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Estimation of productive efficiency in ewes from the natural grasslands of Southern Brazil: A pilot approach

Estimativa da eficiência produtiva de ovelhas em pastagens naturais do Sul do Brasil: uma abordagem piloto

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Abstract: This pilot study quantified the proportion of ewes classified as Efficient, Inefficient, Productive, and Unproductive, using the data collected from an entire production cycle during 2024, provided by a sheep farm. For classification, two models were employed: a generalized linear model (GLM) using four body condition scores (BSCs) evaluations as explanatory variables, and a Bayesian mixed model (BMM) with four repeated measurements. The GLM results classified 8.82 % of ewes as Efficient, 7.84 % as Inefficient, 42.16 % as Productive, and 41.18 % as Unproductive. Conversely, the BMM categorized 19.61 % as Efficient, 4.90 % as Inefficient, 31.37 % as Productive, and 44.12 % as Unproductive. This study provides initial insights into productive efficiency indicators used in ewes, suggesting that further research over extended periods, preferably with the same animals, is required for achieving more conclusive results. Nevertheless, this approach presents a replicable evaluation model applicable to diverse scales and environments. In conclusion, GLM model proved superior in identifying ewes with favorable combinations of BSCs, coefficients of variation, and total weight of lambs at weaning.

Keywords: ewe classification; body condition score; productive efficiency indicators; generalized linear model; Bayesian mixed model.

Resumo: Este estudo piloto quantificou a proporção de ovelhas classificadas como Eficientes, Ineficientes, Produtivas e Não produtivas, usando dados coletados ao longo de um ciclo produtivo completo durante 2024, fornecidos por uma propriedade ovina. Para a classificação, foram empregados dois modelos: um modelo linear generalizado (GLM) utilizando quatro avaliações de escores de condição corporal (ECCs) como variáveis explicativas, e um modelo misto bayesiano (BMM) com quatro medições repetidas. Os resultados do GLM classificaram 8,82 % das ovelhas como Eficientes, 7,84 % como Ineficientes, 42,16 % como Produtivas e 41,18 % como Não produtivas. Por outro lado, o BMM categorizou 19,61% como Eficientes, 4,90 % como Ineficientes, 31,37 % como Produtivas e 44,12 % como Não produtivas. Este estudo fornece percepções iniciais sobre indicadores de eficiência produtiva em ovelhas, sugerindo que pesquisas adicionais por períodos mais longos, preferencialmente com os mesmos animais, são necessárias para obter resultados mais conclusivos. Ainda assim, esta abordagem apresenta um modelo de avaliação replicável, aplicável a diferentes escalas e ambientes. Em conclusão, o modelo GLM mostrou-se superior na identificação de ovelhas com combinações favoráveis de ECCs, coeficientes de variação e peso total dos cordeiros ao desmame.

Palavras-chave: classificação de ovelhas; escore de condição corporal; indicadores de eficiência produtiva; modelo linear generalizado; modelo misto bayesiano.

1. Introduction

The search for animals that can cope with environmental challenges is a key commitment made by scientists and breeders, given the impacts of climate change on food production. Animals that can adapt to a lesser extent to variations in production environments not only damage the rearing system but also pose a risk of food shortage. De Barbieri *et al.* (1) described that sheep production, particularly under pastoral conditions and extensive exploration, involves low-input systems in marginal areas. This effect is due to a global increase in the use of agricultural areas to produce food for humanity. Sheep breeding under these conditions requires considerable resilience or robustness, or, as described in this paper, productive efficiency, to improve production, adaptability, and sustainability amidst climate transitions and predatory wildlife. Ensuring the supply of high-quality food for humans requires identifying robust sheep varieties that can thrive under these conditions.

Knap (2) approached robustness to identify animals that exhibit enhanced production under various environmental conditions, useful in breeding practice. Thus, robustness in this study [productive efficiency (PE) in the context of natural grasslands of south Brazil] was defined by combining the high production potential and resilience to external stressors. To identify the animals with these trait combinations, it is necessary to measure certain characteristics throughout a productive cycle under pastoral conditions. Vialoux (3) described that the body condition score (BCS) and its variations during the productive cycle of an ewe could serve as a resilience indicator for these animals. However, a maternal production trait, such as total weaning weight (TWW), could serve as a potent indicator of the productivity of ewes as a herd. Resilience and productive traits together facilitate the identification and selection of more robust matrices.

Ewes can be categorized throughout a productive cycle based on their robustness or productive efficiency under natural grassland conditions. Specifically, those that consistently maintain higher BCS with minimal variations, while achieving robust production outcomes are considered more efficient in utilizing available resources because they expend less energy on maintenance and production functions (4). Ewes that exhibit lower or greatly varied BCS, yet fail to achieve satisfactory production, are considered unproductive. However, among the efficient and unproductive classifications, some ewes maintain a higher, stable body condition score but display lower production, while others with lower, fluctuating scores nonetheless achieve strong production outcomes. These may be aptly described as inefficient and productive ewes (4).

Thus, we propose a hypothesis that during the productive cycle we can identify ewes with combinations of traits that reflect different levels of productive efficiency (robustness). Specifically, ewes that maintain a good BCS with minimal variations and demonstrate a high capacity for weaning heavier lambs are considered more robust. This study aims to quantify the proportion of animals with combinations that classify them as Efficient, Inefficient, Productive, and Unproductive.

2. Material and methods

The dataset used was provided by a sheep farm that collected information of an entire production cycle during the year 2024 to achieve the internal selection of matrices. The farm was located in the municipality of Herval, Rio Grande do Sul State, Brazil, with geographic coordinates 31°57'15.9"S, 53°30'55.6"W. The climate is humid subtropical (Cfa, Koppen classification) with rainfall distributed throughout the year, an average of 1440 mm. The farm was managed under natural grasslands, with an average forage mass and growth rate of 900 kg/ha and 8.7 kg/ha/day, respectively.

The raw data were obtained from 231 ewes with 18 variables. However, after editing, 102 ewes and 11 variables were considered, excluding observations with missing values and remaining with variables of ewe dams (identification, age, breed, and four BCS measurements) and the progeny (sex, birth type, breed, and weaning weight). The units of measurement for the variables were: identification as alphanumeric; age as a numeric value, expressed in years; breed as alphanumeric; BCS measurements as qualitative ordinal numeric values, ranging from 1 (very thin) to 5 (very fat); sex, with 1 for male and 2 for female; birth type, with 1 for single and 2 for twins; and weaning weight, expressed in kg. A summary of the final dataset can be found in Table 1.

Table 1. General data descriptions for all traits are presented as the mean ± standard deviation.

Traits		Mean ± standard deviation
Sex		
Male	42 %	-
Female	58 %	-
Birth Type		
Single	96 %	-
Multiple	4 %	-
Breed Dam		
Corriedale	54 %	-
Lacaune × Corriedale	46 %	-
Age Dam (years)	-	3.22 ± 2.01
Weaning Weight (kg)	-	18.77 ± 4.82

Assessments of BCS were conducted at fixed points throughout the production cycle: before the onset of the breeding season, pre-mating (March 2024), at the end of pregnancy (July 2024), mid-lactation (September 2024), and at weaning (December 2024). Notably, only the evaluations performed during pre-mating accurately reflected the true physiological status of the ewes, as it preceded the onset of environmental and metabolic challenges imposed by gestation and lactation. The mating season lasted 45 days. At weaning, all ewes were evaluated simultaneously, and lambs were separated from their dams. The average age of the lambs at weaning was 90 days.

The BCS is a measure of subcutaneous fat storage ascertained through the palpation technique of the lumbar vertebrae, with scores ranging 1–5 (representing a very thin animal to very fat animal), with a sensitivity of 0.25 points (edited from Russel [5]).The weaning weight was measured after a fast for 8 to 12 h using a scale with an accuracy of 0.2 kg and a maximum capacity of 4000 kg.

2.1 Data description

The dataset comprising 102 observations presented average BSC (mean ± standard deviation) of 3.283 ± 0.478, 3.193 ± 0.497, 2.466 ± 0.341, and 2.491 ± 0.305, for pre-mating, end of pregnancy, middle lactation, and weaning, respectively. The average total weaning weight per ewe was 18.771 ± 4.824 kg. The average ewe age was 3.262 ± 0.991 years, with frequencies of 6.86 %, 16.67 %, 29.41 %, 36.28 % and 10.78 % for 1, 2, 3, 4, and >4 years old, respectively. The frequencies of the ewe breed were 53.93 % and

46.07 % for the Corriedale and Lacaune x Corriedale, respectively. The average for lamb birth type was 1.076 ± 0.266, with frequencies of 96.08 % and 3.92 % for simple and multiple lambs born to a single ewe, respectively, with 42.37 % males and 57.63 % females. The lamb breed distributions were 33.90 %, 44.07 % and 22.03 % for Corriedale, half-blood Dohne Merino, and half-blood Hampshire Down, respectively.

2.2 Modeling and adjustments

We used two models for classifying the ewes based on productive efficiency: a generalized linear model (GLM) with four BSCs evaluations as explanatory variables and a Bayesian mixed model (BMM) with four repeated measurements, using the R statistical packages “stats” [(5)] and “brms” [(6)], respectively. From the initial data, the average BCS (GLM by applying the γ-distribution and the logarithmic link functions), the BCS_CV (using the γ-distribution and the logarithmic link function), and the TWW (employing the Gaussian distribution) were calculated.

The TWW was the sum of the weaning weight of the lambs weaned per ewe. For the mixed model, a new column describing the variable order was created, which was computed using the BSC measurement order (1: pre-mating; 2: end of pregnancy; 3: mid-lactation, and 4: weaning).

The BCS, BCS_CV, and TWW were fit to the GLM using the predictors lamb sex, lamb birth type, age ewe, breed ewe, and breed lamb. A stepwise regression analysis was performed using the Akaike Information Criterion (AIC) to select the best-fitting model. The final GLM equations used included:

BCS = Lamb Sex + Lamb Birth Type + Age Ewe + Breed Ewe + Breed Lamb

BCS_CV = Lamb Sex + Lamb Birth Type + Age Ewe + Breed Ewe + Breed Lamb

TWW = Lamb Sex + Lamb Birth Type + Age Ewe+ Breed Ewe + Breed Lamb

The residuals of the selected model were calculated and stored as a new variable. However, BCS_CV did not present any significance for either model predictor. Thus, for this trait, the new variable employed was the deviation of the mean of all observations.

For the mixed model, two Bayesian mixed-effects models were fitted using the “brm” function of the “brms” R package [(6)]. The models analyzed the variability in the BSC data. The first model includes the fixed effects of age ewe, breed ewe, and random effects for ewe and order (order as a repeated measure). The second model includes the fixed effects of order, age, and ewe breed, and a random effect for ewes. The models were compared using the Leave-One-Out Cross-Validation (LOOCV) technique to determine which model better fits the data. The final Bayesian equations were as follows:

BCS 1 = Age Ewe + Breed Ewe + 1|Ewe + 1|Order

BCS 2 = Age Ewe + Breed Ewe + Order + 1|Ewe

The results of these models provided solutions for the BCS and calculated the error deviation, which was expressed as a percentage of the average estimated errors across four BCS measurements.

2.3 Productive efficiency groups

For forming the productive efficiency groups, three variables were used for each model. For GLM, the variables were the residuals of the BCS (RES_BCS) of four measurements, the deviation of BCS CV (DEV_BCS_CV) among four measurements, and the residual of the TWW (RES_TWW).

Table 2 presents the criteria employed to classify the ewes based on their productive efficiency per GLM. Ewes with RES_BCS ≥ 0, DEV_BCS_CV ≤ 0, and RES_TWW ≥ 0 were categorized as Efficient. Animals with RES_BCS < 0 and RES_TWW ≥ 0 were classified as Productive. Ewes with RES_BCS ≥ 0, DEV_BCS_CV ≤ 0, and RES_TWW < 0 and RES_TWW < 0 were classified as Unproductive.

Table 2. Productive efficiency classification using generalized linear model.

Productive efficiency classification	GLM modeling				
	Residual BCS average		Residual BCS coefficient of variation		Residual TWW
Efficient	≥0	And	≤0	and	≥0
Inefficient	≥0	And	≤0	and	<0
Productive	<0	Or	>0	and	≥0
Unproductive	<0	Or	>0	and	<0

Table 3. Classification of productive efficiency using Bayesian modeling.

Productive efficiency classification	Bayesian modeling				
	Solution BCS		Deviation BCS error		Residual TWW
Efficient	≥0	and	≤0	and	≥0
Inefficient	≥0	and	≤0	and	<0
Productive	<0	or	>0	and	≥0
Unproductive	<0	or	>0	and	<0

The variables used for the mixed model (Table 3) were the solution for BCS (SOL_BCS) using order as a repeated measure, the deviation of BCS estimate error [DEV_BCS_ERROR (%)] of four measurements, and RES_TWW. In this context, ewes that presented a SOL_BCS ≥ 0, DEV_BCS_ERROR ≤ 0, and RES_TWW ≥ 0 were classified as Efficient. The ewes that presented a SOL_BCS < 0 or DEV_BCS_ERROR > 0 and RES_TWW ≥ 0 were categorized as Productive. The ewes that presented a SOL_BCS ≥ 0, DEV_BCS_ERROR ≤ 0, and RES_TWW < 0 were included within Inefficient. The ewes that presented a SOL_BCS < 0 or DEV_BCS_ERROR > 0 and RES_TWW < 0 were classified as Unproductive.

Tables 1 and 2 indicate that some ewes maintained their body condition and produced fewer or lighter lambs; others, due to higher milk production, weaned heavier lambs but lost BCS; some ewes did not give birth to healthy lambs and failed to maintain their BCS. Such a situation corresponds to the productive efficiency classification of the present research, which is Inefficient, Productive, Unproductive, and Efficient.

2.4 Statistical analyses

The BCS, BCS_CV, and TWW were subjected to variance analysis using the ANOVA R package [7] for obtaining the productive efficiency using two models. When significant inter-group differences were observed, a Tukey test was performed using the "stats" R package [7]. The results were presented using the "ggplot2" R package [8].

Pearson and Spearman correlations among the BCS, BCS_CV, TWW, RES_BCS, DEV_BCS_CV, RES_TWW, SOL_BCS, and DEV_BCS_ERROR were established and plotted using the "GGally" R package [9]. For calculating the confusion matrix between the productive efficiency classification models, the "cvms" R package [10] was used. To gain deeper insights into the distribution of BCS throughout the productive cycle, a Pearson's chi-squared test was conducted using the "stats" R package [7].

3. Results

GLM models that best fit the data for BCS and TWW had AIC values of 30.09 and 581.11, respectively. For BCS, the model included the predictors of age and breed of the ewe; for TWW, the model included lamb birth type and breed of the ewe. For the variable BCS_CV, no predictor presented any marked effects; therefore, its deviation was calculated based on the mean of the BCS_CVs of all observations.

The BMM that best fits the data for the BCS variation includes the fixed effects of order, age, and breed of the ewe, and a random effect for the ewe. A LOOCV comparison of the models revealed that the best model presented an Expected Log Predictive Density that was superior by 1.1 points to the model that included the fixed effects of age of the ewe, breed of the ewe, random effects of the ewe, and order (with a standard error difference of <0.3).

Figure 1A shows the percentage of productive efficiency classifications calculated using the GLM model to obtain the BCS and TWW residuals as well as the DEV_BCS_CV. The proportion of Efficient ewes was only 8.82 %, and the greatest proportion was for the Productive ewes at 42.16 %. The proportion of Inefficient ewes was only 7.84 %, and that of Unproductive ewes was 41.18 %. In Figure 1B, only the Unproductive ewes presented significantly lower BCSs than Efficient, Inefficient, and Productive, with respective values of 2.74 ± 0.263, 3.01 ± 0.178, 3.04 ± 0.267, and 2.90 ± 0.280. For BCS_CV, the Efficient group was better than the Productive (lower coefficient variation values), but no marked differences were observed between the Inefficient and Unproductive classifications, with values of 13.6 ± 3.47, 19.5 ± 6.04, 15.4 ± 2.28, and 17.5 ± 6.64, respectively (Figure 1C). With significant differences, the TWW was greater for Efficient and Productive but lower for Inefficient and Productive, with values of 20.5 ± 4.09, 22.5 ± 3.61, 14.5 ± 3.01, and 15.4 ± 3.04, respectively (Figure 1D).

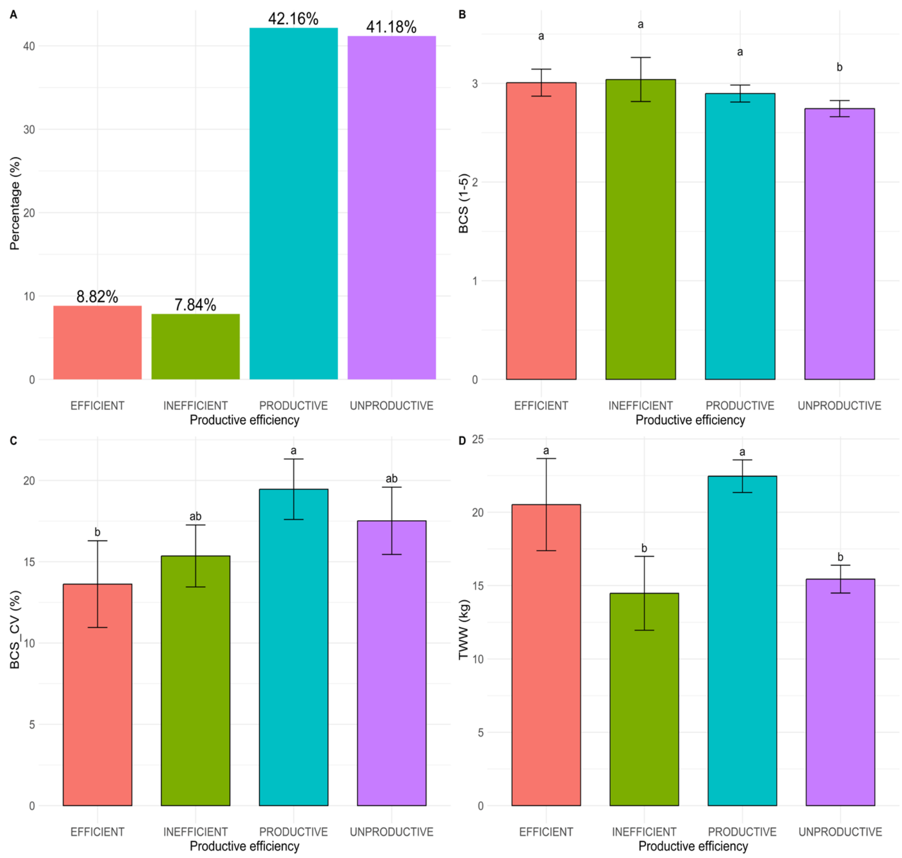

Figure 1. Productive efficiency classification achieved by the GLM model. (A) The percentage of animals classified as Efficient, Inefficient, Productive, and Unproductive. (B) Average body condition score (BCS), on a scale of 1–5, where 1 represents an extremely thin animal and 5 represents an extremely fat one. (C) Coefficient of variation in the body condition score, expressed as a percentage. (D) Total weaning weight per ewe (kg).

Figure 2A shows the percentage of productive efficiency classifications derived using the BMM to obtain the SOL_BCS and DEV_BCS_ERROR. The Efficient proportion was 19.61 %, and Unproductive ewes demonstrated the greatest proportion at 44.12 %. The Inefficient proportion was 4.90 %, and the Productive one was 31.37 %. A significant difference was observed between the Efficient and Unproductive classifications (Figure 2B), with values of 3.03 ± 0.154 and 2.76 ± 0.275, respectively, but not between the Inefficient (3.06 ± 0.212) and Productive (2.85 ± 0.299) classes. For BCS_CV, no marked variations between the classifications were noted (Figure 2C). With significant differences, the TWW was greater in Efficient and Productive and lower in Inefficient and Productive groups, with respective values of 22.6 ± 4.40, 21.8 ± 2.24, 14.9 ± 2.24, and 15.3 ± 3.12 (Figure 2D).

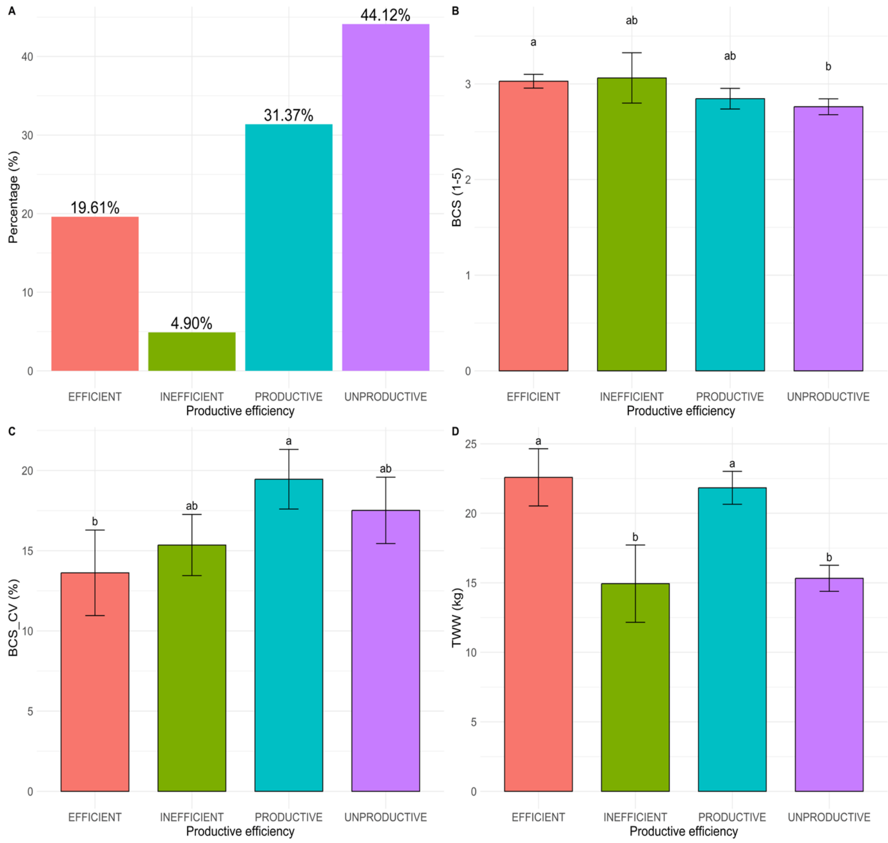

Figure 2. Productive efficiency classification achieved by employing the Bayesian mixed model. (A) The percentage of animals classified as Efficient, Inefficient, Productive, and Unproductive. (B) Average body condition score (BCS), on a scale of 1–5, where 1 represents an extremely thin animal and 5 represents an extremely fat one. (C) Coefficient of variations in the body condition score (%). (D) Total weaning weight per ewe (kg).

Figure 3 shows a pair plot matrix describing the relationships between BCS, BCS_CV, TWW, RES_BCS, DEV_BCS_CV, RES_TWW, SOL_BCS, and DEV_BCS_ERROR. Each cell within the lower triangle of the matrix demonstrates a scatter plot representing the relationship between two variables. The blue dots are individual data points, and the red line indicates the linear regression fit. The R values represent the Spearman correlations, which indicate robust positive correlations ($p < 0.001$) between BCS and RES_BCS (R = 0.96), BCS and SOL_BCS (R = 0.96), BCS_CV and DEV_BCS_CV (R = 1), and RES_BCS and SOL_BCS (R = 1), as well as between TWW and RES_TWW (R = 0.84). Weak positive correlations ($p<0.001$) were identified between BCS with BCS_CV (R = 0.44), DEV_BCS_CV (R = 0.44), TWW (R = 0.37), and RES_TWW (R = 0.35); BCS_CV with RES_BCS (R = 0.44) and SOL_BCS (R = 0.44); RES_BCS with DEV_BCS_CV (R = 0.44) and RES_TWW (R = 0.35); and SOL_BCS with DEV_BCS_CV (R = 0.44), RES_TWW (R = 0.35) and TWW (R = 0.30).

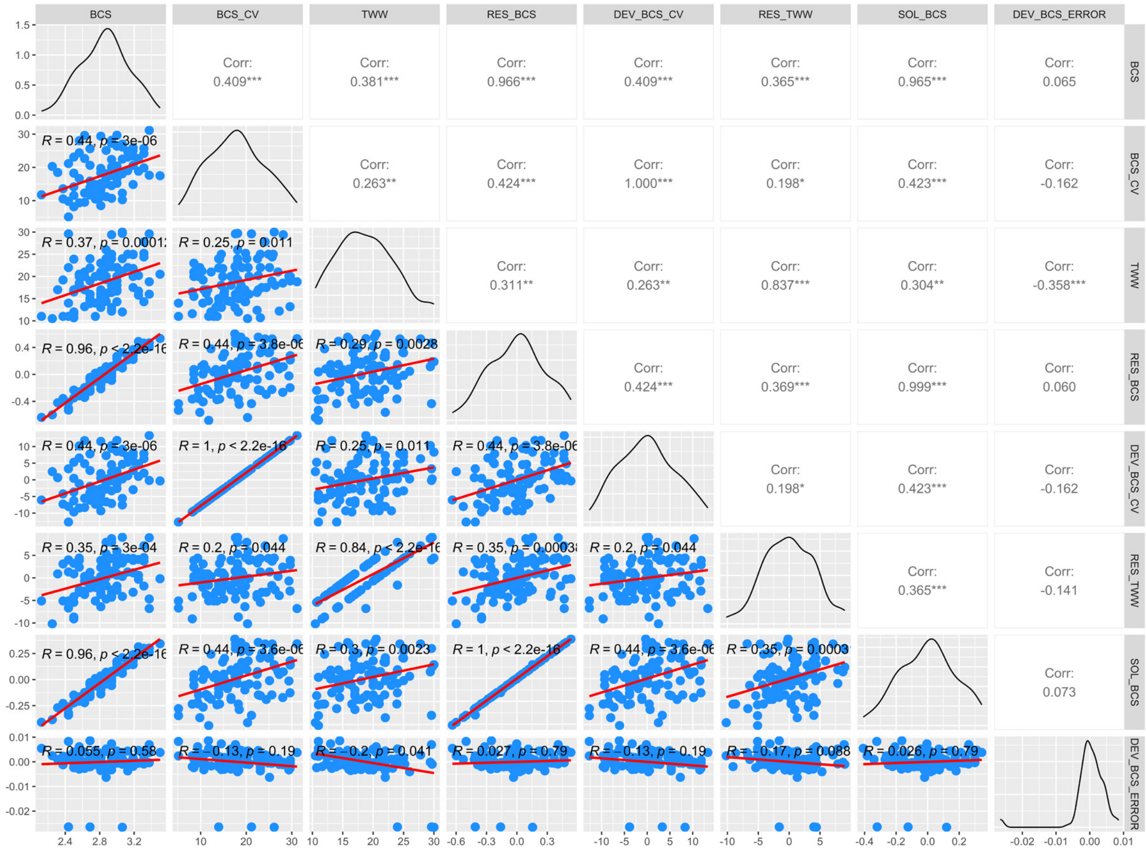

Figure 3. Spearman correlations among the variables: average body condition score (BCS), body condition score coefficient of variation (BCS_CV), total weaning weight per ewe (TWW), residual of the body condition score (RES_BCS), deviation of the body condition score coefficient of variation (DEV_BCS_CV), residual of the total weaning weight per ewe (RES_TWW), solution of the body condition score (SOL_BCS), and deviation of the body condition score estimate error (DEV_BCS_ERROR).

The upper triangle of Figure 3 presents the Pearson correlation coefficients (Corr) for each pair of variables. Very strong correlations (p<0.001) between BCS with RES_BCS (Corr: 0.96) and SOL_BCS (Corr: 0.96), BCS_CV and DEV_BCS_CV (Corr: 1.00), and RES_BCS and SOL_BCS (Corr: 0.99), as well as between TWW and RES_TWW (Corr: 0.83). There were weak positive correlations (p <0.001) between BCS with BCS_CV (Corr: 0.40), TWW (Corr: 0.38), DEV_BCS_CV (Corr: 0.40), and RES_TWW (Corr: 0.36); BCS_CV with RES_BCS (Corr: 0.42) and SOL_BCS (Corr: 0.42); TWW with RES_BCS (Corr: 0.31) and SOL_BCS (Corr: 0.30); RES_BCS with DEV_BCS_CV (Corr: 0.42) and RES_TWW (Corr: 0.36); and SOL_BCS with DEV_BCS_CV (Corr: 0.42) and RES_TWW (Corr: 0.36), as well as, between TWW and DEV_BCS_ERROR (Corr: -0.35).

The confusion matrix compares the classifications made by the GLM model (rows) with those made by the BMM (columns) and displays the counts and percentages of the classifications, at an accuracy of 0.72 (Figure 4). Of the nine ewes classified as Efficient by the GLM, 44.4 % (n = 4) were also classified as Efficient by the BMM, whereas 55.6 % (n = 5) were reclassified as Productive by the BMM. This comparison highlights the degree of concordance and divergence between the classifications of productive efficiency obtained through different statistical approaches. The GLM model classified 62.5 % ewes (n = 3) as Inefficient, which was the same as BMM, and 37.5 % ewes (n = 5) as Unproductive. The GLM categorized 62.8 % ewes (n = 27) as Productive, which was similar to BMM, and 37.2 % ewes (n = 16) as Efficient. The GLM categorized 95.2 % ewes (n = 40) as Unproductive, which was the same as BMM, and 4.8 % ewes (n = 2) as Inefficient.

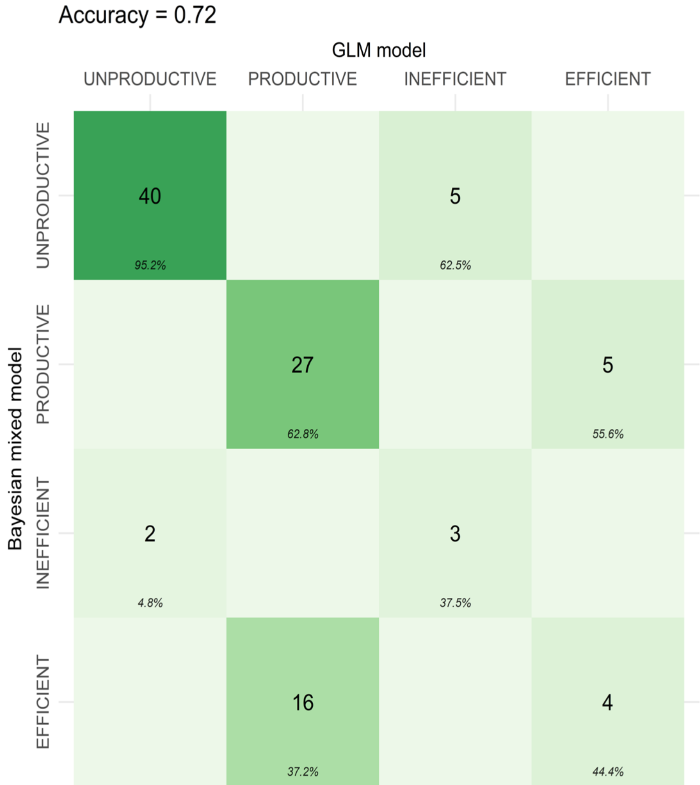

Figure 4. Confusion matrix calculation indicating the classification of productive efficiency using the GLM and the Bayesian mixed model.

Table 4 presents the distribution of BCS, revealing a remarkable effect of measurement order as ascertained by the chi-squared test. Notably, during mid-lactation, a higher percentage of ewes had a BCS ≤ 2. This trend suggested that the ewes experience a decline in BCS throughout the productive cycle (Figure 5).

Table 4. Pearson's chi-squared test indicating the percentage of ewes with a BCS of ≤ 2 across different measurement points.

Order of BCS measurements	Percentage of ewes with a BCS ≤ 2	P-value calculated with a Pearson's chi-squared test
1	0.0 %	0.001243
2	1.9 %	
3	10.7 %	
4	7.8 %	

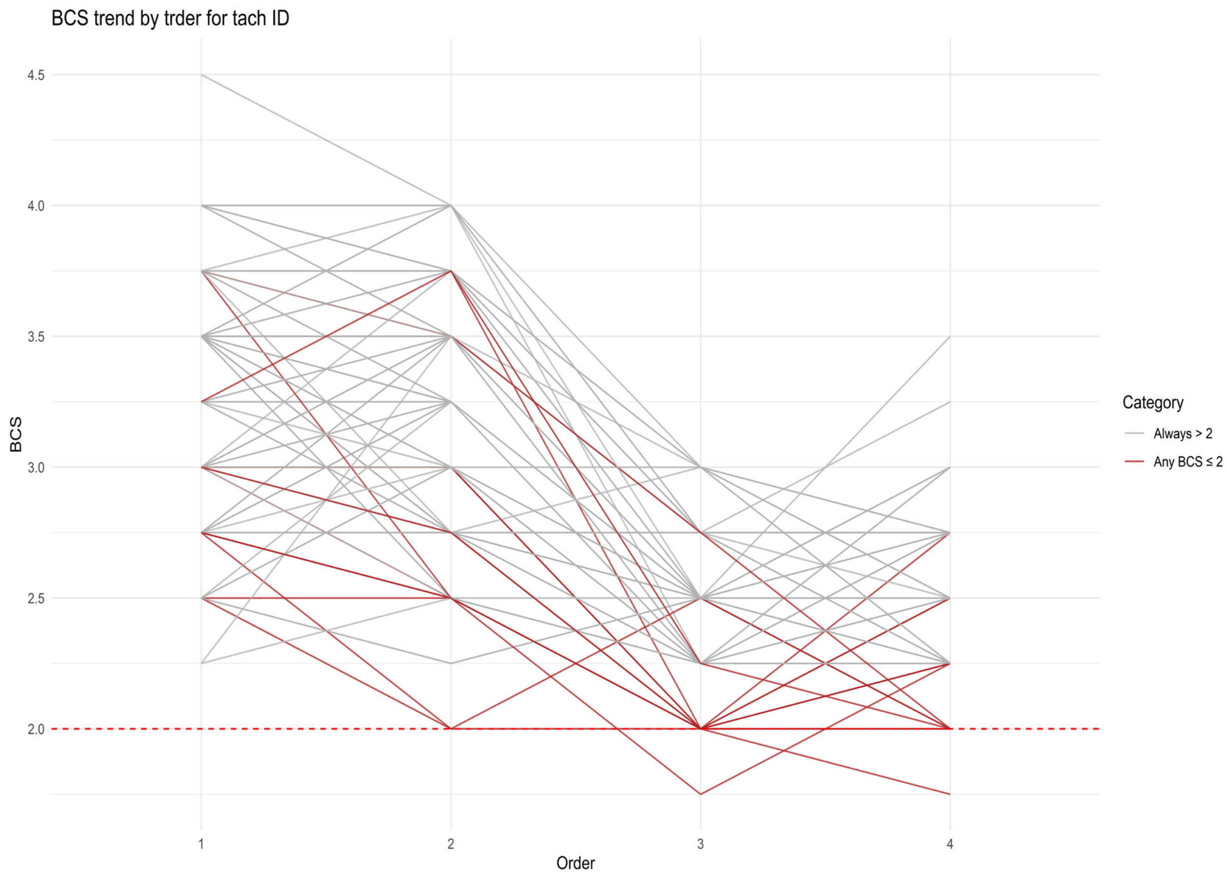

Figure 5. Distribution of individual ewe body condition scores (BCS) throughout the productive cycle, illustrating a threshold at BCS 2.

4. Discussion

During the production cycle, it is possible to identify ewes with combinations of traits that reflect different levels of productive efficiency (robustness). However, the results depend on the data adjustment model used. When using the GLM, the productive efficiency proportions differed from those obtained with the BMM. The GLM model yielded the least number of Efficient ewes; however, it presented favorable values for BCS, BCS_CV, and TWW. In contrast, the BMM did not indicate any significant differences in BCS_CV among all productive efficiency classifications. This finding suggests that the GLM model may be more applicable in production settings, primarily to maintain lower BCS_CV as a crucial tool for identifying productive efficiency (robustness), as described by Young and Thomson [(4)].

Such variations in BCS along the productive cycle are not only proposed in this study, but also by Macé *et al.* [(11)], where this trait was used together with body weight changes throughout the ewe cycle. The findings indicated that besides being inheritable characteristics, BCS and body weight changes represent valuable traits for improving individual robustness in sheep. This result provides coherence with those of the present pilot approach that proposes a modeling of the measured farm information, facilitating actions such as discarding or selection.

Young and Thomson [(4)] described that at a commercial herd level, over a long productive cycle, ewes, especially under pastoral conditions, exhibit natural variations in BCS due to the high energy demands created during pregnancy and lactation. However, some ewes maintain their body status and produce fewer or lighter lambs; others, due to high milk production, wean heavier lambs but lose BCS;

some ewes do not produce healthy lambs and fail to maintain their BCS. Additionally, there are some (as seen in the GLM) or several (as seen in the BMM) ewes that maintain their BCS and produce lambs with greater weaning weights. Such a situation corresponds with the productive efficiency classifications: Inefficient, Productive, Unproductive, and Efficient, respectively, presented in this research.

In this context, robustness (productive efficiency), despite being a complex trait, is crucial for defining sustainable herd management goals. However, studies addressing robustness from characteristic definition to genomic approaches are lacking (12). It is often unclear which approach is best applicable for a particular herd. Using the example presented by Young and Thomson (4) in "Breeding Focus 2014-Improving Resilience," we explored a hypothetical situation where the critical BCS for maintaining herd production was set at 2. In scenario 1where ewes maintain their BCS far from the critical value, this approach is preferable when BCS is also variable, but ewes occasionally drop BCS below the critical level (scenario 2). In such a comparison, even with variability, it is preferable to maintain BCS away from the critical 2.

On the other hand, scenario 3 with lower BCS variations but a BCS close to the critical value is preferable, as it requires lesser food for maintenance and carries a lower risk of weakened lamb production than scenario 2. However, the best among them is scenario 4, where ewes not only exhibit lower BCS variations but also maintain a BCS distant from the critical value (4). In contrast, when examining BCS differences throughout the productive cycle, ewes that experienced declines at certain points in BCS to 2 were observed (Figure 5). As summarized in Table 4, the proportion of ewes whose BCS dropped to ≤2 during the cycle was 0.0 %, 1.9 %, 10.7 %, and 7.8 % at the first, second, third, and fourth measurements, respectively. Consequently, identifying the percentage of ewes with lower BCSs relative to the flock average supports the effectiveness of this approach in pinpointing less robust animals. This observation provides a reliable criterion for making informed culling decisions (Figure 5).

In his study, we must consider not only BCS variation and lamb production (in kg), but also the average BCSs of the ewes throughout the production cycle. Thus, the GLM and BMM presented favorable BCS and TWW for Efficient classification except for BCS_CV, indicating that these sheep can reproduce for a longer duration in the given environment.

Given the low proportion of animals classified as Efficient, emphasis should also be placed on those classified as Productive. A study on Romney ewes (13) found that BCS directly influences the TWW, especially when BCS was measured at scanning, lambing, and weaning stages. In the present study, BCS and TWW presented moderate correlations, with a weak positive correlation between BCS_CV and TWW (Figure 3). This finding indicates that greater BCS and BCS_CV values are associated with increased TWW. However, such a correlation is not entirely favorable, as animals with greater TWW exhibit higher BCS_CV, which is less desirable for those seeking animals with minimal BCS oscillations during the productive cycle.

Considering the unfavorable correlation between BCS_CV and TWW as a drawback, approximately 63 % of the combinations did not follow it. Ewes with lower BCS_CV but greater TWW could be identified within this group. As shown in Figure 4, despite such an adverse relationship and the variations observed between the models, any short-term classification error may not have a remarkable economic impact. Even if an efficient animal is misclassified, the select or discard program can identify animals unless they are productive.

Although this study offers a preliminary framework for identifying the indicators of productive efficiency and robustness, further research is essential to draw more definitive conclusions. Ideally, future evaluations should span multiple years and involve the same ewes, as the present analysis covers only one flock over a single production cycle (2024). To strengthen the validity of robustness as a selection criterion, repeating these analyses across various environments and seasons, involving a broader range of farms and a larger sample of animals is recommended. Llonch *et al.* (14) highlighted that reliable robustness assessment is crucial. Integrating robustness-associated traits into animal breeding programs or farm routines can enhance their ability to identify favorable animals, providing a comprehensive assessment that balances the major consequential adaptive strategies adopted by the animal. Additionally, such an approach can provide a replicable evaluation model applicable to diverse scales and environments.

5. Conclusion

In this pilot approach used for assessing productive efficiency (or robustness), the distribution of ewes classified as Efficient, Inefficient, Productive, and Unproductive was examined using generalized linear model (GLMs) and Bayesian mixed model (BMMs). The findings indicated that the GLM model excelled at identifying ewes with the most advantageous profiles for BCS, BCS_CV, and TWW. These results highlight the practical value of GLM as a tool for discerning productive efficiency, offering meaningful guidance for selection strategies during flock management.

Supplementary material

Graphical Abstract (only available in the electronic version).

Conflicts of interest statement

The author declares that there are no conflicts of interest regarding the publication of this paper.

Data availability statement

The entire dataset that supports the results of this study has been made available on SciELO Data from the Ciência Animal Brasileira/ Brazilian Animal Science and can be accessed at the following DOI: https://doi.org/10.48331/SCIELODATA.AGWLIU.

Author contributions

Conceptualization, Data curation, Formal analysis, Funding acquisition, Project management, Methodology, Supervision, Investigation, Visualization, Writing (original draft, proofreading and editing): F. Amarilho-Silveira.

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