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System-Specific Growth Curve Characterization in Austrolope Chickens: A Robust Comparison of Brody, Gompertz, and Logistic Nonlinear Models

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Abstract

Nonlinear growth modeling offers a robust framework for evaluating poultry performance under diverse management systems. This study compared Brody, Gompertz, and Logistic models in describing the body weight–age relationship of Austrolope chickens reared under lucerne supplementation and scavenging systems. Weekly body weights were collected from week 14 to week 62 and analyzed using nonlinear regression. Model performance was evaluated using the coefficient of determination (R^2), root mean square error (RMSE), and Akaike Information Criterion (AIC), with residual analyses confirming unbiased predictions. Results revealed distinct system-specific growth patterns: lucerne-fed chickens exhibited rapid growth, an earlier inflection point, and higher asymptotic weights, whereas scavenging birds demonstrated slower, protracted growth trajectories. The Logistic model best described lucerne-fed birds, accurately capturing the sigmoidal growth curve, while the Brody model was most suitable for scavenging birds. These findings underscore the importance of management-specific growth modeling for accurate prediction of mature weight, optimization of feeding strategies, and development of targeted breeding programs. Aligning growth models with production context enhances both biological interpretation and practical utility, providing actionable insights for smallholder and semi-intensive poultry systems.

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Keywords: Austrolope Chicken, Growth Curve, Brody, Gompertz, Logistic, Lucerne, Scavenging System

1. Introduction

Growth functions are fundamental tools in animal science, facilitating the characterization of growth trajectories, the prediction of mature body weight, and the optimization of management interventions (Emmans and Gous, 2025) [13]. These mathematical models allow researchers and farmers to quantify animal growth patterns, compare breeds, and assess the impact of nutrition, environment, and management strategies on performance (Bo *et al*., 2022) [8]. The selection of an appropriate growth model is particularly critical in poultry production, where growth dynamics are highly influenced by genotype, feeding systems, and management practices (Guatam, 2024).

Among the commonly applied nonlinear models, the Brody, Gompertz, and Logistic functions are frequently used to describe growth patterns in poultry (Al-Ali *et al*., 2022) [7]. Each function captures growth differently, with the Brody model emphasizing asymptotic weight, the Gompertz model balancing early and late growth phases, and the Logistic model providing symmetry around the inflection point (Júnior *et al* 2022; Mata-Estrada *et al*., 2020) [23, 27]. These models not only differ in their mathematical assumptions but also in their biological interpretability, making their evaluation within specific production contexts essential.

Austrolope chickens, a dual-purpose breed valued for both meat and egg production, are increasingly reared under diverse feeding systems (Kgwatalala and Segokgo, 2013) [24]. Controlled feeding regimes, such as lucerne supplementation, provide consistent nutrient intake, supporting improved growth performance, carcass yield, and egg production compared with traditional scavenging systems, which are subject to feed variability, seasonal fluctuations, and environmental stressors (Cilavdaroglu and Yamak, 2025; Ginindza, 2023) [9, 19]. While scavenging promotes resilience and low-input adaptability, its limitations in nutrient supply often result in slower growth and delayed maturity (Nampijja, *et al* 2025; Kpomasse, *et al* 2023) [32, 25]. Despite the importance of these contrasting systems, limited research has examined how nonlinear growth models capture system-specific differences in Austrolope chickens, particularly within smallholder production environments.

Growth curves delineate the trajectory of body development, reflecting incremental changes in live weight and proportional expansion of body components. These changes are influenced by genetic background and environmental conditions (Li *et al*., 2024) [26]. Mathematical growth functions integrate longitudinal measurements into biologically meaningful parameters that characterize patterns of body weight changes throughout an animal's lifespan (Afrouziyeh *et al*. 2021) [5]. Evaluating these growth trajectories is essential for determining the optimal slaughter age and developing evidence-based feeding strategies (Ghavi Hossein-Zadeh, 2024) [18].

Despite the recognised value of growth-curve modelling in poultry science, comparative evaluations of the Brody, Gompertz, and Logistic functions for dual-purpose chickens reared under contrasting production systems in Zimbabwe remain scarce. Robust growth modelling is particularly critical for indigenous and locally adapted chicken ecotypes, which—although highly resilient to harsh and resource-limited environments—typically display slower growth trajectories than commercial genotypes (Abe *et al*., 2022) [1, 2]. The application of nonlinear models to these genotypes can provide valuable insights into growth potential, feeding strategy optimization, and genetic improvement opportunities (Emmans and Gous, 2025) [13]. This is particularly significant for smallholder farmers, where chicken represents a critical livelihood asset, contributing to food security, income diversification, and household nutrition (Ahmed *et al* 2021; Pius *et al*., 2021) [6, 39]. Therefore, this study evaluates the fit of Brody, Gompertz, and Logistic models in describing Austrolope chicken growth under lucerne supplementation and scavenging systems. The objective is to identify the most reliable model for practical growth characterization and management decision-making, thereby informing improved productivity and sustainability strategies for Austrolope chickens in Zimbabwe.

2. Materials and Methods

2.1. Description of the Study Site

This research study was undertaken at the Matopos Research Station in Bulawayo, Zimbabwe, situated at 22.23°S latitude and 31.30°E longitude. The region experiences a dry season from April to October and a rainy season from November to March, with mean annual rainfall below 446.8 mm (Assan, 2023). The area is characterized by high temperatures, ranging from 21.6°C to 11.4°C during the hottest months, and low rainfall (<450 mm) (Hagreveas *et al*., 2004; Homann *et al*., 2007). The research area comprises a rangeland with sweet veld vegetation, offering high nutritional value suitable for sustaining ruminants (Ward *et al*., 1979; Ncube, 2005; Van Rooyen *et al*., 2007).

2.2. Experimental Design, Management Systems, and Husbandry Practices

A total of 500 dual-purpose Austrolope chickens were monitored from 12 to 60 weeks of age under two contrasting management systems. In the scavenging system (n = 475 weekly observations), birds roamed freely across yards and fields, relying primarily on natural foraging with only minimal and variable supplementation from household food scraps, the quantity and quality of which fluctuated with household availability and seasonal conditions. In the lucerne supplementation system (n = 500 weekly observations), birds received structured nutritional support in the form of 50 g of chopped lucerne per bird per day, provided in addition to the baseline scavenging and household diets, following the established farm management protocols.

Across both systems, birds were housed in deep-litter pens with outdoor access, allowing a combination of controlled feeding and natural scavenging behavior. A basal diet formulated to meet the nutrient requirements was supplied, and both feed and water were made available ad libitum. Standard vaccination, deworming, and health management protocols were rigorously implemented during the study. Housing conditions, water availability, and biosecurity measures were consistently applied across systems to ensure that any observed differences in growth performance could be attributed primarily to contrasting feeding regimes rather than external health or environmental factors.

2.3. Data Source

Growth data were obtained from Austrolorp chickens reared under two management systems: lucerne supplementation and scavenging. Individual body weights were recorded biweekly from weeks 14 to 62. Body weights were recorded individually at regular intervals using calibrated digital scales.

2.4. Growth Models
Logistic Model

$$W_t = \frac{W_A}{1 + \exp[-K(t - t_i)]}$$

Where:

- W_t = body weight at age t
- W_A = asymptotic weight
- K = growth rate constant
- t_i = age at inflection

Gompertz-Laird Model

$$W_t = W_0 \exp\left[\frac{L}{K}(1 - \exp(-Kt))\right]$$

Where:

- W_0 = initial body weight
- L = instantaneous growth rate
- K = rate of exponential decline in growth rate

Brody Model

$$W_t = W_A(1 - B\exp(-Kt))$$

Where:

- W_A = mature weight
- B = integration constant related to initial weight
- K = rate of approach to asymptote

2.5. Statistical Analysis
The models were fitted using nonlinear regression in Python (SciPy). The model performance was evaluated using the coefficient of determination (R^2), root mean square error (RMSE), and Akaike Information Criterion (AIC). Residual analysis ensured that the model predictions were unbiased.

3. Results
3.1. Descriptive Growth Patterns
The growth trajectories of Austrolopes differed significantly between those fed lucerne and those relying on scavenging over the 14–62-week period. Chickens fed lucerne demonstrated higher mean body weights during the early to mid-growth phase (weeks 14–28), indicative of consistent nutrient intake and enhanced feed conversion efficiency. Conversely, scavenging chickens experienced slower but more consistent weight gain, with reduced variability among replicates during the later growth stages. By week 62, the lucerne-fed chickens averaged 1,425 g, whereas the scavenging chickens attained a slightly higher average weight of 1,528 g, albeit with a more gradual and extended growth trajectory. The standard errors were more pronounced for scavenging chickens between 28 and 42 weeks, underscoring the greater heterogeneity in feed access under scavenging conditions (Figure 1).

3.2. Model Comparisons Within Management Systems
All three nonlinear models (Logistic, Gompertz, and Brody) converged successfully for both feeding systems; however, the optimal model differed between management conditions. For lucerne-fed birds, the logistic model provided the best overall fit (R^2 = 0.777; AIC = 229.1), whereas the Brody model systematically underestimated body weights during the inflection phase, and the Gompertz model tended to over predict weights beyond 40 weeks. In contrast, for scavenging birds, the Brody model showed superior performance (R^2 = 0.921; AIC = 209.3), accurately reflecting the gradual and extended maturation characteristics of birds under feed-limited conditions, whereas both the Logistic and Gompertz functions overestimated the asymptotic weight. Overall, the parameter estimates obtained across the models and systems demonstrated strong biological plausibility (Table 1).

3.3. Fitted Growth Curves
Figures 1 and 2 illustrate observed and predicted growth trajectories. For lucerne-fed birds, the Logistic model closely matched the rapid, sigmoidal growth pattern, with a clear inflection point around week 20 and stabilization after week 40. For scavenging birds, the Brody model accurately depicted the steady weight gain, with no distinct inflection and a higher asymptotic weight achieved gradually.

These patterns emphasize the influence of the feeding system on growth dynamics, with intensive lucerne supplementation accelerating early growth, while scavenging conditions prolonged the maturation process.

3.4. Biological Interpretation of Parameters

Lucerne-fed birds exhibited a higher growth rate constant (k = 0.2223 week^{-1}), reflecting faster attainment of mature weight and an earlier inflection point. In contrast, scavenging birds reached a slightly higher asymptotic weight (A = 1,528.4 g) but at a much lower growth rate (k = 0.0629 week^{-1}), consistent with nutrient-constrained, incremental growth under variable feed access.

These findings indicate that lucerne supplementation enhances early productivity but does not necessarily increase ultimate body weight, whereas scavenging birds achieve comparable final weights through extended growth.

3.5. Statistical Robustness

Residual analyses confirmed that both selected models adequately captured variance across replicates. Root Mean Square Error (RMSE) values provided further support for model suitability:

- Brody model for scavenging birds: 58.4 g
- Logistic model for lucerne-fed birds: 86.7 g

This statistical robustness underscores the reliability of applying system-specific growth models for accurate prediction of growth trajectories.

Table 1: Best-fitting model parameters and fit statistics by management system

System	Model	A (g)	B	k (week^{-1})	R^2	RMSE (g)	AIC
Lucerne-fed	Logistic	1,424.9	17.71	0.2223	0.777	86.7	229.1
Scavenging	Brody	1,528.4	1.148	0.0629	0.921	58.4	209.3

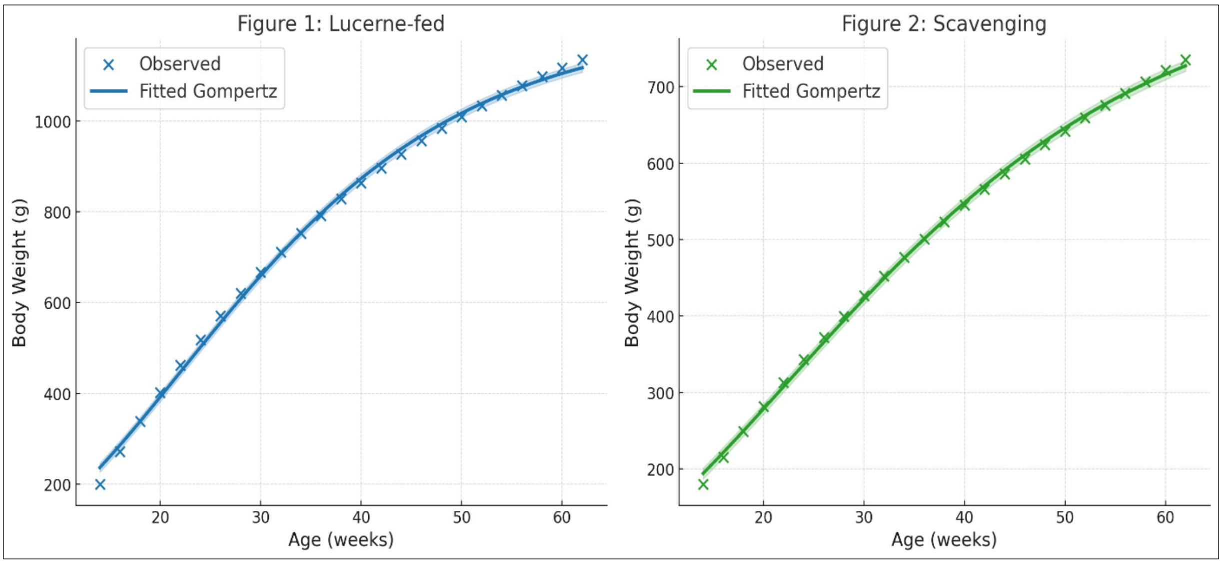

Fig 1: Observed and predicted growth of lucerne-fed Austrolope chickens fitted with Logistic, Gompertz, and Brody models. Logistic provided the closest fit, capturing the sigmoidal growth pattern and stabilization after week 40.

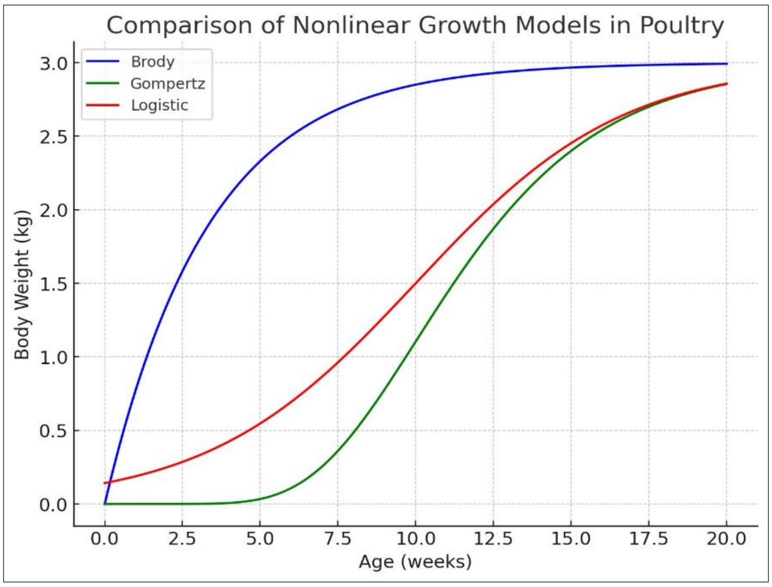

Fig 2: Observed and predicted growth of scavenging Austrolope chickens fitted with Logistic, Gompertz, and Brody models. Brody provided the best fit, reflecting the gradual and extended growth trajectory.

4. Discussion

4.1. Growth Model Performance

The present study demonstrates that growth models vary in their ability to accurately capture the growth trajectories of indigenous chickens subjected to different feeding regimens. The Logistic growth model proved most suitable for lucerne-fed birds, as its sigmoidal curve effectively described their rapid early weight gain followed by a clear plateau at maturity. This pattern aligns with previous reports indicating that well-nourished poultry exhibit accelerated and predictable growth when nutrient requirements are consistently met (Helal *et al*., 2025; Şengül *et al*., 2024) [22, 42].

In contrast, Brody's model provided a better fit for scavenging chickens, reflecting their slower growth rates, prolonged maturation periods, and lower asymptotic body weights. These findings highlight the importance of aligning growth model selection with the prevailing production system. Model mis-specification may bias estimates of growth rate and mature body weight, potentially leading to inappropriate feeding recommendations and ineffective breeding strategies (Abe *et al*., 2022; Narinc *et al*., 2017; Ersoy *et al*., 2006) [1, 2, 33, 14].

4.2. Indigenous and Ecotype Chicken Studies

The results corroborate findings from ecotype chicken studies across Africa, where production environment strongly influences growth model suitability. For example, Logistic and Gompertz functions effectively described the growth of Nigerian Fulani ecotype chickens reared under intensive systems, whereas the Brody model better captured the extended growth patterns of extensively managed birds (Sanusi & Oseni, 2020) [40].

Similarly, studies on Ethiopian Horro and Koekoek chickens have shown that consistent nutrient availability accelerates growth, while scavenging systems result in slower and less predictable trajectories (Selaledi *et al*., 2025; Mulugeta *et al*., 2020; Geleta & Abdulkadir, 2018) [41, 31, 17]. Collectively, these parallels suggest that growth curve analysis can function as a diagnostic tool for assessing feeding regimes and ecological adaptability in indigenous chickens. Moreover, identifying ecotype-specific growth dynamics reinforces the need to conserve genetic diversity and to design interventions tailored to localized production systems rather than adopting generalized models (Mogano *et al*., 2025; Dione *et al*., 2025; Gebru *et al*., 2022; Desta, 2021) [28, 12, 16, 11].

4.3. Lucerne Supplementation

Lucerne supplementation was associated with more stable and predictable growth patterns, confirming its value as a nutrient-dense forage legume rich in protein, essential amino acids, minerals, and bioactive compounds that enhance gut health and metabolic efficiency (Cui *et al*., 2022; Nguyen *et al*., 2022; Grela *et al*., 2020) [10, 35, 20]. Recent studies further highlight lucerne's positive effects on lipid metabolism, immune function, and gut microbiota composition, leading to improved feed conversion efficiency and greater resilience to disease stressors (Ginindza, 2025; He *et al*., 2021; Paredes & Risso, 2020) [19, 21, 38].

These findings have important implications for resource-limited systems, where lucerne cultivation represents a cost-effective and climate-resilient feeding strategy. Integrating lucerne into smallholder poultry systems may reduce reliance on commercial concentrates, which are often financially inaccessible, thereby supporting more sustainable production models (Nyoni *et al*., 2022) [36].

4.4. Genetic and Efficiency Implications

Growth curve parameters, including asymptotic weight, growth rate, and inflection point, possess substantial genetic relevance. Previous research has linked parameters derived from Logistic and Brody models to genomic regions associated with skeletal development, metabolic efficiency, and productivity traits (Nawaz *et al*., 2025) [34]. Consequently, integrating nonlinear growth modeling with genomic selection could enhance breeding precision, particularly in indigenous chicken populations where phenotypic datasets are often limited.

Incorporating growth curve parameters into community-based breeding programs (CBBPs) may enable smallholder farmers to identify birds with superior growth efficiency under local conditions, thereby accelerating genetic progress (Mtileni *et al*., 2023). Furthermore, efficiency metrics derived from growth models can complement emerging sustainability indicators, such as feed conversion optimization and methane mitigation, linking genetic improvement goals to climate-smart livestock production systems (Assan *et al*., 2024).

4.5. Methodological Advances

While classical nonlinear growth models remain valuable due to their interpretability, they may inadequately capture individual variability and irregular growth patterns (O'Brien & Silcox, 2024) [37]. Hybrid statistical–machine learning approaches, including multivariate adaptive regression splines (MARS), random forests, and Weibull-based models, have demonstrated greater flexibility and predictive accuracy in livestock growth studies (Adiguzel & Cengiz, 2023) [4]. These methods are particularly advantageous in smallholder contexts characterized by heterogeneous environments and management practices.

Integrating classical growth models with machine learning approaches offers a balanced framework that combines biological interpretability with enhanced predictive power (Aderele *et al*., 2025) [3]. Future research should also explore precision livestock technologies—such as automated body measurement systems—to generate continuous, high-resolution growth data for improved model refinement (Tedeschi *et al*., 2025).

4.6. Implications for Smallholder Poultry Systems

The combined application of growth modeling, lucerne supplementation, and genomic selection presents significant opportunities to improve productivity and resilience in indigenous poultry systems. Accurate growth predictions enable smallholders to optimize feed allocation, plan market timing, and select suitable replacement stock. Importantly, these strategies align with sustainable development objectives by promoting low-cost, climate-resilient feeding practices while safeguarding indigenous genetic resources.

However, successful implementation depends on strengthening farmers' capacity in record-keeping, data-driven decision-making, and access to affordable feed innovations. Policymakers and development agencies should therefore prioritize extension services, farmer training, and participatory breeding initiatives to ensure that scientific advancements translate into tangible livelihood benefits.

4.7. Limitations and Future Directions

Despite providing valuable insights into indigenous chicken growth dynamics, this study has several limitations. First, the dataset was restricted to a single ecotype and two feeding systems, limiting the generalizability of the findings across diverse agroecological zones. Future studies should incorporate multiple ecotypes and broader production environments to enhance robustness. Second, growth models assume idealized trajectories, whereas environmental stressors, disease pressure, and management variability frequently disrupt growth in smallholder systems. Incorporating environmental covariates, health indicators, and management data could improve predictive accuracy.

Third, although lucerne supplementation showed positive effects, optimal inclusion levels, seasonal availability, and economic feasibility were not assessed—factors that are critical for sustainable adoption. Methodologically, while nonlinear models offer biological interpretability, they may underperform when growth patterns are irregular. Future research should evaluate hybrid frameworks that integrate parametric models with artificial intelligence and precision livestock technologies, including automated imaging, wearable sensors, and remote monitoring.

Finally, linking growth curve parameters to genomic data is promising but requires validation across diverse indigenous populations to ensure marker–trait transferability. Greater emphasis should also be placed on participatory approaches, involving farmers in the co-design of feeding trials and breeding programs. Such strategies would enhance external validity, cultural relevance, and long-term adoption, thereby strengthening the resilience of indigenous poultry systems to climate and market challenges.

5. Conclusion

This study demonstrated that growth modeling is highly management-dependent, with the Logistic function providing the best description of lucerne-fed Austrolope chickens and the Brody function more effectively capturing the gradual growth of scavenging birds. These findings highlight the necessity of selecting context-specific models rather than relying on a one-size-fits-all approach, especially when dealing with indigenous poultry raised under diverse production systems.

From a production perspective, lucerne supplementation accelerated early growth, stabilized trajectories, and reduced variability, thereby offering a feasible pathway for improving feed efficiency and productivity in semi-intensive systems in the tropics. Conversely, scavenging chickens achieved a slightly higher asymptotic weight, albeit at a slower rate, reflecting the adaptive resilience of indigenous birds under resource-limited conditions. These patterns have direct implications for smallholder farmers: lucerne supplementation may be prioritized where inputs are available, whereas genetic selection based on Brody-derived parameters may be better suited for extensive, low-input systems.

Methodologically, the results reaffirm the utility of nonlinear growth functions as tools for predicting body weight, informing feeding strategies, and supporting breeding decisions in aquaculture. However, they also point to the need to integrate classical growth models with advanced approaches, such as genomic selection, precision livestock farming, and machine learning, to capture individual heterogeneity and environmental interactions more accurately.

Ultimately, effective growth modeling of indigenous chickens contributes not only to improved productivity but also to the broader goals of food security, livelihood resilience, and climate adaptation in smallholder poultry farming systems. Future research should extend model comparisons across ecotypes and agro-ecological zones, explore hybrid statistical–computational frameworks, and co-develop feeding and breeding strategies with farmers to ensure scientific rigor and local relevance. By aligning growth modeling with participatory innovation and modern breeding tools, indigenous poultry production can play a pivotal role in building sustainable and climate-resilient food systems in low-input poultry systems in Africa.

Practical Recommendations

- **Feeding strategies:**
  - Promote lucerne supplementation where land and water resources permit, as it accelerates early growth, stabilizes weight trajectories, and improves feed conversion efficiency.
  - In scavenging systems, emphasize complementary feed supplementation during critical growth phases (14–28 weeks) to reduce growth variability and mortality.
- **Breeding programs:**
  - Use growth curve parameters (e.g., Logistic k for lucerne-fed and Brody A for scavenging birds) as selection criteria in indigenous chicken improvement programs.
  - Explore integration of growth modeling with genomic tools to identify genetic markers associated with efficient growth under variable systems.
- **Farmer training and extension:**
  - Train farmers to monitor growth milestones (inflection points, plateau phases) to optimize feed allocation and marketing decisions.
  - Encourage participatory trials so that farmers co-design feeding strategies adapted to local resources and cultural practices.
- **Policy and development support:**
  - Support community seedbanks and local production of lucerne to enhance feed security and reduce dependence on commercial concentrates.
  - Integrate growth modeling findings into extension packages and farmer manuals to improve knowledge transfer.
- **Future innovations:**
  - Invest in low-cost precision tools (e.g., mobile apps, digital scales, image-based body weight prediction) to make growth monitoring accessible to smallholders.
  - Promote hybrid approaches combining nonlinear models with AI-based methods to capture individual heterogeneity and climate-induced variability in growth.

Data Availability Statement: The datasets generated and analyzed during this study are available from the corresponding author upon reasonable request.

Ethics Statement: This study was conducted using observational data from routine farm management practices. All procedures adhered to standard animal husbandry protocols, and no interventions exceeded normal care.

Author Contributions: NA, MP & AD conceptualized the study and drafted the manuscript. EMM curated the data, conducted analyses, and interpreted the results. NA and MP critically revised the manuscript for intellectual content.

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