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Assessment of final body weight and feed conversion ratio in batches of growing pigs with statistical modeling

Anderson Luís Garla Oliveira[1], Newton Tavares Escocard de Oliveira[1], Paulo Levi de Oliveira Carvalho[1], Silvana Teixeira Carvalho[1], Érica Beatriz Schultz[2], Jansller Luiz Genova[2]*

[1]Universidade Estadual do Oeste do Paraná – Depto. de Zootecnia, R. Pernambuco, 1777 – 85960-000 – Marechal Cândido Rondon, PR – Brasil.
[2]Universidade Federal de Viçosa – Depto. de Zootecnia, Av. Peter Henry Rolfs s/n – 36570-900 – Viçosa, MG – Brasil.
*Corresponding author <janslllerg@gmail.com>

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ABSTRACT: This study was conducted to assess prediction models for production indexes in batches of growing pigs using performance regressors (period of the year and farm size). A database containing 663 records on the performance of pig batches (18.83 ± 4.37 to 111.26 ± 10.59 kg body weight (BW) at housing and finisher, respectively) from a private company was used to assess the following average animal characteristics: initial number of animals (INA), initial BW (IBW), initial age (IA), final BW (FBW), final age (FA), daily feed intake (DFI) and feed conversion ratio (FCR). Data were categorized by period (P) of the year (P_1 = Nov to Apr and P_2 = May to Oct), and farm size (FS): 0 ≤ INA ≤ 1,000, FS_1; 1,001 ≤ INA ≤ 2,000, FS_2; 2,001 ≤ INA ≤ 3,000, FS_3; and INA > 3,000, FS_4. The analysis resulted in representing 58 % of the variance of FCR data. The INA impaired FCR, and having larger pig batches improves FCR and profitability. The FBW prediction errors ranged from 2.47 to 3.38 %. Feed conversion ratio prediction errors ranged from 3.27 to 4.47 %. Based on the joint criteria of non-bias and accuracy, the models for predicting the FBW of growing pig batches have practical value in animal science on account of their accuracy. In addition, increasing the initial number of housed pigs in batches affects the FCR regardless of the period of the year.

Keywords: daughter equations, growth performance, pig farming, production parameters, statistical models

Introduction

Pig production has transitioned from traditional to modern and intensive systems. Therefore, studies are conducted to benefit producers and the agroindustry. In this regard, farm management depends on performance indicators that are easily measured, monitored (Pierozan et al., 2016; Borges et al., 2018), and aid project financial availability. In Brazil, a great diversity of production systems is found. This challenges measuring and monitoring of the main management indicators (Agostini et al., 2015).

Despite the economic importance of rearing phases, only a few studies have been conducted to assess the financial impact and production variables and their correlation under Brazilian conditions (Borges et al., 2018). Thus, good practices such as pig nutrition, performance analysis, and production standards via statistical modeling (Silva et al., 2016; Callegari et al., 2020) are necessary. They have a low impact on analysis investments, interpretation, and prediction of conditions. However, evaluating the productive traits of farms and pig batches is paramount to establishing production strategies and investments (Callegari et al., 2020).

To this end, statistical models have contributed to the prediction and evaluation of animal production systems (from planning to decision-making) under various conditions. Therefore, properly validated statistical models can predict production indexes and quantify the main production factors (Silva et al., 2016) as an outcome of the increasing efforts of researchers to perform studies involving statistical modeling under the conditions of Brazilian pig production (Agostini et al., 2015; Pierozan et al., 2016; Silva et al., 2016; Borges et al., 2018).

With reliable and accurate statistical models, the animal slaughter weight at a certain age and consuming a feed amount can be predicted (Pierozan et al., 2020), allowing for specific strategies to optimize pig production. Therefore, this study was conducted to adjust prediction models for FBW and FCR in growing pig batches using production indexes. The non-bias and accuracy of the adjusted models in a vertically integrated pig production system were also assessed.

Materials and Methods

A database on the performance of pig batches (18.83 ± 4.37 to 111.26 ± 10.59 kg BW at housing and finisher, respectively) from a private company was used to assess the following average animal characteristics (Table 1): initial number of animals (INA), initial body weight (IBW, kg), initial age at housing (IA, days), final body weight (FBW, kg), final age (FA, days), daily feed intake (DFI, kg) and feed conversion ratio (FCR, kg kg^{-1}).

The average performance was screened, and 663 batch records (n = 180 from 2013, n = 227 from 2014, and n = 256 from 2015) were used. The number of batches per farm was from one to eight. The criterion adopted

Table 1 – Descriptive statistics of performance indexes of 663 growing pig batches, regardless of the period of the year and farm size.

Variable	Average	Standard deviation	Minimum	Maximum
Initial number of animals (n)	1,658	1,112	300.00	6,656
Initial age at housing (days)	59.37	6.750	21.00	72.00
Final age (days)	162.77	10.670	118.00	207.00
Body weight at housing (kg)	18.83	4.370	5.70	28.40
Final body weight (kg)	111.26	10.590	72.60	150.60
Daily feed intake (kg)	2.14	0.159	1.56	2.59
Feed conversion ratio (kg kg^{-1})	2.41	0.136	1.90	2.79

for the performance variables in deciding whether to exclude batch dates was founded on influential observations based on the normal distribution curve of studentized residual values greater than or equal to three standard deviations in absolute value that were considered influential. Then, data were categorized according to period (P) of the year and farm size (FS). Records (n = 157 pig farms) from Nov to Apr were rated as belonging to period 1 (P_1) and those from May to Oct to period 2 (P_2). Ratings for FS were as follows: 0 ≤ INA ≤ 1,000, then FS_1 = 1; 1,001 ≤ INA ≤ 2,000, then FS_2 = 2; 2,001 ≤ INA ≤ 3,000, then FS_3 = 3; and INA > 3,000, then FS_4 = 4. The criteria used to classify the farms by size was based on a commercial production standard recommended by the company.

Influential observations, normality, homogeneity, and linearity of the residues of multiple linear regression models were verified by studentized residual analysis. Whenever studentized residuals exceeded three standard deviations, data were removed so as not to affect β_0 and β_1 estimates in regression analysis. Next, the normality of the regression model residues (obtained stepwise) was evaluated by the Shapiro-Wilk test.

Observed FCR and FBW were estimated by multiple linear regression models using the INA, IBW, IA, FA, and DFI of pig batches. The models included all variables as fixed effects except the residual error, which was considered a random factor. To this end, the ordinary least squares (OLS) method and dummy variables (binary values) for the regressors P dummy (PD) and dummy of FS (DFS_1, DFS_2, and DFS_3) were used. The selection of regressors was based on stepwise. The selection criterion for the stepwise regression was the vast number of potential predictors to include in the statistical model.

The following complete model was initially adjusted according to Eq. (1):

$$y_i = b_0 + b_1x_{i1} + b_2x_{i2} + b_3x_{i3} + b_4x_{i4} + b_5x_{i5} + b_6x_{i6} + b_7x_{i71} + b_8x_{i72} + b_9x_{i73} + b_{10}x_{i6}x_{i1} + b_{11}x_{i6}x_{i2} + b_{12}x_{i3} + b_{13}x_{i6}x_{i4} + b_{14}x_{i6}x_{i5} + b_{15}x_{i71}x_{i1} + b_{16}x_{i71}x_{i2} + b_{17}x_{i71}x_{i3} + b_{18}x_{i71}x_{i4} + b_{19}x_{i71}x_{i5} + b_{20}x_{i72}x_{i1} + b_{21}x_{i72}x_{i2} + b_{22}x_{i72}x_{i3} + b_{23}x_{i72}x_{i4} + b_{24}x_{i72}x_{i5} + b_{25}x_{i73}x_{i1} + b_{26}x_{i73}x_{i2} + b_{27}x_{i73}x_{i3} + b_{28}x_{i73}x_{i4} + b_{29}x_{i73}x_{i5} + \varepsilon_i, \quad (1)$$

where i = 1, ... , n is the number of batches; y_i the average FCR and FBW for the i^{th} batch; $X_i = (x_{i1}, x_{i2}, \ldots, x_{i30})^T$ is a transposed matrix of independent variables (average observations) with 30 rows and n columns; $\beta = (\beta_0, b_1, b_2, \ldots, b_{29})^T$ a vector of regression coefficients (parameters) to be estimated; and ε_i a vector of random errors assumed to be independent and normally distributed, with a mean of 0 and variance σ^2.

The independent variable X_{i6} (period of the year) was found to be a dummy variable. The encodings for P_1 and P_2 were 0 and 1, respectively. The regressor X_{i7} was a dummy variable that represented four different FS. Farm size 1 was coded when the three classes of variable X_{i7} were assumed to be zero (e.g. $X_{i71} = 0$, $X_{i72} = 0$, and $X_{i73} = 0$). The effect of FS_2 was expressed when $X_{i71} = 1$, $X_{i72} = 0$, and $X_{i73} = 0$. The effect of FS_3 was coded when $X_{i71} = 0$, $X_{i72} = 1$, and $X_{i73} = 0$, and the effect of FS_4 was determined when the $X_{i71} = 0$, $X_{i72} = 0$, and $X_{i73} = 1$ encoding was observed.

The significance of each parameter was evaluated via a partial t-test ($p < 0.05$). Multicollinearity among regressors was verified via the variance inflation factor (VIF) associated with each regressor. Regressors that had VIF > 10 were removed from the regression model. The quality of regression model fit was assessed by the coefficient of determination (R^2). The accuracy of the estimates was assessed using standard deviations.

Validation step

Average values (n = 413) of INA, IBW, IA, FA, and DFI in the batches of pigs (11.88 to 27.65 kg BW, and an average of 22.53 ± 2.44 kg BW) reared between 2017 and 2019 were replaced in the 16 regression models that were estimated based on batches from 2013 to 2015. In order to obtain predicted FCR (PFCR) and predicted FBW (PFBW), eight daughter models were fitted for both FCR and FBW. The observed FBW (OFBW) and observed FCR (OFCR) were those obtained in the field by the company.

The fitting of 1st-degree linear regression models for OFBW and OFCR (y) over the respective PFBW and PFCR (x) was performed using OLS. In the 1st-degree model fitting, the significance of the angular coefficient (b_1) suggested the influence of x to explain the variation in y when the partial two-tailed t-test to the null hypothesis ($\beta_1 = 0$) was performed.

Non-bias of 1st-degree models and regression equations were verified in a single step using average performance data in batches from 2013 to 2015. A model was considered non-biased or with no intercept and slope bias when the joint hypothesis ($\beta_0 = 0$ and $\beta_1 = 1$) for the linear regression parameters was accepted by the F-test (Montgomery et al., 2012).

In the matrix, H_0 was given by $T\beta = \theta$ against H_a: $T\beta \neq \theta$, where $T = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$, is an identity order 2 matrix, $\beta = \begin{bmatrix} b_0 \\ b_1 \end{bmatrix}$, a vector of estimates, and $\theta = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$, a column vector related to the β vector expectation. The calculated F statistic to test $T\beta = \theta$ related to the non-bias of a model was given by

$$F_{HO} = \frac{\text{Numerator}}{\text{Denominator}} = \frac{(\beta - \theta)' \times (X'X) \times (\beta - \theta)}{m \times MS_{Res}},$$

where $(X'X)$ is the matrix

$$\begin{bmatrix} n & \sum_{i=1}^{n} X_i \\ \sum_{i=1}^{n} X_i & \sum_{i=1}^{n} X_i^2 \end{bmatrix},$$

X = PFBW or PFCR, m the number of equations to be tested in H_0 (m = 2) and MS_{Res} the residual variance in the regression variance analysis, relative to the contribution of the independent from the regression (Montgomery et al., 2012).

The bias of the 1st-degree models was assessed using accuracy index estimates

$$\left(C_b = \frac{2}{v + \frac{1}{v} + u^2}, v = \frac{\sigma_X}{\sigma_X} \text{ and } u = \frac{(\mu_X - \mu_Y)}{\sqrt{\sigma_X \sigma_Y}} \right)$$

(Lin, 1989). In addition, the accuracy of FBW and FCR prediction models in batches (according to each period combination and FS) was assessed via Pearson's correlation coefficient estimates (r_{XY}) between PFBW (X) and OFBW (Y) and PFCR (X) and OFCR (Y). Next, the mean squared prediction error (MSPE) was calculated (Kobayashi and Salam, 2000; Oliveira and Warpechowski, 2009). Additionally, the relative error (RE) of each batch and the mean relative error (MRE) of each model were calculated.

Statistical differences were set at $p < 0.05$ in all hypothesis tests. All statistical analyses were performed using the R Core Team (2022).

Results and Discussion

Prediction

The estimated regression equation for FBW as a function of the performance, period of the year (P), and farm size (FS) regressors was (Table 2, Eq. (2)):

$$FBW = -46.13 + 0.002\ INA + 0.874\ IBW - 0.851\ IA + 0.851\ FA + 23.72\ DFI - 0.021\ PD \times IA - 0.737\ DFS_2 \times DFI - 0.001\ DFS_3 \times INA\ (R^2 = 0.908) \quad (2)$$

After replacing binary values for P and FS, eight daughter equations were made from FBW mother equation. For pig batches reared in P_1, the estimated daughter equations were according to Eq. (3), (4), and (5):

$$FBW_{FS1\ and\ FS2} = -46.13 + 0.002\ INA + 0.874\ IBW - 0.851\ IA + 0.851\ FA + 23.72\ DFI \quad (3)$$

$$FBW_{FS3} = -46.13 + 0.002\ INA + 0.874\ IBW - 0.851\ IA + 0.851\ FA + 22.98\ DFI \quad (4)$$

$$FBW_{FS4} = -46.13 + 0.0008\ INA + 0.874\ IBW - 0.851\ IA + 0.851\ FA + 23.72 DFI \quad (5)$$

For pig batches reared in P_2, the estimated daughter equations were given by Eq. (6), (7), and (8):

$$FBW_{FS1\ and\ FS2} = -46.13 + 0.002\ INA + 0.874\ IBW - 0.873\ IA + 0.851\ FA + 23.72\ DFI \quad (6)$$

$$FBW_{FS3} = -46.13 + 0.002\ INA + 0.874\ IBW - 0.873\ IA + 0.851\ FA + 22.98\ DFI \quad (7)$$

$$FBW_{FS4} = -46.13 + 0.0008\ INA + 0.874\ IBW - 0.873\ IA + 0.851\ FA + 23.72\ DFI \quad (8)$$

The estimated regression equation as a function of performance, P, and FS regressors, was (Table 3, Eq. (9)):

$$FCR = 1.1762 - 0.00006\ INA + 0.003\ IBW + 0.0009\ FA + 0.504\ DFI + 0.014\ PD \times DFI + 0.00002\ DFS_2 \times INA + 0.00003\ DFS_3 \times INA\ (R^2 = 0.579) \quad (9)$$

The significance ($p < 0.05$) for PD, DFS_2, and DFS_3 allowed us to determine the identity of the models during the multiple regression analysis with dummy variables. Thus, the significance of the interaction PD $\times$ DFI ($p < 0.0001$) in the FCR mother model allowed

Table 2 – Multiple linear regression model identity of final body weight for growing pigs as a function of performance, period of the year, and farm size (FS) regressors (n = 655 batches).

Regressor[1]	Parameter estimation	Standard deviation	p-value	VIF	R^2 (%)
Intercept	–46.13	2.55	< 0.0001	0	90.83
NA	0.002	0.00032	< 0.0001	8.09	
AWH	0.874	0.06238	< 0.0001	4.58	
AAH	–0.851	0.03843	< 0.0001	4.06	
AAE	0.851	0.01464	< 0.0001	1.50	
DFI	23.72	1.01	< 0.0001	1.60	
PD × AAH	–0.021	0.00447	< 0.0001	1.15	
DFS_2 × DFI	–0.737	0.25817	0.0044	2.91	
DFS_3 × NA	–0.001	0.00026	< 0.0001	7.21	

[1]NA = number of animals housed in the batch; AWH = average weight of the batch in housing; AAH = average age of the batch in housing; AAE = average age of the batch at the end of housing; DFI = daily feed intake; PD = period dummy: Nov to Apr (P_1) and May to Oct (P_2); PD × AAH = interaction between PD and AAH; DFS_2 = dummy of FS_2 (1.001 NA ≤ 2.000); DFS_3 = dummy of FS_3 (2.001 NA ≤ 3.000); DFS_2 × DFI = interaction between DFS_2 and DFI; DFS_3 × NA = interaction between DFS_3 and NA; p-value = probability of significance; VIF = variance inflation factor; R^2 = coefficient of determination.

Table 3 – Identity of multiple linear regression model of feed conversion ratio for growing pigs as a function of performance, period of the year, and farm size (FS) regressors (n = 662 batches).

Regressor[1]	Parameter estimation	Standard deviation	*p*-value	VIF	R^2 (%)
Intercept	1.176	0.0668	< 0.0001	0	57.94
NA	–0.00006	0.000009	< 0.0001	8.99	
AWH	0.003	0.00098	0.0006	1.54	
AAE	0.0009	0.00037	0.0129	1.29	
DFI	0.504	0.02729	< 0.0001	1.60	
PD × DFI	0.014	0.00340	< 0.0001	1.16	
DFS_2 × NA	0.00002	0.000006	0.0019	3.24	
DFS_3 × NA	0.00003	0.000007	< 0.0001	7.95	

[1]NA = number of animals housed in the batch; AWH = average weight of the batch in housing; AAE = average age of the batch at the end of housing; DFI = daily feed intake; PD = period dummy: Nov to Apr (P_1) and May to Oct (P_2); PD × DFI = interaction between PD and DFI; DFS_2 = dummy of FS_2 (1.001 ≤ NA ≤ 2.000); DFS_3 = dummy of FS_3 (2.001 ≤ NA ≤ 3.000); DFS_2 × NA = interaction between DFS_2 and NA; DFS_3 × NA = interaction between DFS_3 and NA; *p*-value = probability of significance; VIF = variance inflation factor; R^2 = coefficient of determination.

for separate modeling of FCR in pig batches reared in P_1 and P_2. Daily individual feed intake and INA were the estimates that differentiated equations when the PD × DFI regressor was included in the model.

The ordinary least squares method has been the most used method to obtain estimates in regression models (Esteves et al., 2017; Oliveira et al., 2018; Oliveira et al., 2019). Estimated mother equations were obtained from the adjustment of models containing 30 parameters. All parameter estimates were significant at the end of stepwise because their standard deviations were proportionally much lower than the estimates obtained. Thus, higher t-statistics calculated values were provided (Tables 2 and 3).

The observed R^2 showed that the estimated regression equation explained about 58 % of the variation in FCR as a function of performance regressors (P and FS). Thus, there was an indication that this variation in FCR was explained when considering the independent variables that are part of the equation (Table 3).

Among selected regressors, the highest correlation was between DFI and FCR (r_{XY} = 0.708). This was the first regressor to be part of the model and explained most of the variation (50.23 %) in FCR. Independent variables explained 25 and 46 % of the variation of DFI and FCR, respectively (Borges et al., 2018). These values differ from those (41 and 55 % for DFI and FCR, respectively) reported by Silva et al. (2015). Furthermore, the final models proposed by Agostini et al. (2015) explained 62 and 24.8 % of the total variance for total feed intake and FCR, respectively. These differences in results from previous modeling studies may be due to the difference in variability in the model parameters (Pierozan et al., 2016).

The moderate precision of the mother equation given by R^2 (57.94 %) should not be considered alone as a restriction to its use in animal science and industrial practice because it is necessary to validate the daughter equations in independent samples (Castilho et al., 2015; Esteves et al., 2017; Oliveira et al., 2018; Oliveira et al., 2019). From the original mother equation containing dummy variables, eight daughter equations were created by the identity of the models after replacing the dummies for 0 or 1, according to P and FS.

Original daughter equations for pig batches reared in P_1 were according to Eq. (10), (11), and (12):

$$FCR_{FS1\ and\ FS2} = 1.176 - 0.00006\ INA + 0.003\ IBW + 0.0009\ FA + 0.504\ DFI \quad (10)$$

$$FCR_{FS3} = 1.176 - 0.00004\ INA + 0.003\ IBW + 0.0009\ FA + 0.504\ DFI \quad (11)$$

$$FCR_{FS4} = 1.176 - 0.00002\ INA + 0.003\ IBW + 0.0009\ FA + 0.504\ DFI \quad (12)$$

Estimated daughter equations for pig batches reared in P_2 were given in Eq. (13), (14), and (15):

$$FCR_{FS1\ and\ FS2} = 1.176 - 0.00006\ INA + 0.003\ IBW + 0.0009\ FA + 0.519\ DFI \quad (13)$$

$$FCR_{FS3} = 1.176 - 0.00004\ INA + 0.003\ IBW + 0.0009\ FA + 0.519\ DFI \quad (14)$$

$$FCR_{FS4} = 1.176 - 0.00002 INA + 0.003\ IBW + 0.0009\ FA + 0.519\ DFI \quad (15)$$

Optimal growth performance was observed in pigs housed under hot conditions (Agostini et al., 2015), showing the importance of the period of the year to productive traits. These results agree with those observed by Maes et al. (2004), who reported more significant mortality in pigs housed during a cold season. The authors suggested this could be due to respiratory diseases being more common in cold seasons. Feed conversion ratio improvement was observed in pig batches housed in the summer/autumn compared to batches housed in winter/spring (Silva et al., 2016). The above-mentioned authors attributed these differences to performance level, genotype, or marginal response to weight gain.

The effect of INA on the differentiation among estimated daughter equations (derived from the FCR mother equation) within the same period is explained by the presence of DFS_2 × INA and DFS_3 × INA regressors in the FCR prediction model (Table 3). The effect of DFS_2 suggested a different equation for pig batches reared in FS_3 concerning batches reared on farms with other sample sizes. The effect of DFS_3 suggested that FCR in pigs reared in FS_4 differed from FCR in pigs reared on farms of different sizes.

The effects of environmental or housing factors on pig performance have been previously reported (Borges et al., 2018). Indeed, room restriction affected large groups of pigs, modifying feed consumption patterns (Borges et al., 2018). Pig batch sizes and farm sizes are variable not only due to the production phase, but also due to the complexity of environmental factors such as the availability and location of raw materials (Pierozan et al., 2016).

As regards INA, we observed this regressor impaired FCR. Greater FCR estimated reductions (–0.00006) were observed in pig batches reared in FS_1 and FS_2 compared to those reared in FS_3 (–0.0004) and FS_4 (–0.00002). Thus, the greater the number of animals housed per batch, the more the estimated FCR will be reduced. This is an essential practical finding and suggests that pig farmers should use larger batches to improve feed efficiency and increase their profitability. For FS_4 / P_1 and FS_4 / P_2 categories, there was an estimated influence (–0.00002) of INA on FCR. This suggests an estimated reduction of 0.115 in FCR, representing a 5 % decrease if farmers had batches initially containing 5,000 pigs.

When cost results are simulated based on the values for the averages of FCR (2.41), IBW (18.83 kg), and FBW (111.26 kg) we observed in the present study, a reduction of 0.115 in FCR would result in less than 53,100 kg of feed per batch of 5,000 housed pigs. Such a result would benefit a decrease of about US$ 24,375.22 in the growing phase, based on US$ 0.46 kg^{-1} of feed.

Pig batches kept in pens that house less than 20 animals showed lower DFI (a decrease of 0.026 kg) and better FCR (Borges et al., 2018). Similar results were observed by Ferguson et al. (2001), who reported that animals housed in single pens had greater DFI than those housed in groups of 13 pigs. These results corroborate those previously reported by Pierozan et al. (2016), who observed a decrease in DFI and an improvement in FCR when growing-finishing pigs were housed in pens with less than 20 animals. Such results show that farmers should meet the housing density kg^{-1} BW of growing pigs. This finding is supported by a Vermeer et al. (2014) study, which observed a decrease in the growth rate of growing pigs housed in large groups.

Considering all other parameters constant, housing pig batches with greater IBW provided an estimated increase of 0.003 in FCR. However, housing lighter animals is not of interest in pig production due to health problems, lower slaughter weight, and more days to reach slaughter weight, which represent important economic losses for the producer.

In addition, it is possible to state that daughter equations, derived from the mother model for FCR, have easy applicability because INA, IBW, FA, and DFI (regressors) are easily and frequently measured by animal science companies that aim for profit. It should be noted that the DFI improved FCR. However, this was more evident in batches reared from May to Oct (0.519) than those reared from Nov to Apr (0.504).

Thus, in addition to looking at the number of predictors included in the model, their convenience of measuring should be considered so equations could be made less costly and more applicable (Pozza et al., 2008). Therefore, the implications of batch and FS on the performance of growing pigs can be quantified using data regression analyses due to economic advantages (Turner et al., 2003). In addition, frequent updates of performance traits to be analyzed in a statistical model are possible (Borges et al., 2018).

Validation

In general, ascending and well-defined clouds were obtained for other FBW prediction models. Values of r_{XY} were between the observed and the predicted and ranged from 80.50 % (FBW_A, Figure 1A) to 92.20 % (FBW_C, Figure 2C), which suggests high accuracy. These indexes provided models that were medium to high in magnitude to the OFBW data. The coefficients of determination [$R^2 = (r_{XY})^2$] ranged from 64.80 to 85.01 %, respectively (Figures 1A-D and 2A-D).

However, the equations FBW_A, FBW_B, FBW_C, FBW_D (Figure 1A-D), FBW_B, and FBW_C (Figure 2B and C) showed a trend in F-test for the $\beta_0 = 0$ and $\beta_1 = 1$ hypothesis. Thus, they were not validated for this item, suggesting systematic errors in the measurement of OFBW or PFBW. Systematic errors in the PFBW may be due to measurement errors in some daughter equation regressors (INA, IBW, IA, and FA) (Figures 1A-D and 2A-D). However, these errors are challenging to identify.

Nevertheless, the F-test least square approach to the general linear hypothesis has been questioned in some specific situations. In this test, the rejection of joint H_0 may occur in a highly reproducible assay due to a very small residual error (Lin, 1989). The slope angle of biased models (FBW_A, FBW_B, FBW_C, FBW_D are shown in Figure 1A-D, FBW_B, and FBW_C are shown in Figure 2B and C) relating to the abscissa axis (37.59°; 38.88°; 39.02°; 36.94°; 38.01°, and 37.54°, respectively) was similar to those obtained for non-trending models FBW_A (39.00°) and FBW_D (39.72°) which is shown in Figure 2A and D. The bias of the FBW_C model (Figure 1C) we observed was conflicting when we compared its slope angle (39.02°) or intercept (19.85 kg) values with those of the non-biased FBW_A (39.00° and 20.62 kg, respectively, Figure 2A).

It is worth mentioning that sample size is a factor that should be carefully observed as it can interfere with the results of the F-test. Small samples produce larger table statistics, tend to increase the error mean square in the denominator and reduce values of the X′X matrix in the numerator. As a result, lower values of the calculated statistic and higher *p*-values were observed. Thus, using small samples increases the odds of accepting $\beta_0 = 0$ and $\beta_1 = 1$ and inferring a model's non-bias. Given this, smaller sample sizes in FBW_D (n = 30, Figure 1D), FBW_A (n = 30, Figure 2A), and FBW_D (n = 27, Figure 2D) plus models related to others can be observed. This probably influenced the results of non-bias or agreement of the

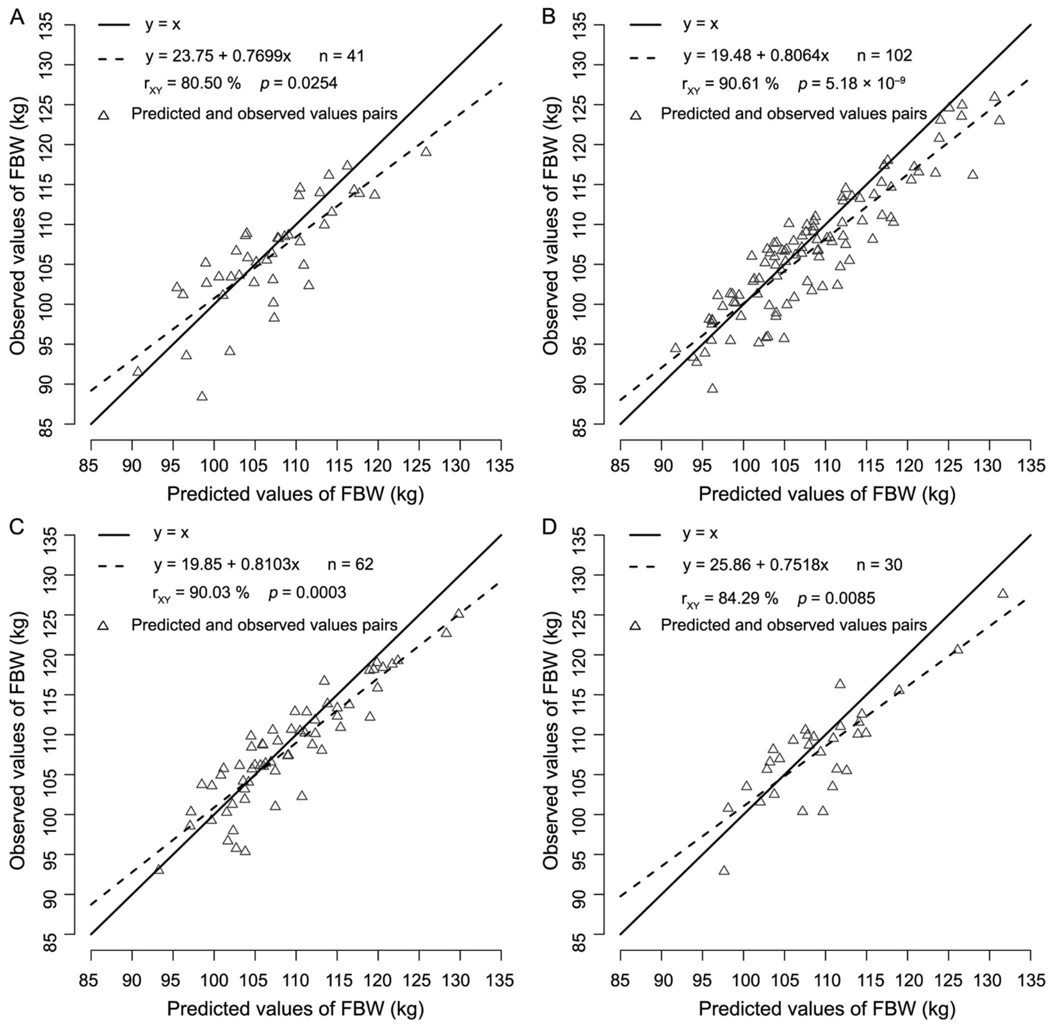

Figure 1 – Graphical assessment of the validation test of the 1st-degree models of the observed values of average final body weight (FBW) on the predicted FBW (dashed line) of pigs in the growing phase from Nov to Apr (P_1) according to farm size: A) up to 1,000 pigs housed; B) 1,001 to 2,000 housed; C) 2,001 to 3,000 housed; and D) more than 3,000 pigs housed. Straight from the ideal condition (solid line); n = pairs of observations in the sample; r_{XY} = sample correlation coefficient between pairs of x and y values for precision; *p* = probability of significance for null hypothesis $\beta_0 = 0$ and $\beta_1 = 1$ of partial t test for non-bias or agreement.

least square F-test for FBW_A (FS_1 in P_2) and FBW_D (FS_4 in P_2) models shown in Figure 2A and D, since validations are more difficult to occur at higher n levels.

Thus, in the quantification of systematic errors of prediction models, estimated bias correction factor values (C_b) ranging from 0.976 for FS_4 in P_1 (FBW_D, Figure 1D) to 0.994 for FS_4 in P_2 (FBW_D, Figure 2D) were observed. Bias correction factor values close to 1.00 suggest high proximity between the lines, that is, accuracy between OFBW and PFBW. These were contrary to the F-test results for FBW_A, FBW_B, FBW_C, FBW_D (Figure 1A-D), FBW_B, and FBW_C (Figure 2B and C) models.

It is worth mentioning that C_b seems to have been a more coherent and reliable metric than the F-test applied to $\beta_0 = 0$ and $\beta_1 = 1$ hypothesis. The bias correction factor calculation considers the standardized bias of means (u), a measure of location regarding dispersion, and the relationship between population standard deviations (σ) of predicted and observed values (v) of FBW. In the present study, the relationships among dispersion varied in a short range (1.045 FBW_A to 1.200 FBW_C are shown in Figures 1A and 2C, respectively). This suggests a low contribution of heterogeneity within each sample (OFBW and PFBW), which overestimates the accuracy index, that is, C_b (Atkinson and Nevill, 1997), a component of the correlation coefficient of agreement expressed by the concordance correlation coefficient (CCC) = $C_b \times r_{XY}$ (Lin, 1989).

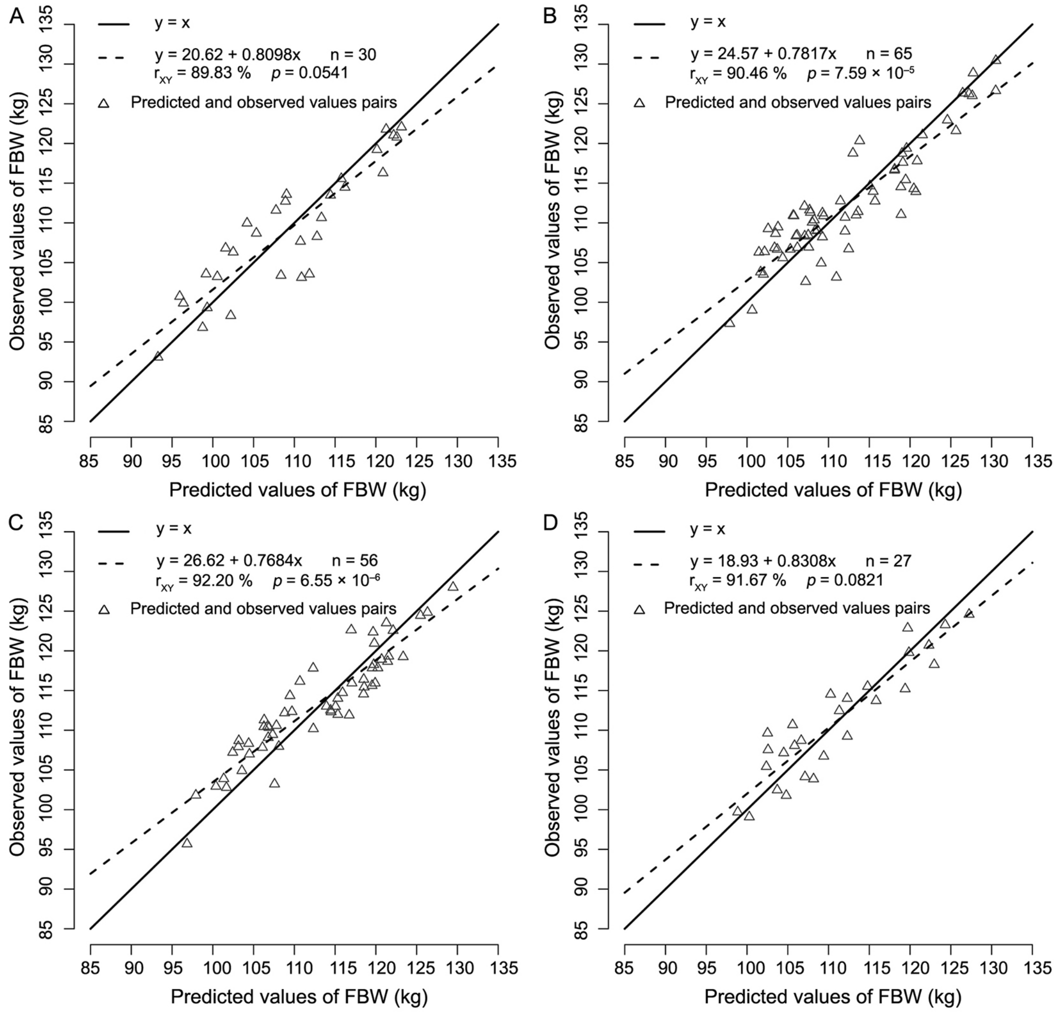

Figure 2 – Graphical assessment of the validation test of the 1st-degree models of the observed values of average final body weight (FBW) on the predicted FBW (dashed line) of pigs in the growing phase from May to Oct (P_2) according to farm size: A) up to 1,000 pigs housed; B) 1,001 to 2,000 housed; C) 2,001 to 3,000 housed; and D) more than 3,000 pigs housed. Straight from the ideal condition (solid line); n = pairs of observations in the sample; r_{XY} = sample correlation coefficient between pairs of x and y values for precision; *p* = probability of significance for null hypothesis $\beta_0 = 0$ and $\beta_1 = 1$ of partial t test for non-bias or agreement.

The MSPE of FBW prediction models were: 9.88 (FBW_C, Figure 2C); 10.04 (FBW_D, Figure 2D); 11.64 (FBW_C, Figure 1C); 12.23 (FBW_B, Figure 2B); 14.65 (FBW_A, Figure 2A); 16.05 (FBW_B, Figure 1B); 17.17 (FBW_D, Figure 1D); and 19.82 kg^2 (FBW_A, Figure 1A). These results showed a relatively small amplitude of MSPE values (9.88 to 19.82 kg^2). The MRE of the models were: 2.47 (FBW_D, Figure 2D); 2.48 (FBW_C, Figure 2C); 2.50 (FBW_C, Figure 1C); 2.53 (FBW_B, Figure 2B); 2.97 (FBW_B, Figure 1B); 2.99 (FBW_A, Figure 2A); 3.31 (FBW_D, Figure 1D); and 3.38 % (FBW_A, Figure 1A). The non-biased FBW_D model showed the lowest prediction error followed by the FBW_C (Figure 2D and C). Although information on model prediction errors is limited, we can state that the difference in the prediction of FBW observed in batches was within an acceptable range (2.47 and 3.38 %) found in the literature. Based on the average FBW of 109.19 (7.63) kg of the 413 batches, predicted error ranged from 2.70 to 3.69 kg.

Intercepts and angular coefficients related to the joint null hypothesis were analyzed to assess FBW prediction models (Figure 2A-D). We observed that batches reared in P_2 and containing up to 1,000 and more than 3,000 pigs were non-biased (0.054 for FBW_A and 0.082 for FBW_D are shown in Figure 2A and D).

The non-bias ($p > 0.05$) of the 1st-degree equations suggests that the models did not show systematic errors and that their accuracy was represented only by their respective precision indexes (Monico et al., 2009). These equations were obtained via regression observed as a function of $PFBW_A$ and $PFBW_D$ models (Figure 2A and D). In addition, these models were related to the ideal condition represented by the bisector of the first quadrant. Thus, the degree of accuracy of the FBW_D model was slightly higher than FBW_A because the estimate of the sample correlation coefficient was greater for FBW_D than for FBW_A.

The visual graphic analysis of the validation test for FBW_A and FBW_D models (Figure 2A and D) showed the lines of 1st-degree linear models formed angles of 39.00 and 39.72 degrees, respectively, with the axis of the abscissas. These results are similar ($p > 0.05$) to the angle of 45° that the ideal condition line makes with the axis of the abscissas (Figure 2A and D). Final body $weight_A$ and FBW_D models showed reasonable accuracy. Estimated correlations between FBW_A and $OFBW_A$ (r_{XY} = 89.83 %) and FBW_D and $OFBW_D$ (r_{XY} = 91.67 %) were high. This suggests clouds of compact points with ascending directions and distances of small magnitude between observed and predicted values on the 1st-degree line.

Thus, the joint assessment of non-bias (F-test) and high precision of the above-mentioned models, suggested that the OFBW was similar to the PFBW when the following equations (Eq. (16) and (17), Figure 2A and D) were used for FS_1 and FS_4 in P_2, respectively:

$$FBW_A = -46.13 + 0.002\ INA + 0.874\ IBW - 0.873\ IA + 0.851\ FA + 23.72\ DFI \quad (16)$$

$$FBW_D = -46.13 + 0.0008\ INA + 0.874\ IBW - 0.873\ IA + 0.851\ FA + 23.72\ DFI \quad (17)$$

For instance, FBW_A and FBW_D models can be used to predict the FBW of growing pig batches in the reported categories.

Seven out of eight adjusted FCR prediction models were valid due to a lack of trend as suggested by the non-significant ($p > 0.05$) results of the F-test (applied to $\beta_0 = 0$ and $\beta_1 = 1$ hypothesis) that we observed (Figures 3A-D and 4A-D). The FCR_B model was the only one not validated (Figure 3B). It showed a trend and systematic errors. A total of 102 pairs of predicted and observed observations were used to adjust the FCR_B model. This corroborates the case that the larger the sample size, the lower the chances of accepting $\beta_0 = 0$ and $\beta_1 = 1$ in the F-test. In this way, validation of the non-bias of a model becomes more difficult.

We observed that the coefficient of accuracy estimates (C_b) ranged from 0.670 for FS_4 in P_1 (FCR_D, Figure 3D) to 0.883 for FS_2 in P_2 (FCR_B, Figure 4B). Other C_b that were close to the 1.00 were 0.873 (FCR_A, Figure 4A), 0.831 (FCR_D, Figure 4D), 0.820 (FCR_A, Figure 3A), 0.812 (FCR_C, Figure 4C), 0.798 (FCR_C, Figure 3C), and 0.794 (FCR_B, Figure 3B). In general, adjusted models for batches of pigs reared in P_2 showed greater C_b than those reared in P_1 (Figures 3A-D and 4A-D).

In the graphical analysis, we observed that FCR_A and FCR_D model lines (Figure 4A and D) were very close (almost overlapping) to the equity line. However, their C_b coefficients were not so close to 1.00, because C_b depends on σ calculation for samples of OFCR and PFCR. This suggests that C_b is an agreement index, that is, conditioned to the variability among batches (Barnhart et al., 2007). High heterogeneity among batches can increase the CCC. This index incorporates a measure of accuracy C_b and a measure of precision $r_{XY,}$ which is a disadvantage for the use of CCC (Lin, 1989) to measure the agreement between pairs of values (Atkinson and Nevill, 1997).

The σ ranged from 0.053 (sample of PFCR for the FCR_D model, Figure 3D) to 0.146 (sample of OFCR for the FCR_A model, Figure 4A). That C_b of FCR_A and FCR_D models (Figure 4A and D) did not reach 1.00 is due to a greater contribution of the scale change component v. Thus, the greater the difference between σ in observed and predicted samples, the lower the C_b. The standard deviation bias acts as a penalty for the coefficient of accuracy C_b. However, we could not detect in the graphical analysis the slight distance of the least square lines of the FCR_A and FCR_D models related to the equity line (Figure 4A and D).

That the FCR_B model was biased based on the F-test (p = 0.008) (Figure 3B), showing 79.42 % of proximity to the equity line resembles FBW models (FBW_A, $FBW_{B,}$ $FBW_{C,}$ FBW_D are shown in Figure 1A-D, FBW_B, and FBW_C in Figure 2B and C), in which the results of the F-test were questioned due to the low residual error (Lin, 1989) or sample size.

The slope angles we observed ranged from 33.54 (FCR_A, Figure 3A) to 53.71° (FCR_C, Figure 4C). The intercepts ranged from –0.927 (FCR_C, Figure 4C) to 0.845 (FCR_A, Figure 3A). Both models were non-biased according to the F-test ($p > 0.05$) and showed a C_b of 0.820 (FCR_A, Figure 3A) and 0.812 (FCR_C, Figure 4C). However, the biased FCR_B model (Figure 3B) formed an angle of 39.75° with the abscissa axis and intercept at 0.438. These values are intermediate compared to those from FCR_A and FCR_C shown in Figures 3A and 4C, respectively. In addition, FCR_B model (Figure 3B) showed C_b of 0.794, which is similar to those shown by FCR_A (Figure 3A) and FCR_C (Figure 4C). A contradiction was then noticed: why did the F-test validate models with extreme intercept and slope indexes, but it did not do so for a model with more parsimonious indexes? Why did the F-test validate the FCR_D model (C_b = 0.670, Figure 3D) but the FCR_B model (C_b = 0.794, Figure 3B)? Given this, the criterion adopted in the present study for the agreement between the OFCR and the PFCR of pig batches was based on the C_b.

Except for the FCR model fitted for batches in FS_3 and P_2 (FCR_C, Figure 4C) which showed an average degree of accuracy (r_{XY} = 71.83 %), the other FCR prediction models were quite imprecise as suggested by correlations between OFCR and PFCR (Figures 3A-D and 4A-D) that ranged from 35.96 % (FCR_A, Figure 3A)

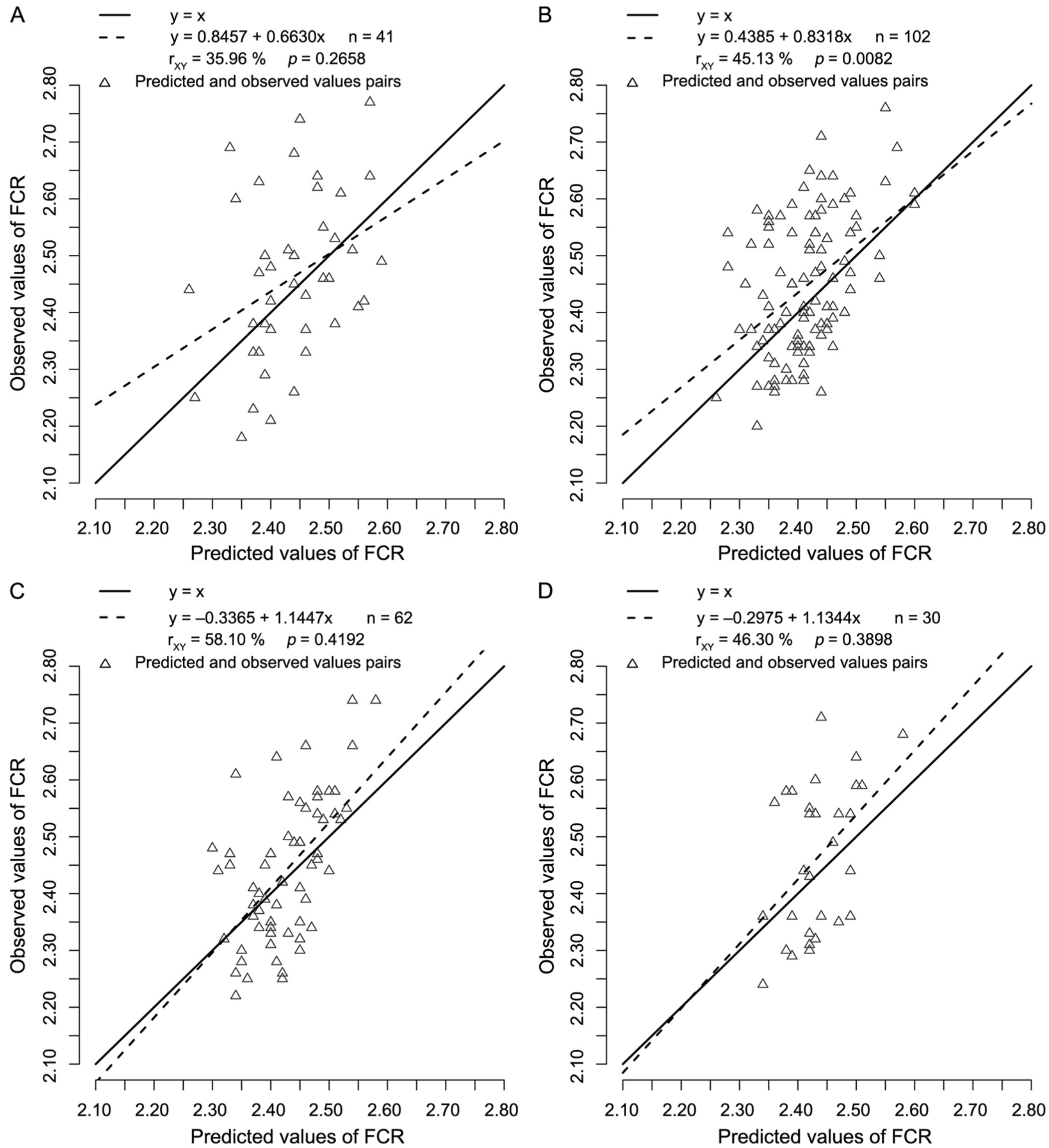

Figure 3 – Graphical assessment of the validation test of the 1st-degree models of the observed values of feed conversion ratio (FCR) on the predicted FCR (dashed line) of pigs in growing phase from Nov to Apr (P_1) according to the farm size: A) up to 1,000 pigs housed; B) 1,001 to 2,000 housed; C) 2,001 to 3,000 housed; and D) more than 3,000 pigs housed. Straight from the ideal condition (solid line); n = pairs of observations in the sample; r_{XY} = sample correlation coefficient between pairs of x and y values for precision; *p* = probability of significance for null hypothesis $\beta_0 = 0$ and $\beta_1 = 1$ of partial t test for non-bias or agreement.

to 58.51 % (FCR_A, Figure 4A). These results showed that the point clouds were dispersed and distant from the adjusted 1st-degree line, suggesting the presence of high-magnitude random errors.

The identification of the leading cause of model imprecision due to a lack of measurements repeatability can be better studied by evaluating MSPE or mean quantitative error. The MSPE, an accuracy index for models, can be divided into three orthogonal components: square of the difference between means (SDM), in which SDM = $()^2$, also known as the quadratic bias of mean; squared difference between σ (SDSD), in which , known as standard deviation bias; and lack of positive correlation weighted by σ (LPC), in which LPC = $2 \times (1 - r_{XY}) \times \sigma_X \times \sigma_Y$.

In the present study, we observed that LPC was the component that most affected FCR precision. Mean squared prediction error ranged from 51.75 % (FCR_D, Figure 3D) to 79.83 % (FCR_B, Figure 4B). These results suggest that low association between the OFCR and PFCR was the main cause of low model precision. A greater SDSD proportion suggests that precision is not observed due to high sample variability in observed or predicted data. Usually, a greater contribution to LPC

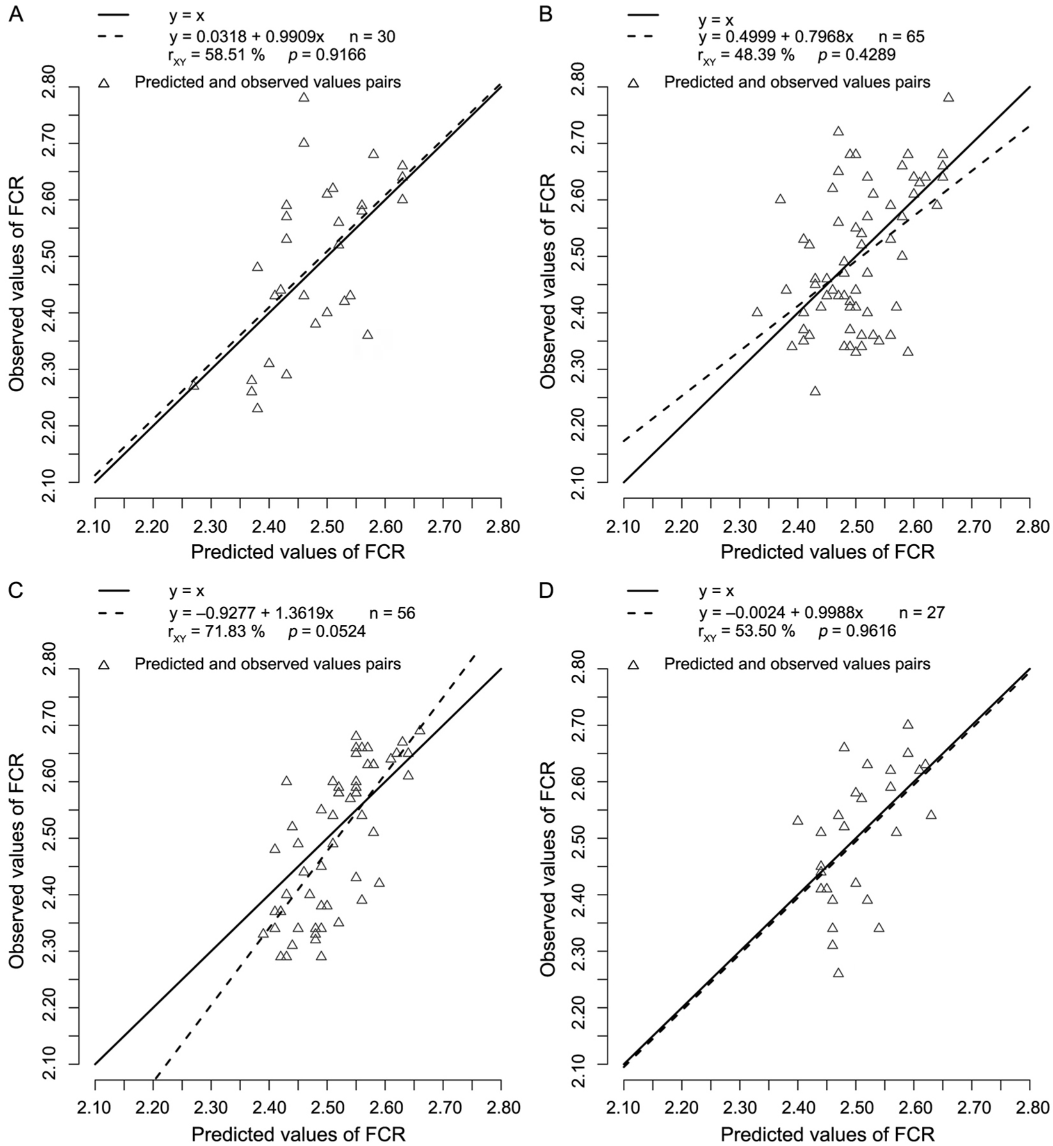

Figure 4 – Graphical assessment of the validation test of the 1st-degree models of the observed values of feed conversion ratio (FCR) on the predicted FCR (dashed line) of pigs in the growing phase from May to Oct (P_2) according to farm size: A) up to 1,000 pigs housed; B) 1,001 to 2,000 housed; C) 2,001 to 3,000 housed and D) more than 3,000 pigs housed. Straight from the ideal condition (solid line); n = pairs of observations in the sample; rXY = sample correlation coefficient between pairs of x and y values for precision; *p* = probability of significance for null hypothesis $\beta_0 = 0$ and $\beta_1 = 1$ of partial t test for non-bias or agreement.

is due to a low association between the observed and the predicted (Kobayashi and Salam, 2000; Oliveira and Warpechowski, 2009).

It is worth mentioning that SDSD was the second component that most influenced the precision of FCR models. Mean squared prediction error ranged from 19.33 (FCR_B) to 41.57 (FCR_C) (Figure 4B and C). Thus, the σ bias was also important on account of the lack of precision we observed. The quadratic bias of means ranged from 0.40 % (FCR_D, Figure 4D) to 7.75 % (FCR_B, Figure 3B) and it had the lowest effect on the poor precision of the models.

The MSPE of models, expressed as kg kg^{-2}, ranged from 0.008 (FCR_C, Figure 4C) to 0.019 (FCR_A, Figure 3A); the lower the MSPE, the more accurate the model. This range we observed in MSPE provided MRE of 3.27 % (FCR_C, Figure 4C), 3.32 % (FCR_D, Figure 4D), 3.33 % (FCR_C, Figure 3C), 3.47 % (FCR_B, Figure 4B), 3.74 % (FCR_B, Figure 3B), 3.77 % (FCR_A, Figure 4A), 4.19 % (FCR_D, Figure 3D), and 4.47 % (FCR_A, Figure 3A). The PFCR ranged from 2.41 (FCR_A, Figure 3A) to 2.51 (FCR_C, Figure 4C). The FCR_C model (Figure 4C) showed the lowest prediction error followed by the FCR_D model (Figure 4D). The range observed for MRE values in FCR prediction was greater than the amplitude observed in FBW prediction. The difference in the prediction of observed FCR was within the acceptable range (3.27 to 4.47 %). Considering the average FCR we observed for the 413 batches, 2.47 (0.13) kg kg^{-1}, the predicted error ranged from 0.081 to 0.110 kg kg^{-1}.

The statistical modeling approach in pig production can be used to study variability in companies and producers separately. This also provides different and complementary information (Agostini et al., 2015). Thus, facility traits, management, nutrition, and herd health directly affect not only the growth performance of the animals but also the selection of parameters for statistic models (Silva et al., 2015; Silva et al., 2016). This provides the means for evaluating performance at the farm or company level (Borges et al., 2018; Callegari et al., 2020).

Collectively, the results of this study using statistical modeling offer pig companies and farms a way to predict the weight of factors (e.g. period of the year, FS, number of animals at housing, average housing age, DFI) on their production indexes and appears to be an effective tool in making management decisions and how this impacts on growth performance indexes (e.g. FBW and FCR). Under the conditions assessed, the main characteristics that affected biological responses were: a) number of pigs housed (more pigs housed, but housing lighter animals); b) FS (the more pigs housed in the batch, the more FCR will be reduced); and c) period of the year (DFI positively influenced FCR, but this influence was stronger in batches from May to Oct).

In conclusion, the prediction models for the FBW of growing pig batches showed non-biased systematic errors of little importance in the prediction as well as reproducibility in the measurements and random errors of small magnitude. In addition, the prediction models for average FCR are not biased, but they lack precision and have random errors of great importance. Based on the joint criteria of non-bias and accuracy, the models for predicting the FBW of growing pig batches have practical value in animal science due to their accuracy. In addition, increasing the initial number of housed pigs in batches affects the FCR regardless of the period of the year, showing that farmers must meet the housing density kg^{-1} BW of growing pigs.

Authors' Contributions

Conceptualization: Oliveira ALG, Oliveira NTE, Carvalho PLO. **Data curation:** Oliveira ALG, Oliveira NTE. **Formal analysis:** Oliveira NTE, Genova JL. **Funding acquisition:** Carvalho PLO, Oliveira ALG. **Investigation:** Oliveira ALG. **Methodology:** Oliveira NTE, Genova JL. **Project administration:** Carvalho PLO. **Resources:** Carvalho PLO, Oliveira ALG. **Supervision:** Oliveira NTE, Carvalho PLO, Carvalho ST. **Writing-original draft:** Oliveira NTE, Genova JL, Schultz EB. **Writing-review & editing:** Oliveira ALG, Oliveira NTE, Genova JL, Schultz EB, Carvalho PLO, Carvalho ST.

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