et al., 2012).

2.2.3. Ridge trace method

The graphical method used to select k, the bias parameter in RR, is called Ridge trace. The biggest advantage of the ridge estimator is that it offers the “ridge trace” method that helps understand which parameter is sensitive to changes in the data. As is known, in the presence of multicollinearity, parameter estimators are sensitive to low changes in the data, and thus simple correlation coefficients are insufficient to reveal the relationship between independent variables (Karakaş, 2008).

In the ridge trace graph, k values are on the horizontal axis and ridge regression coefficients are on the vertical axis. As k values increase in the ridge trace graph, the mean square error of the ridge regression coefficients decreases. To determine a Ridge estimator that produces results lower than the mean square error of the regression coefficients of the the Linear Combination of Models (LCM) estimator, the k value where the regression coefficients become stable despite an increase in the k value is selected as the Ridge parameter (Derman, 2019).

3. Results and Discussion

3.1. Descriptive statistics

Descriptive statistics values of the variables used in the study; standard deviation, average, minimum and maximum values are given in Table 1. In the study, the normal distribution of the data was checked and the Kolmogorov-Smirnov test showed that all variables were normally distributed (p>0.05).

Table 1. Descriptive statistics

Variable	n	Mean	Std. Dev.	Minimum	Maximum
Egg Weight (EW)	238	66.95	4.60	55.37	82.58
Shape Index (SI)	238	73.93	2.64	67.0	80.5
Breaking Strength (BS)	238	1.29	0.52	0.30	2.80
Shell Thickness (ST)	238	1.10	0.08	0.88	1.36
White Index (WI)	238	8.11	1.36	5.071	11.74
Yellow Index (YI)	238	40.66	2.59	32.35	47.16
Haugh Unit (HU)	238	76.76	5.33	64.47	93.51

Table 2. Correlation coefficients between variables

Variable	EW	SI	BS	ST	WI	YI	HU
EW	1						
SI	0.928**	1					
BS	0.888**	0.930**	1				
ST	0.780**	0.796**	0.782**	1			
WI	0.782**	0.806**	0.832**	0.677**	1		
YI	0.151*	0.189**	0.166*	0.185**	0.117	1	
HU	0.827**	0.893**	0.864**	0.739**	0.771**	0.119	1

*: p<0,05, **: p<0,01

In Table 2, Pearson correlation coefficients and significance levels regarding the correlation coefficients of each independent variable with each other and between the dependent variables are given. The highest correlation coefficient was calculated as 0.930 between breaking strength and shape index and was found to be statistically significant ($p<0.01$). Correlation Coefficients were calculated as follows: 0.928 between egg weight and shape index, 0.888 between egg weight and breaking strength, 0.827 between egg weight and haugh unit, 0.806 between shape index and albumen index, 0.893 between shape index and haugh unit, 0.832 between breaking strength and albumen index. The correlation coefficient between breaking strength and Haugh unit was calculated as 0.864 and was found to be statistically significant ($p<0.01$). The lowest correlation was calculated as 0.117 between the white index and the yellow index ($p>0.05$). High correlations observed between independent variables indicate a potential multicollinearity problem. However, since simple correlation coefficients alone are not sufficient, it is not possible to be sure of the existence of a multicollinearity problem.

3.2. Results of egg weight dependent variable

In our study, egg weight was considered as the dependent variable, shape index, breaking strength, shell thickness, white index, yolk index, and Haugh unit as independent variables. Table 3 gives the analysis results for the least squares regression of the model. According to the variance analysis result, the model created was found to be a significant model ($p<0.01$), and the R^2 value was found to be 0.872. In other words, the independent variables (shape index, breaking strength, shell thickness, white index, yellow index, haugh unit) explain the change in the dependent variable (egg weight) by 87.2%.

Table 4 shows the least squares regression analysis results, significance value and coefficients of the model. The shape index coefficient was found to be 1.299 and is significant ($p<0.01$). The fracture thickness coefficient was found to be 5.501 and is important for the model ($p<0.01$). Among the independent variables, the variance inflation factor value of the shape index independent variables was high (VIF>10). The tolerance value of shape index independent variables with high variance magnification factors is very small.

Eigenvalues and condition indices are given in Table 5. When the eigenvalues are equal to 1, multicollinearity does not occur, but since at least one of the eigenvalues is close to zero, a multicollinearity problem is observed. When Table 5 is examined; a multicollinearity problem was detected in eigenvalues 3, 4, 5, 6 and 7. Eigenvalues 3, 4, 5, 6 and 7 caused strong multicollinearity because multicollinearity problems occurred when the condition indices were greater than 30.

When the methods that detect the multicollinearity problem are examined when looking at the egg quality criterion variables (correlation matrix, variance inflation factor, tolerance, eigenvalues and condition indices), it is seen that the multicollinearity problem occurs between the independent variables. Since unbiased least squares regression cannot eliminate the problem of multicollinearity, the results are inconsistent.

Table 3. Least squares variance analysis

Model	df	Sum of Squares	Mean Squares	*F*	*p*
Regression	6	4374.770	729.128	262.429	<0.001
Residual	231	641.806	2.778		
Total	237	5016.576			
R^2	0.872				
R^2_{Adj}	0.869				

Table 4. Least squares multiple regression analysis results

Variable	Coefficients	Standard Error	*t*	*p*	Tolerance Value	VIF
Constant	-31.320	7.679	-4.079	<0.001		
SI	1.299	0.132	9.817	<0.001	0.096	10.393
BS	1.200	0.629	1.909	0.058	0.111	9.006
ST	5.501	2.246	2.449	0.015	0.350	2.860
WI	0.213	0.147	1.449	0.149	0.295	3.394
YI	-0.051	0.043	-1.193	0.234	0.945	1.058
HU	-0.062	0.047	-1.332	0.184	0.188	5.333

Table 5. Eigenvalues and condition indices of correlations of variables

Number	Eigenvalue	Condition Indices
1	6.884	1.000
2	0.104	8.150
3	0.007	31.251
4	0.003	47.113
5	0.002	67.478
6	0.001	104.111
7	0.00078	295.997

The standardized Ridge parameter (*k*) is given in Table 6. According to the table, the multicollinearity problem was eliminated by choosing the constant *k*=0.002 for the independent variables that were expected to be positively related to egg weight.

Table 7 gives the parameters that change depending on the ridge parameter *k*. Since the R^2 value is largest for the constant *k*=0, the constant *k* should be close to zero. According to the expectations of these parameters, the most appropriate *k*=0.002 was chosen and the R^2 value of our study was found to be 0.8709. Sigma is the square root of the mean square error. Since sigma takes its smallest value in the least squares regression, the *k* value should not deviate too much from this value. Sigma value was determined as 1.6744. B'B is the sum of squares of the standardized coefficients, this value should become stationary according to the constant *k*. Our B'B value is 0.5731. The average variance amplification factor is the average of the variance amplification factor values. The largest variance amplification factor gives the largest variance amplification value of the constant *k*. In our research, our variance expansion factor value was determined as 9.8190.

Table 8 gives the results of ridge regression and least squares regression analysis according to the constant *k*=0.002. In Ridge regression analysis, the standard error of each variable decreased, eliminating the problem of multicollinearity. As a result of the analysis, the R^2 value was found to be 0.872 for least squares, while it was 0.869 for Ridge regression. In other words, Ridge regression obtained reliable results with lower standard errors without changing R^2.

Table 9 shows that standard errors have decreased and variance expansion factors have fallen below 10.

Tüylüoğlu and Albayrak (2010) examined the cost of living problem and compared the cost of living levels of the provinces within the scope of 26 Level 2 Regions in Türkiye as of 2008. As a result of the least squares regression analysis, the R^2 value was 99.8% and ridge regression. As a result of the analysis, the R^2 value was determined as 98.3% and the findings are compatible with the findings of our study.

In a study conducted by Yavuz (2017) using eggs taken from randomly mated Japanese quails that were not subjected to selection between the ages of 20-24 weeks, the R^2 value was 76.8% as a result of least squares regression analysis and 73.8% as a result of ridge regression analysis. and the results were found to be compatible with our study.

In a study by Öztürk (2014) in which data on the factors affecting the carcass weights of 30 broilers at Harran University research and application farm were discussed, the R^2 value was 99.2% as a result of the least squares regression analysis and the R^2 value was 97% as a result of the ridge regression analysis. It was determined as 8 and the results are similar to the results of our study.

Table 6. Standardized ridge regression values

k	SI	BS	ST	WI	YI	HU
0.001	0.7378	0.1377	0.0982	0.0632	-0.0285	-0.0693
0.002	0.7310	0.1404	0.0989	0.0635	-0.0282	-0.0664
0.003	0.7243	0.1431	0.0995	0.0639	-0.0279	-0.0635
0.004	0.7179	0.1456	0.1002	0.0643	-0.0275	-0.0607
0.005	0.7116	0.1481	0.1008	0.0646	-0.0272	-0.0579
0.006	0.7054	0.1504	0.1015	0.0650	-0.0269	-0.0552
0.007	0.6995	0.1527	0.1021	0.0654	-0.0266	-0.0526
0.008	0.6936	0.1549	0.1027	0.0658	-0.0263	-0.0500
0.009	0.6880	0.1569	0.1033	0.0662	-0.0260	-0.0475
0.01	0.6824	0.1590	0.1039	0.0665	-0.0257	-0.0450
0.02	0.6336	0.1755	0.1093	0.0704	-0.0231	-0.0230
0.03	0.5942	0.1871	0.1138	0.0743	-0.0208	-0.0048
0.04	0.5617	0.1955	0.1177	0.0779	-0.0189	0.0106
0.05	0.5343	0.2016	0.1210	0.0814	-0.0172	0.0236
0.06	0.5108	0.2061	0.1240	0.0847	-0.0157	0.0349
0.07	0.4905	0.2094	0.1265	0.0878	-0.0143	0.0447
0.08	0.4727	0.2119	0.1288	0.0907	-0.0131	0.0533
0.09	0.4570	0.2136	0.1308	0.0934	-0.0120	0.0610
0.1	0.4429	0.2149	0.1326	0.0959	-0.0110	0.0677
0.2	0.3553	0.2155	0.1432	0.1136	-0.0037	0.1083
0.3	0.3110	0.2100	0.1472	0.1230	0.0008	0.1259
0.4	0.2831	0.2040	0.1483	0.1281	0.0039	0.1347
0.5	0.2634	0.1983	0.1481	0.1309	0.0062	0.1392
0.6	0.2483	0.1931	0.1470	0.1323	0.0080	0.1414
0.7	0.2363	0.1882	0.1456	0.1327	0.0094	0.1422
0.8	0.2262	0.1837	0.1439	0.1325	0.0105	0.1422
0.9	0.2176	0.1795	0.1420	0.1319	0.0114	0.1416
1	0.2101	0.1755	0.1401	0.1309	0.0122	0.1406

Table 7. Ridge regression *k* analysis table

k	R^2	SIGMA	B'B	Mean VIF	Max VIF
0.001	0.8715	1.6707	0.5826	5.2318	10.0996
0.002	0.8709	1.6744	0.5731	5.1269	9.190
0.003	0.8703	1.6781	0.5639	5.0259	9.504
0.004	0.8698	1.6817	0.5552	4.9287	9.933
0.005	0.8692	1.6853	0.5467	4.8349	9.468
0.006	0.8687	1.6888	0.5386	4.7445	8.104
0.007	0.8681	1.6922	0.5308	4.6572	8.837
0.008	0.8676	1.6956	0.5232	4.5729	8.659
0.009	0.8671	1.6989	0.5159	4.4915	8.567
0.01	0.8666	1.7022	0.5089	4.4128	7.557
0.02	0.8618	1.7324	0.4502	3.7492	6.103
0.03	0.8575	1.7590	0.4071	3.2519	5.438
0.04	0.8536	1.7829	0.3741	2.8656	4.845
0.05	0.8500	1.8047	0.3482	2.5571	3.318
0.06	0.8466	1.8249	0.3275	2.3050	3.235
0.07	0.8435	1.8438	0.3104	2.0953	2.192
0.08	0.8404	1.8616	0.2962	1.9182	2.990
0.09	0.8375	1.8784	0.2841	1.7666	2.483
0.1	0.8347	1.8944	0.2738	1.6355	1.9366
0.2	0.8106	2.0279	0.2178	0.9088	1.0257
0.3	0.7902	2.1345	0.1934	0.6067	0.7173
0.4	0.7717	2.2268	0.1783	0.4448	0.5355
0.5	0.7544	2.3094	0.1672	0.3456	0.4458
0.6	0.7382	2.3846	0.1581	0.2793	0.3906
0.7	0.7227	2.4538	0.1504	0.2323	0.3451
0.8	0.7081	2.5180	0.1435	0.1975	0.3072
0.9	0.6940	2.5778	0.1373	0.1709	0.2752
1	0.6806	2.6338	0.1316	0.1499	0.2480

Table 8. Comparison of ridge regression and least squares for ridge coefficient *k*=0.002

Variable	RR Coefficients	LS Coefficients	Std. RR	Std. LS	SE (RR)	SE (LS)
Constant	-28.561	-31.320				
SI	1.241	1.299	0.712	0.745	0.125	0.132
BS	1.318	1.200	0.148	0.135	0.598	0.629
ST	5.692	5.501	0.101	0.098	2.231	2.246
WI	0.219	0.213	0.065	0.063	0.145	0.147
YI	-0.048	-0.051	-0.027	-0.029	0.043	0.043
HU	-0.050	-0.062	-0.058	-0.072	0.046	0.047
R^2	0.869	0.872				
SIGMA	1.685	1.667				

SE: Standard Error

Table 9. Ridge regression coefficients

Variable	Coefficient	Standard Error	Std. Reg. Coefficient	VIF
Constant	-28.561			
SI	1.241	0.125	0.712	9.047
BS	1.318	0.598	0.148	7.963
ST	5.692	2.231	0.101	2.760
WI	0.219	0.145	0.065	3.244
YI	-0.048	0.043	-0.027	1.045
HU	-0.050	0.046	-0.058	4.951

The findings of our study were reported by Yılmaz et al. (2020) in their study, using the 56th day data of wither height, body length, rump height and chest circumference measurements of the Saanen (59) kid raised at Tokat Gaziosmanpaşa University research and application farm, applying Ridge regression analysis by determining the multicollinearity problem and determining the smallest As a result of square regression analysis, the R^2 value was determined as 66.0% and as a result of the ridge regression analysis, the R^2 value was determined as 65.9%, which is compatible with the study findings.

Tırınk et al. (2020) compared the LS method used in multicollinearity determined by the VIF value with the ridge regression method to estimate body weight, and the RR method was based on some body measurements (spine length, rump height, body length, chest depth, The findings of our study are similar to the findings of our study, where the R^2 value was found to be 88.0% as a result of the least squares regression analysis and the R^2 value was found to be 87.6% as a result of the ridge regression analysis.

Yağanoğlu et al. (2010) determined that the model obtained according to the least squares method gave the best fit, but in cases where multicollinearity was detected between independent variables, the principal component regression method, which is an alternative to the least squares method, was more appropriate. As a result of the least squares analysis, R^2 value was obtained as 90.5% and the R^2 value as a result of the PCR analysis was obtained as 87.8%, which is in agreement with our study.

In the study by Çankaya et al. (2019) where they compared the least squares method, Ridge Regression (RR), Principal Component Regression (PCR) estimation methods to estimate the parameters of the multiple regression model if the assumptions underlying the LCM estimation are untenable due to multicollinearity, the most as a result of the least squares regression analysis, the R^2 value was obtained as 63.4% and as a result of the PCR analysis, the R^2 value was obtained as 62.3%, and the results are similar to the results of our study.

It has been shown that if there is multicollinearity between variables in data sets where cause and effect relationships between variables are investigated, using biased regression methods instead of least squares regression normalizes the standard errors of the regression coefficients and therefore gives more reliable results.

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Conflict of interest

The authors declare that there is no conflict of interest.

Ethical Approval

For this type of study, formal consent is not required.

References

Akçay, A., & Sarıözkan, S. (2015). Yumurta Tavukçuluğunda Gelirin Ridge Regresyon Analizi İle Tahmini. *Ankara Üniversitesi Veteriner Fakültesi Dergisi*, *62*(1), 69-74. (in Turkish) https://doi.org/10.1501/Vetfak_0000002660

Arı, A., & Önder, H. (2013). Farklı Veri Yapılarında Kullanılabilecek Regresyon Yöntemleri. *Anadolu Tarım Bilimleri Dergisi*, *28*(3), 168-174. (in Turkish) https://doi.org/10.7161/anajas.2013.28.3.168

Aydın Can, B. (2019). Türkiye'de Yumurta Üretimi, Tüketimi, İhracatı ve Geleceği. International Marmara Sciences Congress (Autumn) 2019, İzmit, Türkiye. (in Turkish)

Çankaya, S., Eker, S., & Abacı, S. H. (2019). Comparison of Least Squares, Ridge Regression and Principal Component Approaches in the Presence of Multicollinearity in Regression Analysis. *Turkish Journal of Agriculture - Food Science and Technology*, *7*(8), 1166-1172. https://doi.org/10.24925/turjaf.v7i8.1166-1172.2515

Derman, D. A. (2019). *Çoklu bağlantı durumunda yanlı regresyon yöntemlerinin incelenmesi* [Master's thesis, Ordu University]. (in Turkish)

Karakaş, S. (2008). *Çoklu doğrusal bağlantı problemi ve yanlı regresyon tahmincileri*. [Master's thesis, İstanbul University]. (in Turkish)

Örk Özel, S., & Gezer, F. (2020). Çoklu Doğrusal Bağlantı Problemi Altında Tahmin Edicilerin Karşılaştırılması: Genelleştirilmiş Maksimum Entropi, Ridge, Liu. *Dumlupınar Üniversitesi Sosyal Bilimler Dergisi*, *66*, 82-96. (in Turkish)

Öztürk, İ. (2014). Hayvansal Üretim Verilerinde Çoklu Bağlantı Probleminin Yanlı Regresyon Yöntemi ile Çözümlenmesi. *KSÜ Doğa Bilimleri Dergisi*, *17*(3), 1-12. (in Turkish) https://doi.org/10.18016/ksujns.77504

Takma, Ç., Gevrekçi, Y., Karahan, A. E., Atıl, H., & Çevik, M. (2017). Yumurta Verimi Üzerine Bazı Özelliklerin Etkisinin Regresyon Ağacı Analizi İle Belirlenmesi. *Ege Üniversitesi Ziraat Fakültesi Dergisi*, *54*(4), 459-463. (in Turkish) https://doi.org/10.20289/zfdergi.386597

Tırınk, C., Abacı, S. H., & Önder, H. (2020). Comparison of Ridge Regression and Least Squares Methods in the Presence of Multicollinearity for Body Measurements in Saanen Kids. *Iğdır Üniversitesi Fen Bilimleri Enstitüsü Dergisi*, *10*(2), 1429-1437. https://doi.org/10.21597/jist.671662

Tüylüoğlu, Ş., & Albayrak, A. S. (2010). Hayat Pahalılığı ve Türkiye'de İllerin Hayat Pahalılığı Sıralamasını Belirleyen En Önemli Faktörlerin Ridge Regresyon Analiziyle İncelenmesi. *Süleyman Demirel Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, *15*(2), 63-91. (in Turkish)

Üçkardeş, F., Efe, E., Narinç, D., & Aksoy, T. (2012). Japon Bıldırcınlarında Yumurta Ak İndeksinin Ridge Regresyon Yöntemiyle Tahmin Edilmesi. *Akademik Ziraat Dergisi*, *1*(1), 11-20. (in Turkish)

Yağanoğlu, A. M., Eyduran, E., Topal, M., Sönmez, A. Y., & Keskin, S. (2010). Çoklu Doğrusal Bağlantı Durumunda Ridge ve Temel Bileşenler Regresyon Analiz Yöntemlerinin Kullanımı. *Atatürk Üniversitesi Ziraat Fakültesi Dergisi*, *41*(1), 53-57. (in Turkish)

Yavuz, E. (2017). *Çoklu doğrusal bağlantı ve yanlı tahmincileri*. [Master's thesis, Kahramanmaraş Sütçü İmam University]. (in Turkish)

Yılmaz, F., Bayyurt, L., Abacı, S. H., & Tahtalı, Y. (2020). Comparison of Least Squares and Some Bias Estimators in Multicollinearity. *Turkish Journal of Agriculture -Food Science and Technology*, *8*(3), 793-799. https://doi.org/10.24925/turjaf.v8i3.793-799.3405