

MODEL FIT AND THE ACCURACY OF METHODS PREDICTING BODY WEIGHT FROM BODY MEASUREMENTS IN INDONESIAN BALI CATTLE (*BOS JAVAINCUS* D'ALTON, 1823) POPULATION

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Abstract. This paper aimed to provide a reliable method to predict Bali cattle's body weight (BW). In total 1051 records were obtained which comprised of BW, Chest Girth (CG), Body length (BL) and Whither Height (WH) data from three age groups (weaning, yearling and mature). Data were analyzed separately for each sex and age groups. The predicted BW data were derived from two linear models and conversion from cattle weight measure tape. The model with CG, BL and WH as predictor has better model fits than the model with only CG. Both models have reliable prediction ability indicated by low RMSE (6.623 - 18.684) and CV-RMSE values of less than 25%. Utilizing measuring tape as prediction tool is not recommended due to its poor performance (CV-RMSE > 25%). Bali cattle is a distinct cattle species with unique characteristics; hence, linear model is a suitable method to predict the BW for further purposes.

Keywords: *cattle body weight, reliable prediction, Indonesian native cattle, linear model fit*

Introduction

Applying linear models to predict cattle weight based on their body measurements is a common practice in livestock industry. Studies revealed that employing linear regression model to predict body weight based on their chest girth (CG) has a high model fit; indicated by the coefficient of determination values (R^2) of more than 60% in crossbred dairy cattle in Kenya (Lukuyu et al., 2016), brown-swiss cattle in Turkey (Ozkaya and Bozkurt, 2009) and also in Ethiopian oxen (Goe et al., 2001). Other predictor variables such as body length (BL) and whither height (WH) were also reported to be informative in explaining the variation in cattle's body weight (Heinrichs et al., 1992; Lukuyu et al., 2016; Ozkaya and Bozkurt, 2009).

The goodness of fit for linear models in predicting livestock's body weight based on their body measurements is usually represented by the coefficient of determination (Gunawan and Jakaria, 2007; Lukuyu et al., 2016; Ozkaya and Bozkurt, 2009). It indeed tells us about how good a model is in explaining the variation of the data; however, it does not tell us about the predictive ability of the model. In order to achieve an accurate prediction model, it needs to be tested; an option is by employing cross validation technique. It is a method in which dataset was partitioned into training and test sets

iteratively; the training set was used to build prediction model and the test set was used to validate the model and then to estimate the accuracy of the model prediction (Efron and Gong, 1983; Kohavi, 1995; Schaffer, 1993).

Another method of obtaining the predicted body weight is by utilizing cattle measuring tape (Rondo®); which basically also an application of linear model with CG as the predictor variable. This measuring tape is widely used by livestock practitioner in various countries in Asia (Samosir and Hakim, 2016; Wangchuk et al., 2018). However, its accuracy in predicting body weight of Bali cattle is yet to be estimated.

Bali cattle (*Bos javanicus*) is an Indonesian native cattle species. It is originated from wild Banteng which was first domesticated in the isle of Bali (Copland, 1996; Mohamad et al., 2009; Sutarno and Setyawan, 2015). Most of Bali cattle were reared in semi-intensive farming system (Sari et al., 2016) and mostly owned by smallholder farmers with 2-5 cattle per household (Martoyo, 2003). Considering this condition, using body measurements as productivity indicator is preferred by both farmers and the distributors. The reason is mainly for the sake of ease of practice, especially when the access to weighing scale is limited. The ability to accurately predict the cattle's body weight is essential in order to avoid the underestimation of the cattle's economical value as well as in aspects related to veterinary services specifically in administering the correct dose of drugs to the livestock (Machila et al., 2008).

Although methods in predicting body weights based on the body measurements in livestock are common, the level on the fitness and predictive ability vary, depend on the breed or species, sex, age as well as environmental factors. It is thus, specific models need to be developed for different livestock commodities with different production systems. Bali cattle are genetically distanced from two other more commonly found cattle species namely *Bos taurus* and *Bos indicus* (Mohamad et al., 2009); hence, in this study we aimed to distinctively build a body weight prediction model specifically for this species.

Materials and methods

Data collection

Data were collected from the progeny test population at the Bali cattle Breeding Center (BPTU-HPT Plulukan, Singaraja, Bali; 8.4268° S, 114.8639° E) to minimize the chance of having systematic environmental effects. In this facility, mature and fertile female cattle were kept in paddocks with 30 individuals per colony. During the month of September – November, one tested bull was moved in into each paddock to mate naturally with the females. Hence, every year, in this breeding center, the calves were born within approximately the same time period. The obtained data comprised of body weight (BW), body length (BL), chest girth (CG) and wither height (WH). The measurements were conducted on cattle at weaning (age 205 days ± 30 days); yearling (age 365 days ± 30 days) and mature (age > 547 days).

The cattle were weighed with electric weighing scale for livestock with maximum capacity of 2000 kg to the closest 500 g. Rondo® tape was used to measure the CG (in cm) as well as to obtain the instantly predicted body weight (in kg), by observing the opposite side of the tape of the CG value. CG value was obtained as the circumference of the chest behind the front shoulders. BL was measured as the distance from the highest point of the shoulders to the pin bone; and WH was measured as the distance from the ground to the highest point of the withers (Lukuyu et al., 2016). Data with

missing values, outliers and any anomalies were removed. In total there were 447 records for weaning age (245 male and 202 female); 376 records for yearling age (202 male and 174 female) and 228 records for mature age (126 male and 102 female).

Data analysis

Data analysis were conducted separately for each age group (weaning, yearling and mature) and sex group (male, female and overall) resulting in total of nine subsets of data. Summary statistics of the observed variables are presented in *Table 1*. T-test with $\alpha = 0.05$ were performed to test the difference between the male and female cattle body weight and body measurements. There were two prediction approaches used in this study: 1) linear regression models and 2) body weight prediction based on the Rondo® measuring tape. Prior to model building, Principal Component Analysis (PCA) biplot was used to visualize the correlations among the observed variables.

Table 1. Summary statistics of the observed variables

Traits	Number of observations	Mean \pm standard deviation			
		Body weight (Kg)	Chest girth (cm)	Body length (cm)	Whither height (cm)
Weaning					
Male	245	87.54 \pm 14.32 ^a	105.48 \pm 10.46 ^a	82.53 \pm 7.11 ^a	87.34 \pm 7.37
Female	202	81.42 \pm 13.45 ^b	103.11 \pm 7.13 ^b	81.31 \pm 5.61 ^b	86.79 \pm 4.52
Yearling					
Male	202	124.28 \pm 16.52 ^a	121.13 \pm 6.09 ^a	91.38 \pm 6.39 ^a	95.64 \pm 4.87 ^a
Female	174	110.81 \pm 7.66 ^b	108.51 \pm 7.51 ^b	88.25 \pm 7.08 ^b	92.32 \pm 4.74 ^b
Mature					
Male	126	199.61 \pm 50.69 ^a	145.10 \pm 13.30 ^a	109.08 \pm 9.78 ^a	110.76 \pm 6.84 ^a
Female	102	163.00 \pm 34.83 ^b	134.63 \pm 10.45 ^b	101.61 \pm 6.41 ^b	103.72 \pm 5.20 ^b

Two basic linear models were built to predict Bali cattle's body weight (BW) based on body measurements at different age and sex groups. The first model (*Model 1*) is a simple linear regression with CG as the predictor. The second model (*Model 2*) is a multiple linear regression with all body measurements (CG, BL and WH) as the continuous independent variables. The models read:

$$BW_{ijk} = \beta_{01ij} + \beta_{11ij}CG_{ijk} + \varepsilon_{1ijk} \quad (\text{Model 1})$$

$$BW_{ijk} = \beta_{02ij} + \beta_{12ij}CG_{ijk} + \beta_{22ij}BL_{ijk} + \beta_{32ij}WH_{ijk} + \varepsilon_{2ijk} \quad (\text{Model 2})$$

where i = weaning, yearling, mature; j = male, female, overall; $k = 1, 2, \dots, n_{ij}$. ε_{hijk} is the error term for individual k in model h for the age group i and sex group j . β_0 's is the intercept. β_1 's, β_2 's, and β_3 's are the regression coefficient for CG, BL, and WH respectively. In total eighteen models were analyzed. The coefficient of determination (R^2) and the standard error of prediction (SEP) were estimated for each model as the parameter of model fitness. Validations were conducted to the eighteen models by means of Leave One Out Cross Validation (LOOCV).

We applied both models (*Models 1* and *2*) to all nine data subsets (based on three age groups and three sex groups); in total 18 equations were made. For each of the nine group, we also obtained predicted BW values from Rondo® measuring tape. To evaluate the prediction quality, we calculated the Root of Mean Squared Errors (RMSE), both as estimated value and as Coefficient of Variation (CV) presented in percentage (%); and AIC (Akaike Information Criterion) which specifically performed to compare *Models 1* and *2* within each subset of data.

Data were analyzed using R programming language (R Core Team, 2020). The R package 'caret' (Kuhn, 2012) was employed for running the LOOCV; package 'tdr' (Lamigueiro, 2018) was used to estimate the predictive ability metrics and as crosscheck for the estimates obtained from LOOCV with 'caret'. Graphical data visualization was assisted by 'ggplot2' (Wickham, 2016) and 'factoextra' (Kassambara and Mundt, 2020) packages.

Results and discussion

Summary statistics of body weight and body measurements

Body weight and body measurements data at weaning were collected at age range of 175 – 235 days; yearling was at age range of 335 – 400 days, whereas mature age was collected above the age of 547 days or 1.5 years (*Table 1*). Male cattle were significantly heavier ($P \leq 0.05$) during weaning age compared to the female cattle. They also had significantly bigger builds in terms of CG and BL when compared to the female cattle. This trend was also consistent for yearling and mature age groups.

Bali cattle is relatively small when compared to *Bos indicus* and *Bos taurus*. The mean weaning weight (WW) of male and female cattle in this study is within the range of Bali cattle WW reared in different locations in Indonesia which were between 64.4 – 83.9 Kg (Martoyo, 2003); but lower compared to the breeding stocks of the same institution where the data was obtained, which were 87.00 – 90.48 kg for female cattle and 88.51 – 98.92 Kg for male cattle (Sari et al., 2016). Yearling weight (YW) of the cattle in this study were also within the normal range of 99.2 – 14.33 Kg (Martoyo, 2003; Sari et al., 2016). The mature weights (MW) in our study on average were 199.61 and 163.00 kg for male and female cattle, respectively. This MW values are lower than other studies, which mentioned the mean of mature weights were ranged between 200 to 300 kg (Lindell, 2013; Martoyo, 2003). The average cattle's age at the collection of MW data in this study was 650 days or around 1.9 years; difference in measurement age might contribute to the variation of MW.

The difference in body weight and body measurements between sexes became larger as they get older (*Fig. 1*). From this figure, it is clearly visible that although there are still increases in body weight after the cattle matured (age > 1.5 years; yellow dots), but the body measurements of CG, BL and WH were relatively constant. However, from weaning to yearling the increases in CG, BL and WH are still observable. These results are reasonable as bone structure and body conformation change during animal's growth due to hormonal and physiological reasons (Ford and Klind, 1989).

Model building

In total eighteen linear regression models were built to predict body weight based on body measurements. The most common and most important body measurement variable

for body weight prediction is CG as it represents the circumference of the cylindrical shape of cattle's body. *Model 1* in this study used CG as the independent variable as suggested by earlier studies (Abdelhadi and Babiker, 2009; Gunawan and Jakaria, 2007; Kashoma et al., 2011; Lukuyu et al., 2016; Ozkaya and Bozkurt, 2009; Tisman et al., 2015; Vanvanhossou et al., 2018).

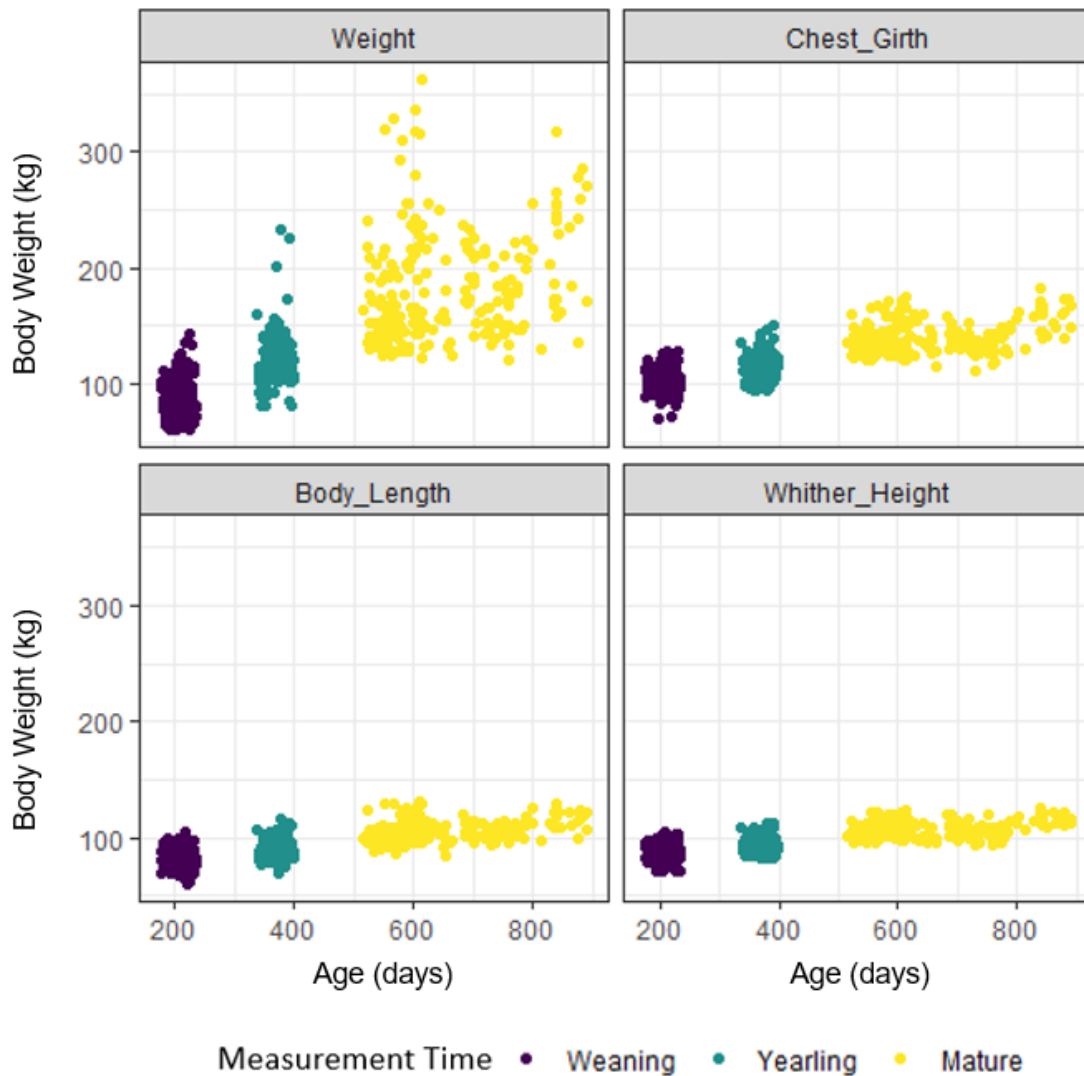


Figure 1. The distribution of body weight and body measurement variables across measurement time

Model 2 incorporates all the body measurements (CG, BL and WH) in a multiple linear regression. Both BL and WH shares low positive correlation with BW (*Fig. 2*); however, the inclusion of these variables might improve the model's fitness and predictive ability (Gunawan and Jakaria, 2007; Sahu et al., 2017).

We visualized the correlations among the observed variables in our study with the aid of a PCA-biplot. PCA-biplot contained information regarding the PCA score and the loading plot; the smaller the angle between vectors on the same side of the plot showed high positive correlation while larger angle showed less correlation (Ott et al., 2010).

The result of PCA analysis showed that the principal component 1 (PC1) explained 90.70% of the total variances whereas PC2 explained 5.20%; hence, these principal components explained sufficient amount of variance to visualize the correlations among explanatory variables in the data without losing much information. *Figure 2* showed that body weight had the highest positive correlation with CG. Studies also suggested that the correlation coefficient between body weight and CG were high; with values between 0.84 – 0.90 in Bali cattle (Gunawan and Jakaria, 2007; Papatungan et al., 2018), 0.57 – 0.80 in Sahiwal cattle (Sahu et al., 2017), 0.92 – 0.95 in Somba cattle (Vanvanhossou et al., 2018) and 0.93 – 0.94 in Tanzanian Shorthorn (Kashoma et al., 2011). The widely used Rondo® measuring tape is also based its prediction on CG value (Machila et al., 2008; Wangchuk et al., 2018).

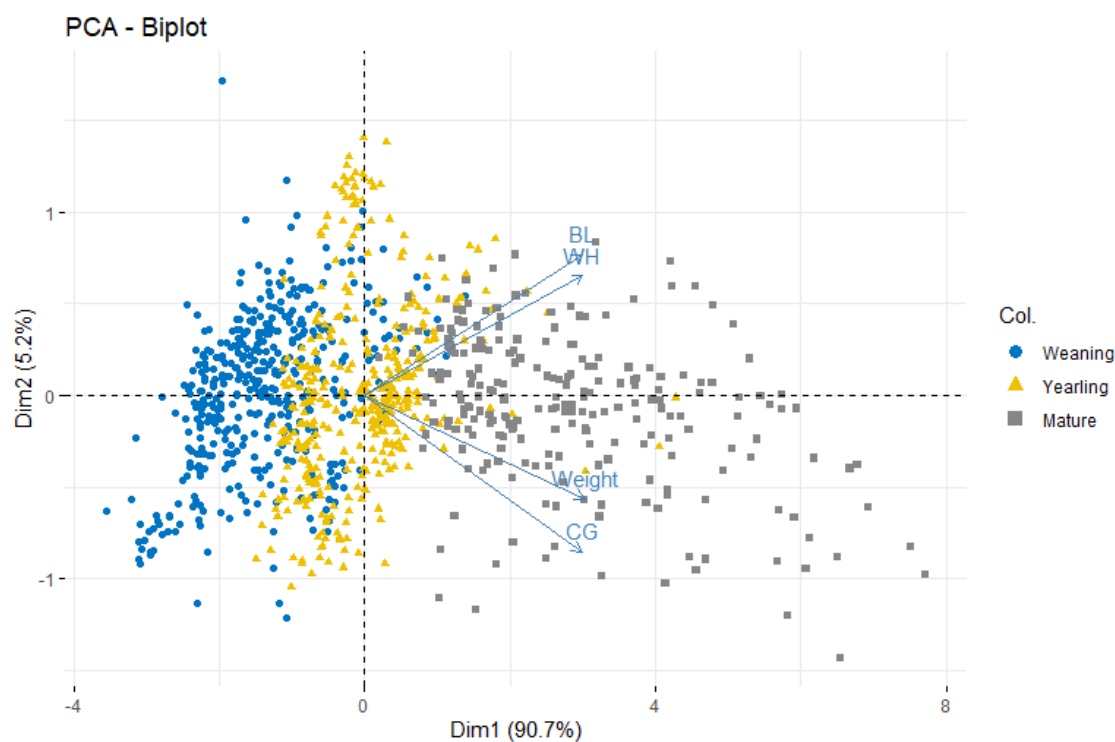


Figure 2. PCA-biplot to show the correlation between body weight and the body measurements in different observation time.

Linear models to predict body weight from body measurements

The linear regression models of body weight on body measurement variables for the three age and the three sex groups are presented in *Table 2*. Internal validity checks were performed by testing for outliers with residual QQ plots for both lowest and highest values in each subset of data. Homoscedasticity was also tested with the plots of fitted-residual values. The results (not shown) indicated that there were no outliers and there were randomly spread residual variances in all subsets of data. The parameter estimates of the linear models along with their standard error of predictions (SEP) are presented in *Table 2*.

Standard error of prediction measures the dispersion of predicted values from the known values; hence it indicates how precise the prediction equation is (Hennig and

Cooper, 2011; Hinton, 2014). In this study, two models were tested on each data subset; and the model with the smaller SEP is considered as giving more precise prediction (Hennig and Cooper, 2011). The results in *Table 2* showed that across all sexes and age groups, *Model 1* with only CG as predictor variable have lower SEP compared to *Model 2* with CG, BL and WH as predictor variables. The adjusted coefficient of determinations (*Table 3*), however, were higher in *Model 2* in all equations. Equations in *Model 2* indeed explained more variances in the data subsets compared to *Model 1*; but *Model 1* gave more precise predictions than *Model 2*.

Table 2. Linear models to predict body weight from body measurements

Equation number	Factors	Linear regression equations	SEP*
	<i>Male</i>		
1	Weaning	BW = 13.627 + 0.700CG	0.858
2		BW = -48.521 + 0.398CG + 0.519BL + 0.587WH	2.734
3	Yearling	BW = -107.629 + 1.915CG	1.737
4		BW = -146.975 + 1.434CG + 0.636BL + 0.413WH	4.027
5	Mature	BW = -298.887 + 3.435CG	5.563
6		BW = -337.483 + 2.464CG + 1.475BL + 0.168WH	10.406
	<i>Female</i>		
7	Weaning	BW = -70.835 + 1.477CG	0.822
8		BW = -103.054 + 1.184CG + 0.401BL + 0.343WH	3.608
9	Yearling	BW = 92.625 + 0.1676CG	0.585
10		BW = 12.218 + 0.209CG + 0.075BL + 0.751WH	1.926
11	Mature	BW = -254.947 + 3.105CG	3.254
12		BW = -326.738 + 2.625CG + 0.668BL + 0.660WH	6.483
	<i>Overall</i>		
13	Weaning	BW = -13.678 + 0.943CG	0.628
14		BW = -70.118 + 0.611CG + 0.553BL + 0.526WH	2.191
15	Yearling	BW = 3.815 + 0.991CG	0.690
16		BW = -78.103 + 0.759CG + 0.483BL + 0.693WH	1.983
17	Mature	BW = -287.439 + 3.352CG	3.095
18		BW = -332.577 + 2.545CG + 1.139BL + 0.302WH	6.234

*Standard error of prediction

The performance of the predictive methods

Both the linear models (*Models 1* and *2*) were subjected to cross validation procedure to compare their performances in predicting cattle's body weight based on the body measurement variables. This approach was taken in order to produce the predictive values from each model to be compared with the observed values in the dataset. Statistical metrics were estimated based on comparing the predicted versus the observed values (*Table 3*).

The adjusted coefficient of determination (R^2) of *Model 1* of male cattle is lowest in weaning data (0.258) and highest on mature data (0.835). In mature data of male cattle, the R^2 of *Models 1* and *2* were similar, whereas in weaning data, *Model 2* performed

much better than *Model 1*. On the other hand, both *Models 1* and *2* performed poorly when applied on the yearling data of female cattle with R^2 of 0.210 and 0.283 respectively. The models were considered as moderately explaining the variance in the weaning and yearling data and highly explaining the variance in mature data subset in all three sex groups.

Table 3. The fitness and accuracy of the prediction models and Rondo® tape

Prediction methods	R ² adj ¹⁾	RMSE ²⁾		AIC ³⁾
		Value	CV ⁴⁾ (%)	
Linear models				
Equation number*				
1	0.258	15.094	17.243	1930.207
2	0.494	13.347	15.247	1838.451
3	0.496	12.223	9.835	1572.096
4	0.577	11.208	9.018	1538.369
5	0.811	22.315	11.179	1141.032
6	0.835	21.122	10.582	1125.910
7	0.610	8.523	10.467	1436.918
8	0.650	8.193	10.062	1416.903
9	0.210	7.692	6.941	1202.348
10	0.283	6.623	5.977	1150.142
11	0.865	12.949	7.944	813.224
12	0.882	12.278	7.533	802.152
13	0.367	12.723	15.008	3343.222
14	0.528	11.496	13.560	3314.384
15	0.383	11.760	9.963	2915.187
16	0.547	10.124	8.576	2801.023
17	0.850	18.684	10.197	1928.153
18	0.869	17.543	9.574	1952.510
Rondo tape				
<i>Male</i>				
Weaning	0.721	25.308	28.987	-
Yearling	0.544	34.758	27.967	-
Mature	0.816	67.323	33.728	-
<i>Female</i>				
Weaning	0.593	22.668	27.839	-
Yearling	0.398	23.061	20.811	-
Mature	0.868	50.859	31.202	-
<i>Overall</i>				
Weaning	0.675	24.148	28.529	-
Yearling	0.441	29.919	25.345	-
Mature	0.854	60.513	33.026	-

¹⁾Adjusted coefficient of determination; ²⁾Root of Mean Squared Error; ³⁾Akaike Information Criterion; ⁴⁾Coefficient of Variation; *Refers to *Table 2*

The overall dataset is the total data regardless of sex. Results of R^2 in *Table 3* showed that *Model 1* fit poorly in weaning and yearling data (0.367 and 0.383), but it

performed well when applied in mature data (0.850). *Model 2* has moderate fitness in weaning and yearling data but high fitness in mature data.

There are, however, explanations on why our fitness estimates were deviated from most of the references which mentioned that linear regression model including CG, which is a variable closely correlated with body weight, normally yielded in high R^2 (Gunawan and Jakaria, 2007; Kashoma et al., 2011; Papatungan et al., 2018; Vanvanhossou et al., 2018). Bali cattle as the object of our study, has not been subjected to any well-designed selection program; thus, their vast genetic variation has yet to undergo any intense selection procedures (Widyas et al., 2017). Although the data were obtained from Bali Cattle Breeding Center, but the currently running breeding program was a conventional and very outdated one; hence, the breeding program's parameters (if existed) are less informative and reliable. The cattle in this study lived in a free-range system; where a colony of cattle stayed in a paddock of pasture with an open shelter (Gunawan and Jakaria, 2011; Widyas et al., 2017). The shelter was also functioned as the place for additional food and water aside from the grasses within the pasture paddocks. In this type of production system, monitoring every cattle's feed consumption is almost impossible. Such free-range cattle production system also introduced natural competition for the resources; especially when their availability was limited; hence, this contributed to higher variation in the cattle's performances.

Weaning to yearling is the most crucial growth period for cattle. Weaning Weight (WW) was measured when the calves were weaned from their mothers (± 7 months old or 205 days). This was a phase where the calves were very vulnerable because they must adapt from milk to solid feed. The adaptation ability, of course, may vary among individuals and stress is a common occurrence during this period. On the other hand, yearling weight (YW) was measured at the age of 12 months or around 5 months after the cattle were weaned. The body weight and body measurements data obtained at yearling were thus very dependent on the ability of the individual to cope and adapt with the condition after weaning. The production system and the resources within the system lead to high variation in the performance of Bali cattle (Lindell, 2013); hence, causing the normally well-performed linear models to be less optimal in this population's data. However, after the cattle reached mature age (above 1.5 years) the trend changed, and the structure of the mature dataset are more similar with what commonly occur in this type of study; showed by increases in model fitness parameter.

RMSE is a statistical metric to measure a model's predictive ability which can be obtained by applying cross validation procedure on a dataset. The bias introduced by RMSE estimate is lower compared to the other parameters obtained without cross validation; it is also more robust for smaller dataset (Suparman, 2012). This metric indicates the absolute fitness of the models and could be a representation of their predictive ability. The value of RMSE can only be compared between models applied on the same data. In this study, *Model 2* where all of the body measurement variables (CG, BL and WH) were included, gave predicted values with higher accuracy compared to *Model 1* where only CG was used. The value of the RMSE does not represent anything because it depends on each dataset within which the models were trained (Kohavi, 1995; Schaffer, 1993). Hence, we introduced the coefficient of variation of the RMSE (CV-RMSE) as a measure of errors between predicted and observed data. CV-RMSE is calculated by normalizing the RMSE by the mean of the observed body weight. The value of CV-RMSE below 25% is considered as having a good model fit and reliable predictive ability (Ruiz and Bandera, 2017). In our study the CV-RMSE

were ranged between 5.977 – 17.243% which made both *Models 1* and *2* were good predictors of cattle's body weight.

To evaluate which model is best in the prediction of cattle's body weight we employ Akaike Information criterion (AIC). This procedure estimates the measure of similarity between models for the same data (Burnham et al., 2011). The best model is the one with the lowest AIC. The results in *Table 3* showed that *Model 2*, with CG, BL and WH as independent variables always had better predictive performance compared to *Model 1* within the same dataset. Further the difference AIC values (ΔAIC) are more than 10 which suggest that the less performed model has no substantial support in the data and deserve no further consideration (Burnham et al., 2011; Wolfinger, 1996).

Rondo® tape is a measuring band in which one side has the unit of cm to measure CG, whereas the subsequent side written the body weight predictive values in kg. We have yet to find information on how the conversion from CG to body weight was made for this tape. Despite this fact, however, this tool is widely used in Indonesia and in Asia (Wangchuk et al., 2018; Widi et al., 2014) due to its practical use. We built a dataset of the predicted body weight based on the conversion of observed CG to body weight using the Rondo® tape and estimate the predictive ability metrics (*Table 3*). The result showed that although there are some high correlation values between the body weight prediction based on the tape versus the observed body weight, but at the same time the RMSE values are considerably high when compared to the prediction using linear models. The CV-RMSE are higher than 25% for all subset of data, suggesting that this tape is less reliable as a predictive tool.

We also calculated the difference between predicted and observed values and plot them against the CG data (*Fig. 3*).

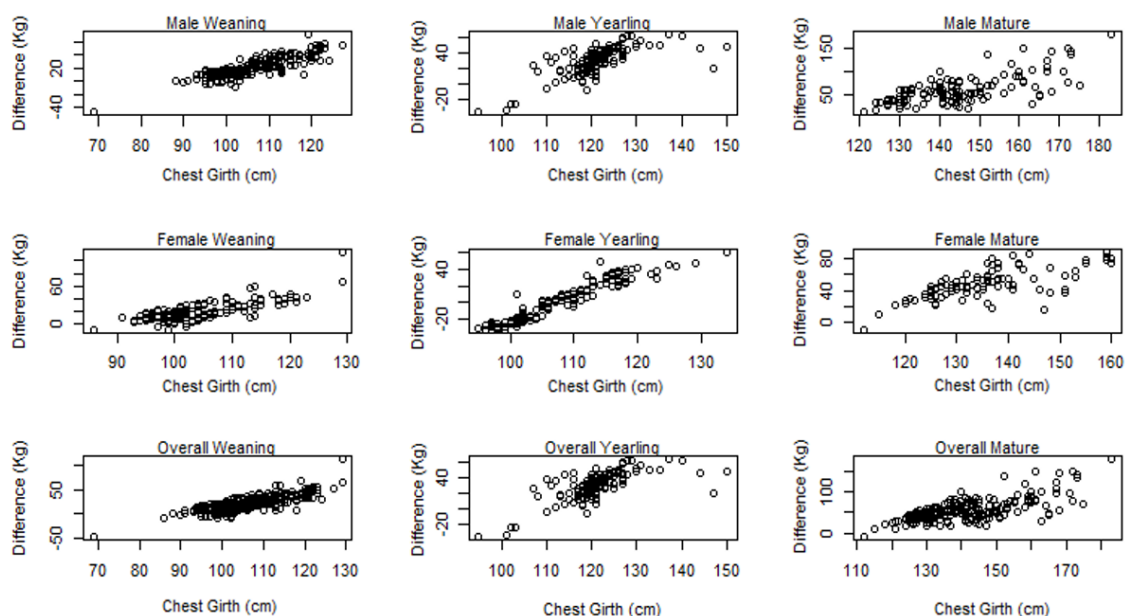


Figure 3. Relationship between the deviation from observed values and cattle's chest girth

It is clear to see that CG had high positive correlation with the difference; thus, the larger the CG, the predicted body weight deviated even further from the observed body weight in all subsets of data. Based on this finding, we do not recommend using

Rondo® tape as a tool to predict Bali cattle's body weight due to its poor accuracy. There are risks of severe over or under-estimation of body weight of Bali cattle which will lead to biased prediction of the performance and economic value of the cattle, inaccurate dose of drug administration, and, if this tool is used in scientific study, it will introduce biased that affect the results of the research.

Conclusions

Bali cattle is a unique cattle species with distinct characteristics and has large genetic distance with the other bovine species. It is why the commonly used practical approaches in predicting body weight based on the body measurements might not be accurate. Rondo® tape is not recommended to be used as body weight prediction tool for these cattle. However, linear models incorporating body measurement variables yielded promising performance in predicting the body weight of this cattle.

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