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Principal Components Regression of Internal Egg Quality Traits in Two Exotic Chicken Breeds in Haramaya

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Abstract

Two exotic chicken breeds, namely Fayoumi, and Koekoek were used in this study to unfold the interdependence among egg quality traits and also to predict egg weight from their orthogonal egg quality traits applying principal component regression. Traits measured included egg weight (EW), albumen height (AH), yolk height (YH), albumen weight (AW), yolk weight (YW), yolk colour (YC), and shell weight (SW). Traits were measured on chickens comprising 967 eggs of Fayoumi, and 772 eggs of Koekoek. Correlations found between investigated traits were positive and highly related (r = 0.614-0.937 in Fayoumi, and 0.496-0.943 in Koekoek breeds respectively). Three principal components (PCs), (PC1, PC2 and PC3) explaining 65.5% (Fayoumi) and 52.7% (Koekoek) of the overall variation in the original variables, were extracted from the factor solution of the PCA with varimax rotation. In principal component regression models, 89% (Fayoumi) and 86% (Koekoek) of the variability in egg weight is accounted for by the model used. From the results found, it can be seen that the use of principal components' scores from chickens' egg quality traits were more appropriate than the use of original traits in egg weight prediction only three components were used and they were all significant. These components could be used in breeding programme as selection criteria for improving egg quality traits.

Keywords

Fayoumi, Koekoek, Multivariate analysis, Egg quality traits

Introduction

Chicken egg is an excellent nutritional food item having a well-balanced source of essential nutrients [1]. The egg contains high-quality protein along with a balanced source of nutrients with its low energy content [2, 3]. The components of eggs are of particular interest to producers and their acceptability to consumers [1]. Egg quality traits (weight, shell weight, shell thickness, yolk weight and albumin) are very important characteristics that influence the quality, grading, and weight of a newly hatched chick, hatching performance and consequently the economic outcome of the enterprise [4, 5].

Information on egg weight along with external and internal egg quality traits will further open the domain for trying out various prediction equations to predict egg weight. Prediction of chick weight before incubation is the pre requisite of breed improvement program [4, 5]. A positive association of hatching chick weight with egg weight has also been reported by [5]. Thus, knowing the weight of the new born chick well in advance will help the policymakers to make decisions at an earlier instance before the eggs are set in the incubator.

Chicken production in Ethiopia operates using 57 million chickens comprising 78.85%, 12.02%, 9.11% being indigenous, hybrid and exotic, respectively [6].

The per capita consumption of chicken meat and egg (kg/person/year) in the country is 0.66 and 0.36 respectively [7]. Meat and egg consumption figures in Ethiopia are much lower when compared with the report by the same source for Uganda (0.97 and 5.1). The indigenous chicken starts egg production late (after 208 days) and produces 66.5 eggs per bird per year [8]. The male counterparts attain 714.4 and 865.5 g body weight at 16 and 18 weeks of age, respectively [9].

The main reason for the poor production performances (egg and meat) is the low genetic potential of the indigenous chicken breeds which represent 88.2% of the national chicken population [10]. Due to this poor performance of the indigenous chicken breeds, the demand for better chicken that combines higher production (egg and meat) and better adaptability has increased in recent years. Currently, efforts are being made by the African Chicken Genetic Gain project to test imported exotic breeds in three African countries (Ethiopia, Nigeria and Tanzania). However, to promote the production and distribution of these breeds on a large scale, performance evaluation is essential.

So far, some research studies on egg quality traits of exotic chicken breeds have been done in Ethiopia [11, 8]. However, the data used were of small sample size and the evaluation was made using uni(bi)variate analysis (analysis of variance, and correlations). The mechanisms underlying egg quality traits are too complex to be explained using uni(bi)ivariate analysis because, on the one hand, each trait is examined separately, resulting in significant overlap of results, and, on the other hand, egg quality traits are biologically related due to pleiotropy or linkage [12-16].

Thus, a lack of information on multivariate analysis of internal egg quality traits, is present. Especially, the estimation of egg weight from egg quality traits applying principal component regression (PCR) model is missing. Therefore, the objective of this study was to comprehend the complex inter-relationships among egg quality traits and evaluate relationships of exotic chicken breeds applying orthogonal conformation traits derived from the PC factor scores. The information obtained will aid the management, conservation, selection and development of breeding programs.

Materials and Methods

Study area location

Haramaya University poultry research farm, which is located at an altitude of 1980 meters above sea level, 9°26'N latitudes and 42°3'E longitude, was used for this study. The mean annual maximum and minimum temperatures are 23.4°C and 8.25°C, respectively and the area has an average annual rainfall of 741.6 mm.

Experimental animals and their management

Two exotic chicken breeds (i.e., Fayoumi, and Koekoek) were used for this study that was reared under similar housing and feeding management conditions. A total of 1737 eggs (965 from Fayoumi, and 772 from Koekoek) were used. The chickens providing the eggs were of the same age (hatched on the same day) and egg collection occurred when the hens were 21 - up to 72 weeks of age and data for egg quality traits were measured on the same day of collection.

The birds were kept in brooder houses with incandescent heating lamps for the first eight weeks. Afterwards, they were reared under the grower house, during the growing period and in the layer house of the deep litter system during the laying period. The birds were offered clean drinking water *ad libitum* and the recommended level of feed (i.e. a standard ration of 20% crude protein (CP) and 2800 Kcal/kg metabolizable energy (ME) during the first eight weeks, 16% CP and 2800 Kcal/kg ME during the growing period (9 to 20 weeks), and 16.50% CP and 1750 Kcal/kg ME during laying stage) according to their requirement. The composition of the feed ingredients during the egg laying were Dicalc.ph (1.2%), Dl-meth (0.05%), L-lysinHcl (0.65%), Limestone (1.4%), Maize (64%), Nougeseed cake (13%), Premix general (0.01%), Salt (0.5%), SBM 45/46 (16.19%) and Wheat middling (3%). All experimental birds were vaccinated against Marek's (day one), Newcastle (Day 3, 28, 63 and 112), Gumboro (Day 14 and 21), Fowl pox (day 72) and Typhoid (Day 45 and 84).

Traits measured

Egg weight (EW), albumen height (AH), albumen weight (AW), yolk height (YH), yolk weight (YW), and yolk color (YC)) were measured. Egg weight was measured on unbroken eggs using a sensitive weighing scale. Then, the internal egg quality parameters were measured by breaking out the eggs on flat glass. After their length was measured using a tripod micrometre, albumen and yolk were carefully separated from each other to measure albumen and yolk weight. Besides, yolk colour (YC) was determined using the Roche yolk colour fan.

Statistical data analysis

All statistical analyses in this study were done by using SAS-program version 9.4 [1].

Univariate analysis

The egg quality traits (EW, AH, AW, YH, YW, SW, and YC) were subjected to descriptive statistics and an independent t-Test to determine the effect of the breed. The linear model employed was:

$$Y_{ij} = \mu + B_i + \varepsilon_{ij}$$

where:

Y_{ij} = Observed value of the egg quality trait

μ = Overall mean

B_i = Fixed effect of the ith breed (i = 2: 1=Fayoumi, and 2=Koekoek)

ε_{ij} = error term

Principal Component (PC) Factor Analysis

Estimating the number of PCs

Screen test and parallel analysis plot were used as criteria for determining the number of PCs.

Scree test

When the eigenvalues are plotted against the corresponding PC, a screen plot is produced, which shows the rate of change in the magnitude of the eigenvalues as the number of PCs increases. The fall is usually rapid at first, then slows down. The maximum number of PCs to extract is thought to be at the "elbow," where the curve bends.

Parallel analysis

A graphical method known as parallel analysis is used to ease the interpretation and help decision making in the selection of the number of PCs extracted. At the cut-off point, when the lines for the screen test and the parallel analysis intersect, the proper number of PCs is chosen.

PC loading

These are the coefficients of correlation between the original attributes and PC scores. A high positive correlation between PC1 and a characteristic suggests that the trait is linked to the direction of the dataset's greatest degree of variance. A strong association between a characteristic and PC2 indicates that the trait is responsible for the data's next largest variance perpendicular to PC1, and so on.

Multivariate analysis

Pearson correlation coefficients among the egg quality traits were calculated using the PROC CORR procedure of SAS and correlation coefficients were estimated as required for principal component analysis (PCA).

Principal component regression (PCR) is a technique appropriate in multivariate analysis to reduce the dimension of a data set consisting of a large number of interrelated variables while retaining as much as possible the variation present in the data set [17-19]. This is achieved by transforming a set of original variables into a new set of variables, the principal components which are ordered so that the first few retain most of the variation present in all of the original variables [20].

A multiple linear regression procedure with the stepwise variable selection option was used to obtain models for predicting egg weight from egg quality traits (a) and established PC factor scores (b).

$$EW = b_0 + b_i x_i + \ b_k x_k \quad (a)$$

$$EW = b_0 + b_i PC_i + \ b_k PC_k \quad (b)$$

Where, EW is the egg weight, b_0 is the regression intercept, b_1 is the i[th] partial regression coefficient of the i[th] egg quality trait, X_i is the i[th] PC factor score. To test the validity of the factor analysis of the data sets, anti-image correlations and Barlett's Test of Sphericity were computed. Communality values were used to test the appropriateness of the factor analysis. PCs were extracted until some stopping criteria is encountered or until p components were formed. In determining the number of PCs to extract, cumulative proportion variance was employed and Chronbach's Alpha was used to test the overall reliability of the factor solution.

Results and Discussions

Univariate analysis

Least-square means (LSM) along with their standard error (SE) of the egg quality traits of the exotic chicken breeds investigated are presented in table 1.

The investigated traits showed a wide range of variability between the two breeds. The Fayoumi breed had significantly ($p < 0.05$) lower mean values than the Koekoek breed in all the traits except SW and YC. The significant variation in the observed traits could be attributed to the genetic make-up of the breeds. The result is in line with [8] who reported the effect of breed on egg quality traits.

Multivariate analysis

Table 2 shows the correlation coefficients of egg quality traits of the exotic chicken breeds. The coefficients of correlation ranged from 0.00 to 0.84, and 0.02 to 0.83 in Fayoumi, and Koekoek breeds respectively.

PC factor analysis

Anti-image correlations (not shown) revealed that partial correlations were low, indicating the presence of real components in the data. This result is in line with the Kaiser-Meyer-Olkin (KMO) sampling adequacy metric [21], which is based on the diagonal of partial correlation and reveals the fraction of variance in traits produced by the underlying factor.

Table 1: Least square means (± SE) of egg quality traits of the four exotic breeds.

Trait (unit)	Fayoumi			Koekoek		
	Min., Max.	CV	LSM ± SE	Min., Max.	CV	LSM ± SE
EW (g)	29.03, 54.20	9.35	$43.11^b \pm 0.14$	36.80, 73.40	9.11	$50.04^a \pm 0.15$
AH (cm)	0.20, 11.00	19.46	$6.87^a \pm 0.04$	0.80, 12.70	20.17	$6.85^a \pm 0.05$
AW (g)	16.31, 39.70	11.47	$25.17^b \pm 0.1$	21.50, 43.52	10.71	$29.66^a \pm 0.12$
YH (cm)	7.30, 17.10	7.66	$14.26^b \pm 0.04$	10.90, 18.71	7.39	$14.89^a \pm 0.04$
YW (g)	7.73, 18.90	12.24	$13.54^b \pm 0.06$	9.13, 21.2	11.86	$15.47^a \pm 0.06$
SW (g)	1.70, 5,93	17.32	$4.07^a \pm 0.02$	1.84, 6.11	17.53	$4.05^a \pm 0.03$
YC (-)	1.00, 5.00	44.91	$1.56^a \pm 0.02$	1.00, 6.00	50.2	$1.59^a \pm 0.03$

a,b when different superscripts are indicated in the same row for a given trait, it means that there is a significant ($P < 0.05$) effect of breed. Min. = Minimum; Max. = Maximum; CV = coefficient of variation; EW = egg weight, AH = albumen height, AW = albumen weight, YH = yolk height, YW = yolk weight, SW = shell weight, YC = yolk color.

Table 2: Pearson correlations among egg quality traits of exotic chicken breeds of Fayoumi (upper diagonal), and Koekoek (lower diagonal).

Trait	EW	AH	AW	YH	YW	SW	YC
EW (g)	**1**	0.08*	0.84*	-0.00*	0.75*	0.39*	-0.06ns
AH (cm)	0.03ns	**1**	0.14*	0.07*	-0.08*	0.02ns	0.01ns
AW (g)	0.83*	0.10*	**1**	-0.06 ns	0.52*	0.18*	-0.09*
YH (cm)	0.19*	0.23*	0.13*	**1**	-0.02ns	0.12*	0.15*
YW (g)	0.72*	-0.11*	0.51*	0.13*	**1**	0.16*	-0.12*
SW (g)	0.58*	0.06ns	0.40*	0.21*	0.32*	**1**	0.10ns
YC (-)	-0.03ns	0.10*	-0.02ns	0.12*	-0.12*	0.06ns	**1**

The P-values for both Wilks' lambda and ASCC (Average Squared Canonical Correlation) were highly significant (P<0.0001). EW = egg weight, AH = albumen height, AW = albumen weight, YH = yolk height, YW = yolk weight, SW = shell weight. * = significant at α = 0.05; ns = not significant.

With a value of 0.782, the KMO measure of sample adequacy was found to be adequate. According to [22], a KMO score of 0.60 or more is deemed appropriate. The applicability of PCA was tested using Bartlett's sphericity test, which tests the null hypothesis that the correlation matrix is an identity matrix. Bartlett's sphericity test yielded a significant result (p-value = 0.001), showing that the PCA is valid.

Eigenvalues, percentage of total variance with rotated component matrix and communalities

Table 3 shows the total variance eigenvalue, the rotated component matrix, and the communalities of the traits studied. After varimax rotation of the component matrix, the result illustrates how much of the overall variation of the observed features was explained by each of the PCs. For the Fayoumi breed, three PCs were identified with eigenvalues of 1.64 (PC1), 1.26 PC2, and 1.03 (PC3). PC1 explained 27.3%, PC2 explained 21%, and PC3 explained 17.2% of the total variance respectively. Similarly, for the Koekoek breed, three PCs were identified with eigenvalues of 1.91 (PC1), 1.32 PC2, and 0.91 (PC3). PC1 explained 31.8%, PC2 explained 22%, and PC3 explained 15.2% of the total variance respectively. Communalities are the proportion of variance that each trait has in common with other traits. Thus, if communality of a trait is high, it suggests that the retrieved components explained a substantial fraction of the variation of the trait. For the Fayoumi breed, the communality values ranged from 0.15 (AH) to 1.00 (AW); while for the Koekoek breed the values ranged from 0.07 (YC) to 0.63 (AW).

The correlation coefficient between the first two PC scores and the original attributes is shown in table 3. They calculate the importance of each egg quality trait in explaining PC variability. In other words, the higher the loadings in absolute terms, the more important the variables are in generating the new PC, and vice versa. For the Fayoumi breed, the first factor (PC1) loaded heavily on AW (0.76), and YW (0.70), the second factor (PC2) loaded heavily on AH (0.99), while the third factor (PC3) loaded heavily on YC (0.39), YH (0.38), and SW (0.33). For the Koekoek breed, the first factor (PC1) loaded heavily on AW (0.78), and YW (0.67), the second factor (PC2) loaded heavily on AH (0.85), while the third factor (PC3) loaded heavily on YH (0.53).

Figure 1 shows a scree-parallel analysis plot of eigenvalues against their PCs. The plot graphically depicts the variance distribution among the components. On the y-axis, the matching eigenvalue for each PC is shown. Where the lines for the screen test and the parallel analysis overlap, there appears to be a definite cut-off point. Thus, for both breeds (Fayoumi and Koekoek), one can summarize the six egg quality traits by the first three PCs.

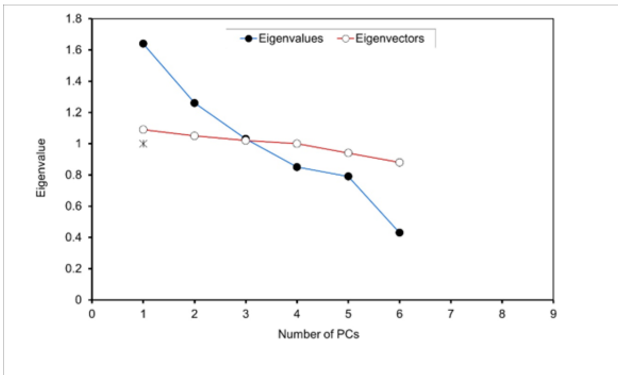

Figure 1a: Scree and parallel analysis plots for Fayoumi breed.

Table 3: Eigenvalues and share of total variance along with factor loadings after rotation and communalities of the egg quality traits of the chicken breeds.

Breed								
	Fayoumi				**Koekoek**			
Trait	PC1	PC2	PC3	Communality	PC1	PC2	PC3	Communality
AW	**0.76**	0.13	-0.07	1.00	**0.78**	0.13	-0.06	0.63
YW	**0.70**	-0.09	-0.07	0.60	**0.67**	-0.12	-0.039	0.47
AH	0.02	**0.99**	0.05	0.15	0.01	**0.85**	0.25	0.78
YC	-0.10	-0.01	**0.39**	0.50	-0.05	0.06	0.25	0.07
YH	-0.03	0.05	**0.38**	0.18	0.21	0.11	**0.53**	0.34
SW	0.26	-0.01	**0.33**	0.16	**0.52**	0.01	0.21	0.31
Eigenvalue	1.64	1.26	1.03		1.91	1.32	0.91	
% of total variance	27.3%	21.0%	17.2%		31.8%	22.0%	15.2%	

EW = egg weight, AH = albumen height, AW = albumen weight, YH = yolk height, YW = yolk weight, SW = shell weight, YC = yolk colour.

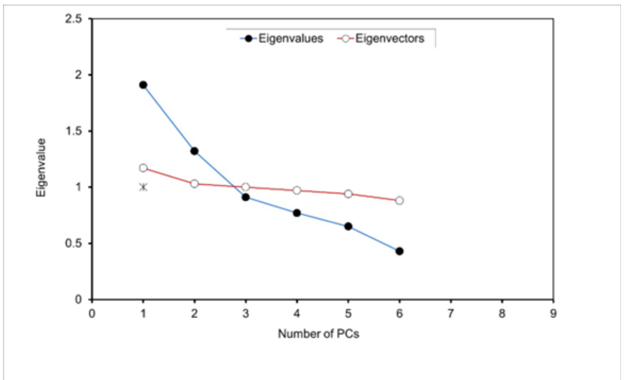

Figure 1b: Scree and parallel analysis plots for Koekoek breed.

MLR models used for egg weight prediction of chickens

To predict egg weight, the interdependent original egg quality attributes and their independent PC factor scores were used. The regression coefficients, standard errors, t-values, p-values, variance inflation factor (VIF) values, and R^2 derived from MLR analysis are presented in tables 4a and 4b. For the Fayoumi breed, the regression of egg weight on AH, AW, YW, and SW was significant, while it was not significant for YH, and YC. On the other hand for the Koekoek breed, the regression of egg weight on AW, YW, and SW was significant, while it was not significant for AH, YH, and YC. The present findings are agree with that of Peters et al. [23] in chickens and [24] in ducks.

To boost egg yields from chicken production, genetic improvement of egg weight is required, which necessitates a thorough understanding of linked qualities that can be addressed during selection. However, inter-dependent predictors should be used with caution because multi-collinearity is linked to unstable regression coefficient estimates [25-27], making it impossible to quantify unique impacts of these predictors. Multi-collinearity problem was not the case in this investigation, which found no VIF value larger than 10, as values greater than 10 suggest extreme collinearity, resulting in an unstable estimation of the corresponding least square regression coefficient, according to [28]. The PC factor scores are employed as predictors for the prediction of egg weights to circumvent this constraint [26, 27s]. These PCs are orthogonal to one other, making weight estimation more accurate. In the present study, the use of the three PC scores as predictors explained 89% and 86% of the total variability in egg weight for the Fayoumi and Koekoek breeds respectively, which is similar to the results found for the model using the original traits as predictors. The three factors selected were thus found to be better as they have a similar result as compared to the model using the original six traits as predictors.

table 4a: MLR of egg weight on original egg quality traits of Fayoumi breed and their PC factor scores

Model	Coefficient	SE	t-value	p-value	VIF
Original egg quality traits as predictors					
Intercept	2.54	0.75	3.38	0.0007	.
AH (cm)	0.10	0.03	2.97	0.0031	1.06
AW (g)	0.81	0.02	44.59	<.0001	1.47
YH (cm)	0.04	0.04	0.89	**0.3746**	1.05
YW (g)	1.02	0.03	32.47	<.0001	1.45
SW (g)	1.21	0.06	19.00	<.0001	1.07
YC (-)	0.11	0.06	1.69	**0.0916**	1.05
R^2 = 0.89; R^2 adjusted = 0.89					
Orthogonal egg quality traits as predictors					
Intercept		0.04	980.27	<.0001	.
PC1	43.11	0.05	85.97	<.0001	1.01
PC2	4.49	0.04	4.94	<.0001	1.00
PC3	0.22	0.08	8.07	<.0001	1.01
R^2 = 0.89; R^2 adjusted = 0.89					

table 4b: MLR of egg weight on original egg quality traits of Koekoek breed and their PC factor scores

Model	Coefficient	SE	t-value	p-value	VIF
Original egg quality traits as predictors					
Intercept	4.83	0.98	4.93	<.0001	.
AH (cm)	-0.02	0.05	-0.41	0.6829	1.11
AW (g)	0.79	0.02	33.93	<.0001	1.50
YH (cm)	0.11	0.06	1.96	0.0503	1.12
YW (g)	0.89	0.04	22.21	<.0001	1.47
SW (g)	1.54	0.10	16.08	<.0001	1.26
YC (-)	0.02	0.08	0.21	0.8362	1.04
R^2 = 0.86; R^2 adjusted = 0.86					
Orthogonal egg quality traits as predictors					
Intercept	50.04	0.06	817.02	<.0001	
PC1	4.91	0.07	69.00	<.0001	**1.00**
PC2	0.16	0.07	2.11	0.0356	**1.09**
PC3	-0.07	0.10	-0.70	0.4854	**1.09**
R^2 = 0.86; R^2 adjusted = 0.86					

Similarly, [29] derived regression equations for estimating egg weight and dimensions in commercial layers. In another related study, [30] obtained a regression model for predicting egg weight, shell weight, shell thickness and hatching chick weight of Japanese qualis; while [31] addressed predicting egg weight, shell weight, shell thickness and hatching weight of Japanese quail using various egg traits as regressors.

Conclusions

To minimise redundancy and forecast egg weight, PC factor analysis was used to discover patterns and determine interdependence in seven egg quality attributes of exotic chicken breeds. Using interdependent egg quality attributes as predictors in MLR analysis did not cause a multi-collinearity problem, according to the findings of this study. The problem of multi-collinearity, on the other hand, was eliminated when independent orthogonal indices (PC factor scores) were utilised as predictors. The findings of this study suggest that egg weight can be more correctly predicted using principle component (PC) factor scores, and the findings could be utilised by poultry farmers and researchers to choose, manage, and estimate market values of hens. These components could be used in breeding programme as selection criteria for improving egg quality traits.

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Conflict of Interest

None.

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