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Research Article

Using a modified growth model for the spotted rose snapper (*Lutjanus guttatus*) in a floating net cage system in northwestern Mexico

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ABSTRACT. Having the most appropriate model to describe farmed fish growth is a tool for improving responsible aquaculture production. Above 39,000 *Lutjanus guttatus* with an initial weight of 14 g were reared in three floating net cages at three harvest densities (15, 20, and 22 kg m^{-3}) for 360 days of commercial culture. We compared Schnute's growth model with a new growth model for shrimps proposed by Ruiz-Velazco. The first model generates eight curves between sigmoidal, acceleration, and deceleration, resembling the von Bertalanffy, Gompertz, and logistic models. The second model is a modification used to estimate the weight of organisms under culture conditions. We selected the best model using information theory based on Akaike information criterion (AIC). The model with the lowest AIC at density D15 was Schnute case 1. At density D20, the Ruiz-Velazco model received the strongest support, with a probability of 98.2%. For the highest density (D22), support for the Schnute case 2 model declined to 63.3% (Table 2). The fitting results indicated that the best-fitting model varied with density, suggesting our results lacked consistency across the three datasets and prevented generalization to a single best model. These findings also suggest that density influences growth trajectories by altering underlying growth dynamics, implying that growth does not follow a universal pattern across densities. Therefore, researchers should test multiple models and use criteria such as AIC to select the most appropriate model when analyzing species growth under different conditions. Researchers should avoid assuming a default model for analyzing fish growth; generalization may be inappropriate, and more suitable models may be available in specific contexts. Adopting a multi-model inference approach is essential for effectively analyzing growth in aquaculture systems.

Keywords: *Lutjanus guttatus*; cage aquaculture; aquaculture model; expected value model; growth curves; multi-model inference

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INTRODUCTION

The spotted rose snapper (SRS, *Lutjanus guttatus*) is a native species distributed from the Gulf of California to Peru. In Mexico, this species represents a strategic opportunity for diversifying aquaculture production due to its suitability for cage farming. It is highly valued in the market and has demonstrated strong performance under culture conditions, including efficient growth in captivity, tolerance to intensive systems, and acceptance of formulated diets.

Furthermore, the SRS is among the most commercially sought species in northwestern Mexico and is considered one of the best candidates for cultivation in floating net cages. With annual catches ranging from 1,456 to 6,345 mt between 2020 and 2023 (CONAPESCA 2023), concerns have been raised about the sustainability of wild populations (Amezcua et al. 2006). In response, several fishery cooperatives along Mexico's Pacific coast have adopted cage culture as an alternative production system.

Growth performance in cage culture is a key factor influencing production efficiency. However, few growth models are specifically designed for aquaculture applications. Traditionally, researchers have employed models such as the von Bertalanffy (Katsenevakis & Maravelias 2008), Richards (Schnute & Richards 1990), Gompertz (1825), and logistic (Ricker 1975) models to analyze fish growth in weight under culture conditions. These models have long served as standard tools for predictive growth modeling in fisheries and aquaculture science.

The Schnute model (1981) is a versatile and generalized growth model characterized by statistically stable parameters. It encompasses several commonly used growth models-such as the von Bertalanffy, Gompertz, and logistic models-as special cases. The Schnute model includes four parameters and four functional cases, allowing it to generate up to eight distinct growth curve shapes, depending on the values of parameters a and b.

Several efforts have been made to improve traditional growth modeling in aquaculture, such as the model proposed by Ruiz-Velazco et al. (2010) for crustaceans. This model was applied to *Penaeus vannamei* cultured in ponds using intensive production technologies (Hernández-Llamas et al. 2013, Estrada-Pérez et al. 2016) and semi-intensive (Ruiz-Velazco et al. 2013, Estrada-Pérez et al. 2015, 2020, González-Romero et al. 2018). It describes organism weight growth in culture and is a modification of the curve developed by Hernández-Llamas & Ratkowsky (2004), incorporating the cultivation period duration (c). One advantage of this model is that it can be easily fitted using standard nonlinear regression techniques. Additionally, the model's parameters are directly interpretable (biological), as they correspond to the initial and final weights during the cultivation period.

Recent growth studies have applied multi-model inference to identify the most appropriate model for a given fish growth dataset. This approach has been successfully used for snapper species reared in cages (Castillo-Vargasmachuca et al. 2016, Jurado-Molina et al. 2023). Although many models were originally developed for wild fish populations, they have also performed well under culture conditions. However, aquaculture conditions differ significantly from those in the wild, as farmed fish are raised in more controlled environments that promote faster growth and shorter production cycles. Therefore, for rearing purposes, it is crucial to know the limits of growth (Baer et al. 2011). Organism growth performance is the most important factor influencing economic profit in commercial aquaculture facilities (Baer et al. 2011). The economic performance of fish harvest increases as the growth rate in weight approaches the inflection point; after that, it decreases (Springborn et al. 1994).

Prein et al. (1993) noted that aquaculture presents specific challenges for growth modeling, as the primary objective is to maximize profits by achieving rapid growth in a shorter time. Despite this, accurate growth prediction remains essential for effective harvest planning. Improved predictions reduce the risk of unexpected financial losses and poor business decisions (Ansah & Frimpong 2015). Moreover, a robust growth model provides critical insights into biomass dynamics and enables more precise performance monitoring (Baer et al. 2011).

The objective of this study is to describe the growth in weight of the SRS (*L. guttatus*) cultured for 360 days at three harvest densities in floating net cages. Specifically, we compare the performance of the Schnute and Ruiz-Velazco growth models in describing individual weight growth under aquaculture conditions.

MATERIALS AND METHODS

This study was conducted at a commercial farm dedicated to SRS cage aquaculture, located on Isla de la Piedra (Stone Island), Sinaloa, Mexico (23º10'45.5"N, 106º24'29"W). The three floating net cages used belong to "Sociedad Cooperativa de Producción Pesquera Pescadores de la Isla de La Piedra, S.R.L. de C.V.". These were constructed using high-density extruded polyethylene; two cages measuring 9 m in diameter and 3.5 m in depth, and one measuring 9 m in diameter and 4.5 m in depth. The monthly growth of the SRS fish was estimated by random sampling from each cage, and their weight was determined with a digital balance (Velab model VE-5000, Mexico; precision = 0.01 g). Fish were anesthetized with 0.2 mg L^{-1} clove oil. These results are part of a commercial pilot demonstration study comparing three harvest densities in fish growth. The 39,120 hatchery-reared SRS juveniles (60 days old) were obtained with initial mean weights of 14.0 ± 4.9 g and initial mean length of 10.8 ± 1.2 cm from Centro de Investigación en Alimentación y Desarrollo (CIAD-Mazatlán) in Sinaloa, Mexico.

These organisms were randomly distributed and stocked at three initial harvest densities, one for each cage: 15 kg m^{-3} (D15 = 9,300 fingerlings), 20 kg m^{-3} (D20 = 12,340 fingerlings), and 22 kg m^{-3} (D22 = 17,480 fingerlings). Water quality was evaluated daily in all cages with a YSI model 85; water temperature ranged from 18.8 to 31.0ºC, with means of 26.3 ± 1.00ºC for D15, 26.7 ± 1.40ºC for D20, and 26.9 ± 0.95ºC for D22. Dissolved oxygen ranged from 5.3 to 7.1 mg L^{-1} with a mean of 6.1 ± 0.55 mg L^{-1} for D15; 6.1 ± 0.55 mg L^{-1} for D20; and 6.2 ± 0.54 mg L^{-1} for D22. We measured salinity with a Salt Meter (ATAGO model PAL-Fish Tank, Japan), and the values ranged from 34.0 to 36.0, with means of 34.6 ± 0.56 for D15, 34.6 ± 0.51 for D20, and 34.5 ± 0.52 for D22. We measured pH with a digital pH meter (Hanna HI 98130, Woonsocket, RI, USA), ranging from 7.0 to 8.5, with means of 7.8 ± 0.60 for D15, 7.5 ± 0.58 for D20, and 7.6 ± 0.62 for D22.

The fish were fed commercial feed containing 50% crude protein and 12% crude lipids, depending on their size. They were fed twice a day (at 8:00 and 16:00 h) for one year, with feed amount adjusted to the monthly biomass (four weeks) per cage. For more details on the characteristics of the feed, see Silva-Carrillo et al. (2012).

This work focused on a growth model based on an equation developed for aquaculture (Ruiz-Velazco et al. 2010). The following four cases of Schnute's model (Schnute 1981) to describe SRS growth:

Case 1, a ≠ 0 y b ≠ 0

$$\mathrm{W(t)} = \left[\mathrm{W_1}^b + \left(\mathrm{W_2}^b - \mathrm{W_1}^b\right)\frac{1-e^{-a(t-\tau_1)}}{1-e^{-a(\tau_2-\tau_1)}}\right]^{\frac{1}{b}} \quad (1)$$

Case 2, a ≠ 0 y b = 0

$$\mathrm{W(t)} = \mathrm{W_1} exp\left[\log\left(\frac{W_2}{W_1}\right)\frac{1-e^{-a(t-\tau_1)}}{1-e^{-a(\tau_2-\tau_1)}}\right] \quad (2)$$

where W (t) is the individual weight in grams at age *t*, W_1 and W_2 are the total weight at the beginning (τ_1 = 30 days) and the end (τ_2 = 360 days) of the time interval; a is a growth parameter with year units; b is related to the inflection point of the growth curve.

Ruiz-Velazco model, used in aquaculture, is:

$$w_t = w_i + \left(w_f - w_i\right)\left(\frac{1-k^t}{1-k^c}\right)^3 \quad (3)$$

where w_i is the initial weight; w_f is the final weight; k refers to the speed at which weight changes from its initial to final value; and c is culture duration in days (360).

The parameters of the growth equation were estimated by minimizing the log-likelihood LL function:

$$-LL = \frac{n}{2}\log(2\pi\sigma^2) + \frac{1}{2\sigma^2}\sum_{i=1}^{n}\left(W_i^{obs} - W_i^{est}\right)^2 \quad (4)$$

The following parameters and their standard errors were estimated using the nls function in the R Statistical Package (R Core Team 2024): W_1, W_2, a, b, k, w_i, w_f.

To select the best model, the lowest Akaike (1973) criterion was used,

$$\mathrm{AIC_c} = 2P - 2LL \quad (5)$$

where AIC: Akaike information criterion, P is the number of parameters to estimate in the model, and LL is the negative log-likelihood function.

Akaike's weight was also used for model comparison:

$$\mathrm{W_i} = \frac{e^{-0.5\Delta AIC_i}}{\sum_{j=1}^{3} e^{-0.5\Delta AIC_j}} \quad (6)$$

where j is an index representing each of the models used in the analysis (Eqs. 1-3) and $\Delta AIC = AIC_j - AIC_{min}$.

RESULTS

The total culture period for *L. guttatus* was 360 days, encompassing all climatic seasons in the marine zone. At the end of the culture period, a total of 1,216 fish were measured at 15 kg m^{-3}, 1,160 at 20 kg m^{-3}, and 1,246 at 22 kg m^{-3}. A comparison of final weights at day 360 is presented in Table 1. The highest mean weight was observed at the 20 kg m^{-3} density (D20), while the lowest mean weight occurred at the 22 kg m^{-3} density (D22). Additionally, the highest weight standard deviation was recorded at D22.

As mentioned, three growth models (Eqs. 1-3) were fitted to data from three initial harvest densities (D15, D20, and D22), resulting in nine modeling scenarios. All models provided a good fit to the observed weight-at-age data (Figs. 1-3), with relatively small differences

Table 1. Comparison of the mean and standard deviation of the weight (W_{360}) of *Lutjanus guttatus* at 360 days of culture regarding stocking density.

Density (kg m^{-3})	W_{360}
15	429.3 ± 47.7
20	436.8 ± 59.6
22	379.9 ± 68.3

in AIC values. Within each density, a different model produced the best fit (Table 2). For density D15, the best-fitting model was the Schnute model (case 1), while the Ruiz-Velazco model performed best at D20. For density D22, the Schnute model (case 2) provided the best fit.

The results based on AIC weights support the model selection. For density D15, the Schnute case 1 model had an 81.58% probability of being the best-fitting model. At density D20, the Ruiz-Velazco model showed the strongest support, with a 98.2% probability. These values provide strong evidence for the selected models at each density. For the highest density (D22), support for the Schnute case 2 model decreased to 63.33% (Table 2).

The parameter estimates are presented in Table 3. In the Ruiz-Velazco model, the estimated growth rate was consistent across all densities. A similar pattern was observed for parameter *a* in the Schnute model (case 2). In contrast, for the Schnute model (case 1), the highest growth rate (*a*) values were associated with the higher densities (D20 and D22).

All models produced W_1 estimates that were lower than the observed mean weight during the first 30 days (20.6 ± 7.1 g). The closest estimate to this observed mean was obtained from the Ruiz-Velazco model at a density of 22 kg m^{-3}. Regarding the W_2 estimates, for D15, all models underestimated the final observed mean weight (429.27 ± 47.71 g). In contrast, for D20 and D22, W_2 estimates exceeded the observed mean weights (436.81 ± 59.6 and 379.9 ± 68.32 g, respectively).

Parameters W_1 and W_2 are common to all models (Eqs. 1-3). It is important to note that, for each density, the confidence intervals for W_2 from the three models overlap (Fig. 4); therefore, at the 95% confidence level, there is no significant difference in the W_2 estimates. Similar results were observed for W_1 at densities D20 and D22. However, for density D15, the W_1 estimates from the Schnute model options S1 and S2 differed significantly (Fig. 5).

DISCUSSION

A critical first step toward establishing a successful aquaculture enterprise is to provide essential information, such as species growth parameters. Most fish growth analyses rely on a single dataset (Castillo-Vargasmachuca et al. 2016, Jurado-Molina et al. 2018). Additionally, researchers often default to the von Bertalanffy growth model (Torres & Chávez 1987, Dennis 1991, Mexicano-Címtora 1999, Araújo et al. 2002, Allman et al. 2005), which remains the most widely used growth model in fisheries literature. More recently, the von Bertalanffy model has also been extensively applied in aquaculture studies.

In recent years, fisheries science has seen a growing number of available growth models and a trend toward evaluating multiple models for a given species or study (Flinn & Midway 2021). Aquaculture research reflects this trend as well. Several studies suggest that alternative models may better fit observed data than the von Bertalanffy model. For example, Castillo-Vargasmachuca et al. (2016) recommended the Schnute model for *L. guttatus* reared in cages, while Ansah & Frimpong (2015) favored the logistic model for *Oreochromis niloticus* reared in ponds. Zarzar et al. (2023) applied the Weibull model to describe growth of *P. vannamei* in a Brazilian shrimp farm. More recently, McGuigan et al. (2023) demonstrated that the von Bertalanffy weight growth model overestimated weight in *Lutjanus campechanus* to biologically implausible levels.

Due to these inconsistencies, some researchers have sought to improve traditional growth analysis methods in aquaculture studies involving fish, crustaceans, and mollusks (Hernández-Llamas & Ratkowsky 2004, Castillo-Vargasmachuca et al. 2016). Some approaches introduce new models to analyze organism growth, while others apply multiple models simultaneously to the same dataset to identify the best fit for the observed data.

In this study, both approaches were used: a relatively new model was employed, and its performance was compared with two variations of the Schnute model. The new model is a modification of those used by Hernández-Llamas & Ratkowsky (2004) and Ruiz-Velazco et al. (2010), who applied them to analyze weight growth in *P. vannamei* in production systems.

As mentioned, most studies rely on a single dataset sampled at a particular site during a specific period. In contrast, our study utilized three datasets collected from

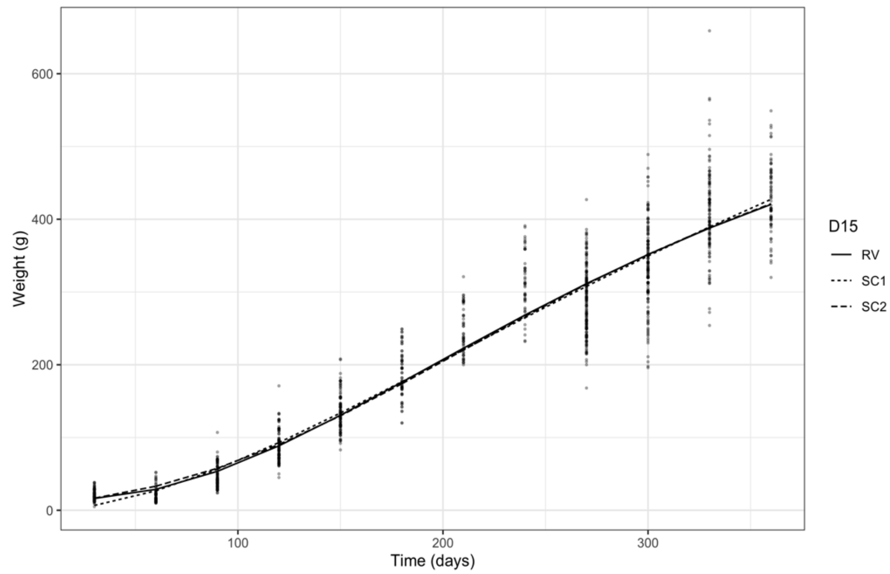

Figure 1. Model fits to observed total weight data for spotted rose snapper cultured in a floating net cage at a density of 15 km m^{-3} (D15). RV: Ruiz-Velazco model; SC1: Schnute model case 1; SC2: Schnute model case 2.

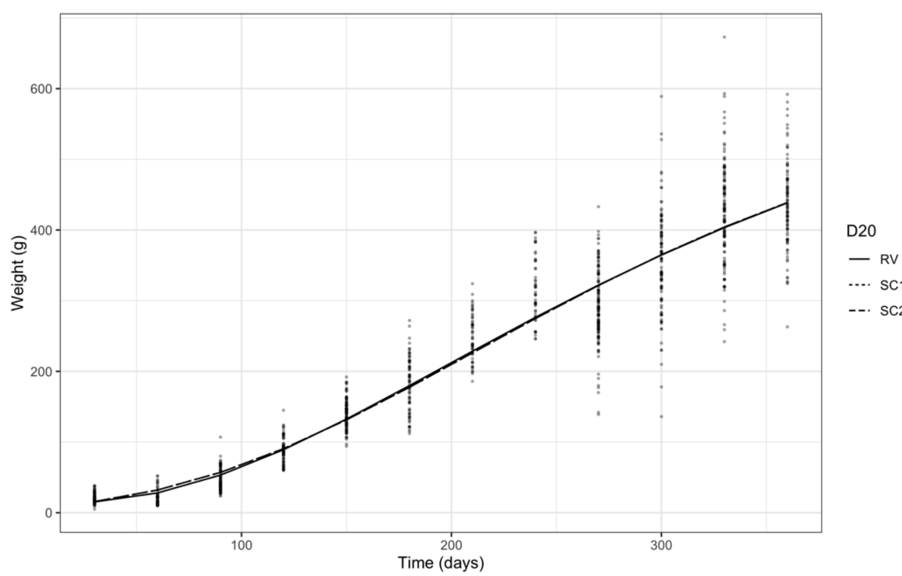

Figure 2. Model fits to observed total weight data for Spotted rose snapper cultured in a floating net cage at a density of 20 km m^{-3} (D20). RV: Ruiz-Velazco model; SC1: Schnute model case 1; SC2: Schnute model case 2.

different cages under varying stocking conditions. An advantage of having multiple datasets is the ability to compare growth performance across different density conditions, which helps identify the optimal stocking density (Jurado-Molina et al. 2023).

Three models were used, and the one that best described growth patterns across varying densities was evaluated. The fitting results indicated that the best-fitting model varied with density, suggesting our results lacked consistency across the three datasets and prevented generalization to a single best model. These findings suggest that density influences growth trajectories by altering underlying growth dynamics, implying that growth does not follow a universal pattern across densities. Therefore, researchers should test multiple models and use criteria such as AIC to select the most appropriate model when analyzing species growth under different conditions.

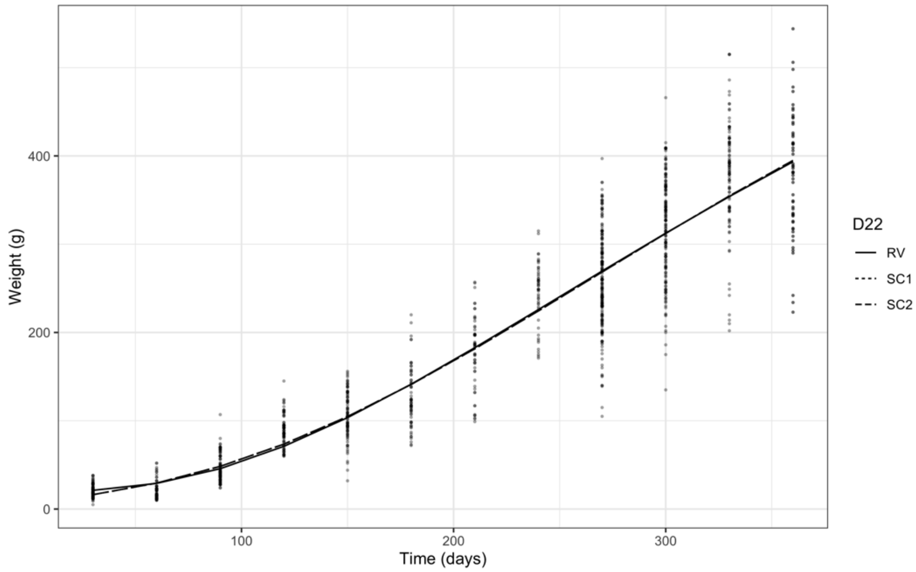

Figure 3. Model fits to observed total weight data for Spotted rose snapper cultured in a floating net cage at a density of 22 km m^{-3} (D22). RV: Ruiz-Velazco model; SC1: Schnute model case 1; SC2: Schnute model case 2.

Table 2. Candidate models used to describe *Lutjanus guttatus* growth reared in floating net cages at different densities (D15: 15 kg m^{-3}, D20: 20 kg m^{-3}, D22: 22 kg m^{-3}). LL; negative log likelihood; AIC; Akaike information criterion used for each candidate model; Wi, weight of evidence in favor of each candidate model; D15, 15 kg m^{-3}; D20, 20 kg m^{-3}; D22, 22 kg m^{-3}. Bold values indicate the highest Akaike weight for each stocking density.

Density	Model	LL	AIC	Wi (%)
D15	Ruiz-Velazco	6284.62	12577.24	18.39
	Schnute C1	6282.13	12574.26	**81.58**
	Schnute C2	6291.08	12590.16	0.03
D20	Ruiz-Velazco	6129.282	12266.56	**98.20**
	Schnute C1	6133.592	12277.18	0.49
	Schnute C2	6133.596	12275.19	1.31
D22	Ruiz-Velazco	6526.929	13061.86	13.37
	Schnute C1	6525.376	13060.75	23.30
	Schnute C2	6525.375	13058.75	**63.33**

The von Bertalanffy, Fox, or Pella-Tomlinson models were not used in this study because the selected models (Eqs. 1-3) provide estimates of W_2, the weight at the end of the growing period. The other models instead estimate the asymptotic weight, which differs conceptually from W_2. All models applied in our work include two parameters: the initial weight (W_1) and the final weight (W_2) during the growing period. While W_1 is less relevant to culture management, W_2 plays a key role, as fish culture profitability depends largely on this parameter. The overlap in the confidence intervals of W_2 suggests that all models produced consistent estimates for this parameter. Therefore, fish farmers can confidently use any of these models to determine the optimal harvest time.

The fish farmer must determine the optimal harvest weight to maximize net profit. In this regard, all three models used in our study can provide this information.

In fisheries, growth information serves as input for stock assessment models, which monitor populations and inform management decisions such as harvest length limits and other regulatory measures (Flinn & Midway 2021). The primary use of growth models in this context is to predict relative (e.g. CPUE) or absolute (e.g. acoustic biomass) abundance indices, thereby optimizing the negative log-likelihood and estimating model parameters. Researchers also use growth models to estimate total biomass and stock status, often incorporating older age classes. For this

Table 3. Parameters estimated for each model in each density for the spotted rose snapper cultured in floating net cages. RV: Ruiz-Velazco model; SC1: Schnute model case 1; SC2: Schnute model case 2. D15: 15 kg m^{-3}, D20: 20 kg m^{-3}, D22: 22 kg m^{-3}. W_1 and W_2: total weight at the beginning (τ_1 = 30 days) and the end (τ_2 = 360 days) of the time interval; *a*: growth parameter with year units; *b*: inflection point of the growth curve.

Model	W_1	W_2	*k*	*a*	*b*	sigma
			D15			
RV	13.84 ± 3.01	420.41 ± 3.23	0.99 ± 0.0002			42.49 ± 0.86
SC1	6.62 ± 3.09	427.39 ± 3.88		0.0034 ± 0.0009	0.50 ± 0.10	42.40 ± 0.86
SC2	16.59 ± 1.72	421.31 ± 3.68		0.007 ± 0.0003		42.72 ± 0.87
			D20			
RV	12.90 ± 3.36	438.46 ± 3.38	0.99 ± 0.0002			47.71 ± 0.99
SC1	15.74 ± 1.84	438.85 ± 3.69		0.007 ± 0.0004	0.0002 ± 0.003	47.88 ± 0.99
SC2	15.75 ± 1.85	438.85 ± 3.69		0.007 ± 0.0003		47.88 ± 0.99
			D22			
RV	19.80 ± 2.96	393.42 ±3.35	0.99 ± 0.0002			45.55 ± 0.91
SC1	16.31 ± 1.79	394.87 ± 3.51		0.006 ± 0.0003	0.0002 ± 0.006	45.52 ± 0.91
SC2	16.32 ± 1.79	394.88 ± 3.51		0.006 ± 0.0003		45.52 ± 0.91

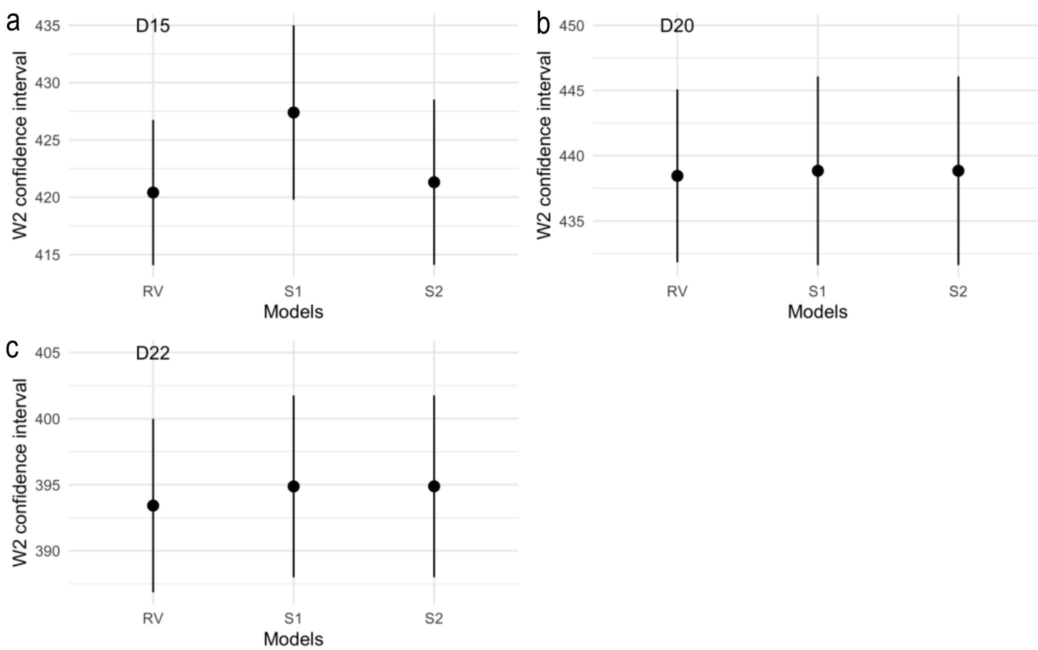

Figure 4. Ninety five percent confidence intervals for total weight at the end of the time interval (W_2) for density of a) 15 km m^{-3} (D15), b) 20 km m^{-3} (D20), and c) 22 km m^{-3} (D22), for the Ruiz-Velazco model (RV), Schnute growth model case 1 (S1), and Schnute growth model case 2 (S2).

reason, estimating asymptotic weight is particularly relevant in fisheries assessments.

In aquaculture, fish farmers typically harvest when growth begins to decline, avoiding older age classes because net profit decreases as biomass gains are minimal at later stages. Therefore, it is more practical to use the models proposed in this study (Eqs. 1-3). The parameter W_2 is critical in fish culture management, as it provides essential information for determining optimal harvest timing to maximize profitability. Consequently, we discourage the use of von Bertalanffy and similar models and recommend employing growth models that include the W_2 parameter to support management decisions in aquaculture better.

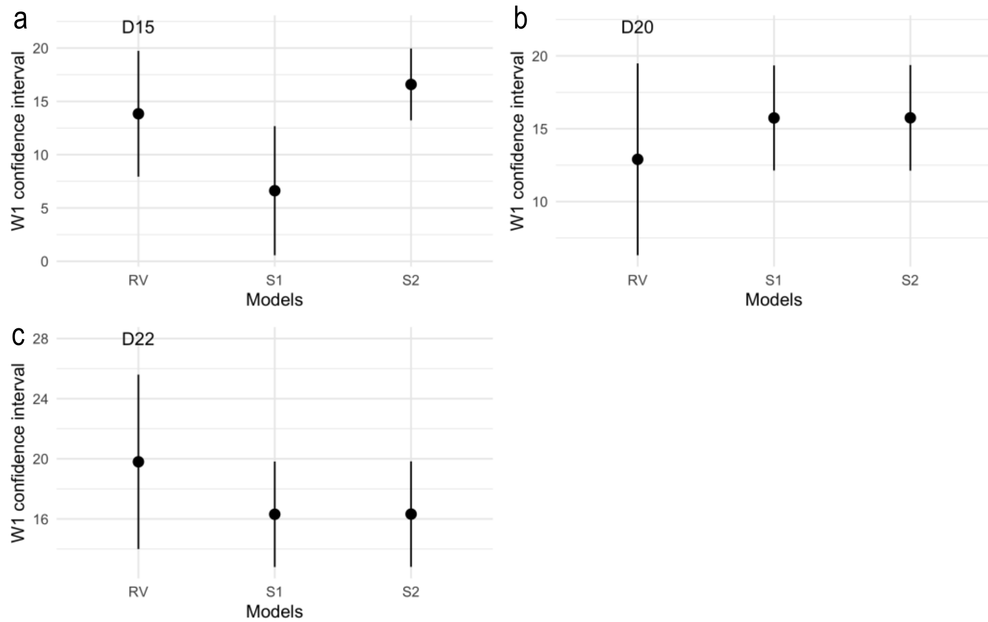

Figure 5. Ninety five percent confidence intervals for total weight at the beginning of the time interval (W_1) for density of a) 15 km m^{-3} (D15), b) 20 km m^{-3} (D20), and c) 22 km m^{-3} (D22), for the Ruiz-Velazco model (RV), Schnute growth model case 1 (S1), and Schnute growth model case 2 (S2).

Future improvements will focus on including density as a covariate in the growth models used (Eqs. 1-3) or within a generalized linear model framework to analyze how density modifies growth over time. Additionally, density can be treated as a random or fixed effect in a nonlinear mixed-effects model, accounting for variability within and between cages. Another improvement will involve assessing variance by comparing residual variance across different density conditions. The availability of multiple datasets will enable estimation of uncertainty using bootstrap or Bayesian methods.

The approach applied in this study aligns with the recent trend of using a multi-model framework for growth curve fitting. Fish farming in cages requires a modern approach that goes beyond conventional growth curves to better model organism growth under farming conditions. Fish species exhibit diverse growth patterns, making it essential to evaluate multiple models to identify the best fit for the observed data. According to the literature, the growth of *L. guttatus* in net cages has been analyzed only by Castillo-Vargasmachuca et al. (2016) and Jurado-Molina et al. (2023) using multi-model inference.

The results of this study indicate that researchers should avoid assuming a default model for analyzing fish growth. These findings suggest that generalization is inappropriate, as no single model performs best across all situations; rather, different models may be more suitable in different contexts. Additionally, the results obtained recommend avoiding traditional fisheries models in favor of those that include the total weight parameter at the end of the culture period (W_2). Therefore, adopting a multi-model inference approach is essential for effectively analyzing growth in aquaculture systems.

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Credit author contribution

C.H. Hernández-López, J. Jurado-Molina, J.M.J. Ruiz-Velazco and N. Estrada-Perez: material preparation, data collection and analysis; C.H. Hernández-López wrote the first draft of the manuscript, and all authors commented on previous versions. All authors contributed to the study conception and design, and read and approved the final manuscript. D. Fischer revised the English language.

Conflict of interest

The authors declare that there are no conflicts of interest regarding this research article.

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