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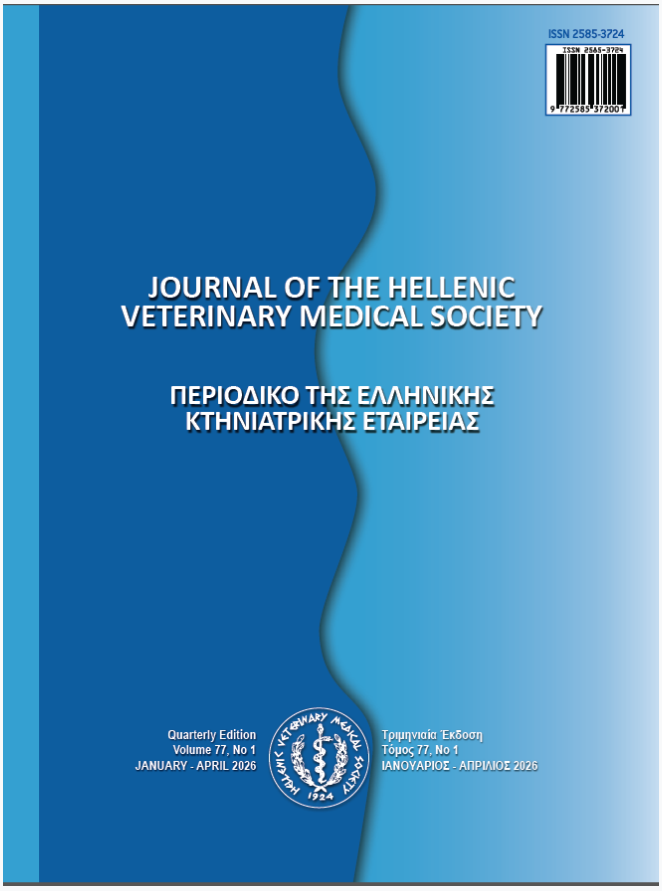

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Modeling Egg Yield Values in *Alectoris Chukar* with Nonlinear models

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ABSTRACT: In this work, nonlinear models were used to simulate the egg production values of breeding partridges raised in intense settings at the Kahramanmaraş Kapıçam Partridge Production Station. A total of 792 individuals in 22 pens (24 males and 36 females each pen) had their daily and cumulative egg production curves over 81 days collected. The Logistic, Gompertz, and Gamma models were used to cumulative yield curves. Gompertz, Logistic, Richard, McNally, Gamma, Cubic Spline, Quadratic, Quadratic Spline, and Modified Compartmental models were used to assess daily productivity. Model performance was assessed using mean squared error, corrected coefficient of determination, accuracy factor, bias factor, Durbin-Watson statistic, Akaike Information Criterion, adjusted Akaike Information Criterion, and Bayesian Information Criterion. The Gamma model best described cumulative yield (MSE: 44.6, R^2: 0.99, accuracy: 1, bias: 1, DW: 1.79, AIC: 221.2, adj. AIC: 221.8, BIC: 317.7), while the McNally model best described daily yield (MSE: 1.2, R^2: 0.99, accuracy: 1.0, bias: 1.05, DW: 1.83, AIC: 97.81, BIC: 33.27).

Keyword: Nonlinear models; Partridge; Cumulative; Daily; Egg production

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INTRODUCTION

The partridge is a well-known and cultivated game bird belonging to the Phasianidae family and the Perdicinae subfamily, with 14 subspecies (Garrison et al., 1977; Degraff et al., 1991). The most recognized partridge species in the world include the Chukar Partridge (Alectoris chukar), Rock or Stone Partridge (Alectoris graeca), Red-footed Partridge (Alectoris rufa), Berber Partridge (Alectoris barbara), Freckled Partridge (Perdix perdix), and Sand Partridge (Ammoperdix griseogularis).

The production of partridges has two primary goals. The first is to add game animals to natural hunting locations and make money from these hunting pursuits. The commercial production of partridges as a substitute meat source is the second goal.

Specifically, compared to research that simulate the egg production curves of broilers, geese, and quail, there are very few studies that model the egg production of breeding partridges. This is perhaps because private sector production is still minimal and partridge production is mostly carried out in state institutions. To assess egg production over the course of the laying period, it is essential to define egg production curves using mathematical formulas. The most widely utilized models for egg curve modeling are simple, biologically interpretable models. Cumulative egg yields in egg yield curves are structurally similar to growth curves. For this reason, growth curves are often used to model cumulative egg yields. Conversely, daily egg yield curves initially increase but tend to stabilize after a certain period (Yalçınöz & Şahin, 2020; Tolun et al., 2023). Additionally, both cumulative and daily egg yield curves of partridges show a distribution similar to that of laying hens.

Egg yield modeling serves to predict early egg production and establish breeding flocks. When the goal is to create breeding flocks, modeling individual egg production curves becomes essential. Relying solely on flock-based modeling does not allow for the selection of individuals with high genetic potential (Yavuz et al., 2019; Abaci et al., 2020; Gök et al., 2021). Historically, various mathematical models have been applied and developed for modeling egg production curves. Researchers have also emphasized the importance of modeling individual egg production curves to enhance the understanding of egg production biology (Gavora et al., 1971; McMillan, 1981; Koops & Grossman, 1992; Grossman et al., 2000; Grossman & Koops, 2001).

The process of modeling egg production curves is an ongoing and continuous endeavor, especially considering advancements in computer technologies and computational techniques, similar to those seen in lactation and growth curve modeling.

On the other hand, the egg production of partridges varies significantly between wildlife and indoor environments (Özek & Bahtiyarca, 2004; Kırıkçı et al., 2006; Tolun et al., 2023). Females typically lay their first egg at approximately 34 weeks of age, and each female partridge can produce between 30 and 80 eggs in a season (McMillan, 1981; Koops & Grossman, 1992; Grossman & Koops, 2001; Çetin et al., 1997; Embury, 1996; Kırıkçı et al., 1999).

The data gathered from egg production becomes especially useful because breeding opportunities are limited and egg production is seasonal, underscoring the significance of precise modeling and evaluation techniques. Additionally, the creation of egg production models provides an alternate approach for poultry genetic research in addition to helping producers forecast income and flock performance (Miyoshi et al., 1996).

In this study, we go over the formulas that are frequently used in the literature to model the daily and cumulative egg production of breeding partridges raised in intensive environments. The objective is to ascertain which model is best suited for these uses.

MATERIALS AND METHODS

In this study, breeding partridges raised under intensive conditions at the Kahramanmaraş Kapıçam Partridge Production Station were utilized. The males had a live body weight ranging from 500 to 550 grams, while the females weighed between 400 and 450 grams. The partridges selected as breeders were chosen from individuals that had reached sexual maturity at a minimum age of 32 weeks, exhibited the desired species characteristics, and met specific breeding criteria. These birds were used during the production season. Prior to being introduced into the breeding facility, both beak and claw care were administered, and the birds were treated to eliminate any internal and external parasites.

For this purpose A total of 22 pens were established at the Kapıçam Partridge Production Center, which operates under intensive conditions and is affiliated with the Kahramanmaraş Provincial Branch Office of the XVth Regional Directorate of the Ministry of Agriculture and Forestry of the Republic of

Türkiye. Each pen housed 24 male and 36 female partridges, totaling 792 females across all pens. Egg production data were collected over 81 days during the production season. Throughout the research period, the breeding partridges were fed a commercial egg-laying bird feed containing 20% crude protein and 2900 kcal/kg metabolizable energy. The feed and water were provided ad libitum, and the pens were illuminated for 18 hours a day. The daily and cumulative egg yield curves obtained at the end of the study were modeled to determine the best-fitting models for each. Initially, modeling was performed on the averages from the 22 pens over the 81 days. After identifying the optimal models for daily and cumulative egg yields, these models were applied separately to each pen.

In Table 1, the cumulative egg yield curves were modeled using the Logistic, Gompertz, and Gamma statistical models, as well as the Schunute, Brody, Richard, Negative Exponential, Von Bertalanffy, Cubic Spline, and Cubic models (McMillan, 1981; Gavora et al., 1982; Yang et al., 1989). For analyzing the daily egg production curves, the Gompertz, Logistic, Richard, McNally, Gamma, Cubic Spline, Quadratic, Quadratic Spline, and Modified Compartmental models listed in Table 2 were utilized (Cason & Britton, 1988; Lokhorst, 1996; Çetin et al., 1997).

STATISTICAL ANALYSIS

To estimate the parameters of these models, the SAS statistical package was used, specifically the NLIN procedure with the Gauss–Newton algorithm (Şahin & Efe, 2010; Cankaya et al., 2014).

The model comparison criteria given in Table 3 were used to evaluate the models for daily and cumulative egg yields. In the model evaluation process, in addition to the commonly used metrics such as mean squared error and the adjusted coefficient of determination, additional criteria related to the calculation of error terms were also considered in the study. With the inclusion of these statistics (accuracy factor, bias factor, Durbin-Watson, Akaike information criterion, adjusted Akaike information criterion, and Bayesian information criterion), more accurate steps in model selection and evaluation can be taken (Schwarz, 1978; Priestley, 1981). Furthermore, the distribution of error terms and the relationships between them are critical for making accurate predictions (Şahin et al., 2011; Tahtalı et al., 2020).

RESULTS

Table 4 presents the modeling results for cumulative egg yields based on the averages from 22 pens. The models used include Logistic, Gompertz, Gamma, Schunute, Brody, Richard, Negative Exponential,

Table 1. Equations used in modeling cumulative egg yields.

Models	Equations
Logistics	$Y_t = \beta_0(1+\beta_1 exp(-\beta_2 t))^{-1}$
Gompertz	$Y_t = \beta_0 exp\ (-\beta_1 exp(-\beta_2 t))$
Gamma	$Y_t = \beta_0^{\beta_1} exp(-\beta_2 t)$
Schunute	$Y_t = Z_2 * Z_3$ $Z_1 = \beta_4^{(\beta_2)^3} - \beta_3^{(\beta_2)}$, $Z_2 = \beta_3^{(\beta_2+Z1)}$, $Z_3 = (1-exp(-\beta_1(X-X_1))/(1-exp(-\beta_1(X_2-X_1)))^{(1/\beta_2)}$
Brody	$Y_t = \beta_0(1-\beta_1 exp(-\beta_2 t))$
Richard	$Y_t = \beta_0(1+\beta_1 exp(-\beta_2 t))^{\beta_3}$
Negative Exponential	$Y_t = \beta_0(1-exp(-\beta_1 t))$
Von Bertalanffy	$Y_t = \beta_0\left(1-\beta_1 exp(-\beta_2 t)\right)^3$
Cubic Spline	$Y_t = \beta_0 + \beta_1 t + \beta_2 t^2 + \beta_3 t^3 + \beta_4 (t-a)^3$
Cubic	$Y_t = \beta_0 + \beta_1 t + \beta_2 t^2 + \beta_3 t^3$

Table 2. Equations used in modeling daily egg yields.

Models	**Equations**
Gompertz	$Y_t = \beta_0 exp\,(-\beta_1 exp(-\beta_2 t))$
Logistics	$Y_t = \beta_0(1 + \beta_1 exp(-\beta_2 t))^{-1}$
Richard	$Y_t = \beta_0(1 + \beta_1 exp(-\beta_2 t))^{\beta_3}$
McNally	$Y_t = \beta_0 t^{\beta_1} exp\,(-\beta 2t + \beta 3t^{1/2})$
Gamma	$Y_t = \beta_0 t^{\beta_1} exp\,(-\beta 2t)$
Cubic Spline	$Y_t = \beta_0 + \beta_1 t + \beta_2 t^2 + \beta_3 t^3 + \beta_4(t-a)^3$
Quadratic	$Y_t = \beta_0 + \beta_1 t + \beta_2 t^2$
Quadratic Spline	$Y_t = \beta_0 + \beta_1 t + \beta_2 t^2 + \beta_3(t-a)^2$
Modified Compartmental	$Y_t = \beta_0 exp(-\beta_1 t)/(1 + exp\,((-\beta_3(t-\beta_4))$

Here, Y_t: represents the egg yield on the tth day, β, $\beta_0, \beta_1, \beta_2, \beta_3$ *and* β_4:: the constants defined for the models, and a represents the node point in the piecewise regression.

Table 3. Model Comparison Criteria

Criteria	**Equations**
Error mean squares	EMS = ESS/EDF
Corrected coefficient of determination	$\bar{R}^2 = 1 - (1 - R^2)(n - 1/(n - p - 1))$
Accuracy factor	$AF = 10^{\sum_{i=1}^{n} \lvert \log(\hat{Y}_i - Y_i) \rvert / n}$
Bias Factor	$BF = 10^{\sum_{i=1}^{n} \log(\hat{Y}_i - Y_i)/n}$
Durbin-Watson	$DW = \frac{\sum_{i=2}^{n}(e_1 - e_2)^2}{\sum_{i=1}^{n} e_1^2}$
Akaike information critteria	$AIC = nxln\left(\frac{ESS}{n}\right) + 2k$
Adjusted Akaike Information Criterion	$_{A}AIC = nxln\left(\frac{ESS}{n}\right) + \left(\frac{n(n+p)}{n-p-2}\right)$
Bayesian information critteria	$BIC = nxln\left(\frac{ESS}{n}\right) + kln(n)$

ESS: error sum of squares, EMS: error mean squares EDF: error degrees of freedom, n: simple size, p: number of indipendent variable, $\hat{Y}_i$: estimated value, Y_i: observation value e_i: error term, k: number of parameters.

Von Bertalanffy, Cubic Spline, and Cubic. Among these, the Gamma model achieved the best result in terms of mean squared error, with a score of 44.6.

Regarding the adjusted coefficient of determination, all models were closely comparable, with the exception of the Negative Exponential model, which had a lower value of 0.97. The Gamma (1.0, 1.0), Schunute (1.0, 1.0), and Cubic (1.0, 1.0) models demonstrated superior performance for both the accuracy factor and bias factor compared to the other models. In contrast, the Negative Exponential model performed worse, yielding an accuracy factor of 1.2 and a bias factor of 0.8.

Analysis of Durbin-Watson values indicated that all models exhibited positive autocorrelation, except for the Gamma model, which had a value of 1.79.

Table 4. Comparison criteria for cumulative egg production based on average values.

Models	EMS	$\bar{R}^2$	AF	BF	DW	AIC	AAIC	BIC
Logistics	1061.9	0.98	1.1	1.0	0.06	332.7	333.3	574.5
Gompertz	479.7	0.99	1.1	1.1	0.06	304.8	305.3	510.1
Gamma	44.6	0.99	1.0	1.0	1.79	221.2	221.8	317.7
Schunute	303.1	0.99	1.0	1.0	0.10	290.2	291.1	476.3
Brody	75.6	0.99	1.1	0.9	0.11	239.8	240.3	360.4
Richard	988.4	0.98	1.0	0.9	0.05	331.8	332.6	572.0
Negative Exponential	10721.7	0.97	1.2	0.8	0.03	412.5	412.8	758.4
Von Bertalanffy	230.7	0.99	1.1	1.0	0.07	279.1	279.6	450.8
Cubic Spline	47.00	0.99	1.0	0.9	0.12	257.2	258.1	170. 4
Cubic	58.53	0.99	1.0	1.0	0.12	230.3	230.9	338.7

When evaluating the Akaike Information Criterion (AIC) and adjusted Akaike Information Criterion (AICc), the Gamma model had the lowest values at 221.2 and 221.8, respectively. For the Bayesian Information Criterion (BIC), the Cubic Spline model exhibited the lowest value at 170.4.

Figure 1 illustrates the cumulative egg yields for the Logistic, Gompertz, Gamma, Schunute, Brody, Richard, Negative Exponential, Von Bertalanffy, Cubic Spline, and Cubic models.

Table 5 presents the modeling results for daily egg yields based on the averages from 22 pens. Among the models examined—Gompertz, Logistic, Richard, McNally, Gamma, Cubic Spline, Quadratic, Quadratic Spline, and Modified Compartmental-the McNally model achieved the best result in terms of mean squared error, with a value of 1.2.

The Gompertz, Logistic, Richard, and McNally models each had an adjusted coefficient of determination of 0.99, indicating strong performance. Conversely, the Quadratic Spline model had the lowest adjusted coefficient of determination at 0.64. In terms of the accuracy factor and bias factor, the McNally model (1.0 for the accuracy factor and 1.05 for the bias factor) outperformed the other models. The Gamma (1.2, 1.20) and Quadratic Spline (1.2, 1.16) models exhibited poorer results in these categories.

Durbin-Watson analysis revealed positive autocorrelation in all models except for the McNally (1.83) and Cubic Spline (1.74) models. Regarding the Akaike Information Criterion (AIC) and adjusted Akaike Information Criterion (AICc), the McNally (97.81, 97.61) and Cubic Spline (96.08, 96.22) models showed the best values. In terms of the Bayesian Information Criterion (BIC), the McNally (33.27) and Cubic Spline (26.04) models also performed

Table 5. Comparison criteria for daily egg production based on average values.

Models	EMS	$\bar{R}^2$	AF	BF	DW	AIC	AAIC	BIC
Gompertz	2.2	0.99	1.1	1.06	0.90	115.7	116.2	74.79
Logistics	2.1	0.99	1.1	1.06	0.91	115.3	115.8	73.76
Richard	2.3	0.99	1.1	1.07	0.88	117.4	117.9	78.58
McNally	1.2	0.99	1.0	1.05	1.83	97.81	98.61	33.27
Gamma	8.1	0.96	1.2	1.20	0.13	172.5	173.0	205.5
Cubic Spline	2.2	0.98	1.1	1.06	1.74	96.08	96.22	26.04
Quadratic	2.7	0.70	1.1	1.09	0.57	122.6	123.2	90.73
Quadratic Spline	9.1	0.64	1.2	1.16	0.21	166.4	166.9	191.4
Modified Compartmental	2.4	0.84	1.1	1.06	1.14	100.4	100.9	39.43

Table 6. Evaluation criteria for Gamma (cumulative) and McNally (daily) models.

Models	EMS	$\bar{R}^2$	AF	BF	DW	AIC	AAIC	BIC
Gamma	66.65±0.3	0.98±0.01	1.1±0.02	0.98±0.02	2.12±0.08	153.5±1.6	154.0±1.5	161.7±3.8
McNally	1691.9±5.7	0.96±0.02	1.1±0.03	0.99±0.02	1.96±0.03	133.5±2.1	134.1±2.3	19.6±3.8

Table 7. Coefficients of Gamma and McNally models.

Models	β_0	β_1	β_2	β_3
Gamma	15.77±0.27	0.9±0.09	-0.006±0.0003	-
McNally	5.13±0.27	0.77±0.095	0.007±0.004	-0.226±0.08

well. The Quadratic Spline model had the least favorable results for AIC, AICc, and BIC, with values of 166.4, 166.9, and 191.4, respectively.

Figure 2 displays the estimated curves for the Gompertz, Logistic, Richard, McNally, Gamma, Cubic Spline, Quadratic, Quadratic Spline, and Modified Compartmental models.

The modeling of average cumulative and daily egg yields indicated that the Gamma model and the McNally model provided the best fit. Consequently, the Gamma model was applied to cumulative egg yields, while the McNally model was utilized for daily egg yields, with analyses performed separately for each pen.

Table 6 presents the values for various metrics, including mean squared error, adjusted coefficient of determination, accuracy factor, bias factor, Durbin-Watson statistic, Akaike Information Criterion (AIC), adjusted Akaike Information Criterion (AICc), and Bayesian Information Criterion (BIC) for both the Gamma and McNally models applied to cumulative and daily egg yields. Additionally, the estimated model parameters for the Gamma and McNally models are detailed in Table 7.

Figures 3 and 4 illustrate the estimated curves for the Gamma and McNally models, respectively, for cumulative and daily egg yields.

DISCUSSION

Although the model adequacy requirements were consistent for both cumulative and daily egg yield estimations, the equations employed differed due to the inherent structural distinctions between these two types of curves. Based on the model comparison criteria for average cumulative egg yield, the

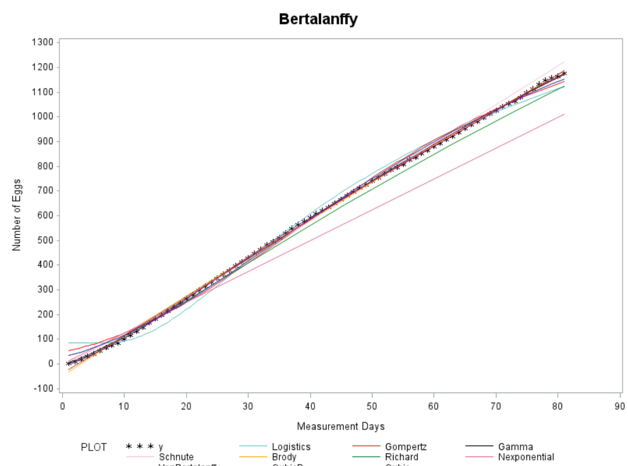

Figure 1. Curves estimated from cumulative mean values for ten different models.

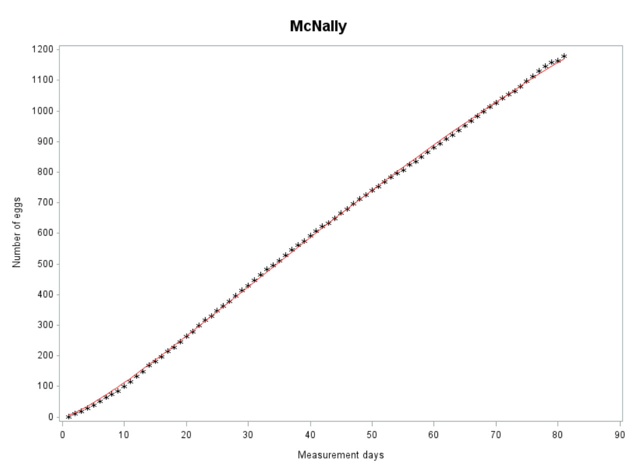

Figure 2. Prediction curve for Gamma model for cumulative values.

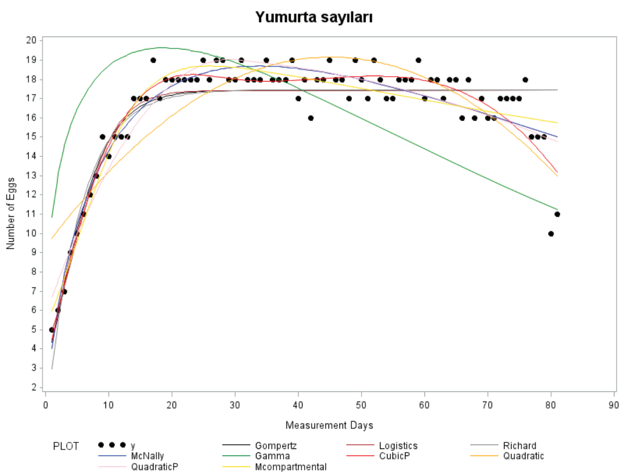

Figure 3. Curves estimated from daily average values for nine different models.

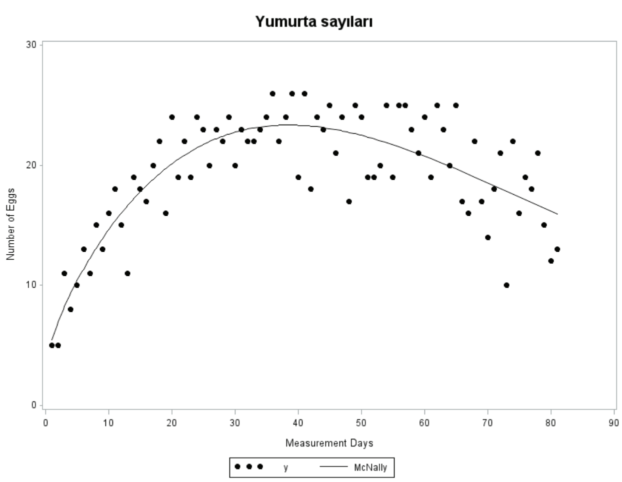

Figure 4. =Curve estimated from daily values for the McNally model.

Gamma model emerged as the most appropriate, while the Negative Exponential model exhibited the poorest fit. Although the Cubic Spline model produced results closely aligned with the Gamma model, its suitability was undermined by a notably low Durbin-Watson statistic, indicating significant positive autocorrelation. As shown in Table 4, all models except for the Gamma model demonstrated positive autocorrelation, which reinforces the importance of evaluating model adequacy through a multidimensional lens. Relying solely on traditional metrics such as adjusted coefficient of determination, mean squared error, accuracy factor, and bias factor can yield misleading conclusions. Instead, complementary statistics such as the Durbin-Watson value, Akaike Information Criterion (AIC), Adjusted AIC (AICc), and Bayesian Information Criterion (BIC) should be taken into consideration to ensure robust model selection.

When the Gamma model, identified as the best performer for cumulative averages, was applied individually to each of the 22 pens (Table 6), slight reductions were observed in the adjusted coefficient of determination, accuracy factor, AIC, AICc, and BIC values. Conversely, small increases were noted in the mean squared error, bias factor, and Durbin-Watson statistics. Despite these variations, the Gamma model maintained a high level of adequacy across all evaluation criteria, thereby confirming its reliability in modeling cumulative egg production curves. These findings are in agreement with the results reported by Turgay et al. (2016) for partridges and are also consistent with Congleton et al. (1981) regarding laying hens.

Regarding daily egg yield, the McNally model demonstrated the best overall performance, while the Quadratic Spline model showed the weakest fit. Although the Cubic Spline model yielded results that were close to those of the McNally model in terms of average daily yield, its performance was less favorable when considering all evaluation metrics comprehensively. While the Gompertz, Logistic, and Richard models displayed similarly high adjusted coefficients of determination, their overall adequacy fell short when all statistical indicators were considered. As such, the Cubic Spline model ranked second in performance after McNally, while the Quadratic Spline remained the least suitable.

When applied individually to the 22 pens, the McNally model showed an increase in mean squared error, accuracy factor, BIC, and Durbin-Watson values, with a slight decrease in adjusted coefficient of determination, bias factor, AIC, and AICc values compared to the pen averages. Despite these fluctuations, the McNally model still provided a satisfactory fit for modeling daily egg production curves. These observations are in line with the findings of Turgay et al. (2016), further reinforcing the validity of the McNally model for this purpose.

CONCLUSION

In this study, cumulative and daily egg production in partridges were modeled using equations commonly found in the literature, with the goal of identifying the best-fitting model based on model adequacy criteria. The results indicated that the Gamma model was the most suitable for modeling cumulative egg yields, while the McNally model was deemed the best for daily egg yields. Given the limited number of studies in the literature addressing both cumulative and daily egg production in partridges, this study is expected to be a valuable contribution to the field.

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Conflict of Interest
The authors do not have any conflict of interest.

Author Statement
All the authors of this manuscript have contributed significantly towards the execution of this work.

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