Eye-balling and heart girth models for live weight estimation of highly admixed Sudani shorthorn zebu cattle for precise production and veterinary services

Ashraf Alkhtib[1], Obaida Almasri[2], Emily Burton[1], Jane Wamatu[3]

[1]Nottingham Trent University, School of Animal, Rural and Environmental Sciences, Southwell, Nottingham, UK.

[2] General Commission for Scientific Agricultural Research, Damascus, Syria.

[3]International Centre for Agricultural Research in Dry Areas, PO Box 5689, Addis Ababa, Ethiopia.

Corresponding author: a.s.alkhtib@gmail.com

Abstract

Cattle production is a key pillar of food security in Africa. Majority of African cattle is highly admixed with unknown breed composition. Accurate estimation of live weight (LW) of these cattle would improve precision of feeding, veterinary services and pricing resulting in an improvement in profitability. This study assessed estimating LW of admixed Sudani zebu cattle using eyeballing and heart girth (HG) models. Live weight and HG of 432 Baggara cattle, an admixed Sudani breed, was measured. Three models (a simple linear, a simple linear with box-cox transformed LW and a quadratic) were generated using 382 heads and validated using 50 heads. A published model (LW (kg) = 3.54*HG (cm) - 322.63) was validated using the data of this study. The error of LW estimation by a breeder and five cattlemen was recorded. All constructed models had high R^2 (0.725 - 0.728). However, the 95th percentile of the prediction error of the constructed and published models was higher than 20%. The 95th percentile of LW estimation error of all participants was high (>20%). Accordingly, HG models and eyeballing are not suitable methods to determine LW of highly admixed zebu cattle for production, veterinary and marketing purposes as they are prone to high rate of error.

Keywords Indigenous cattle linear non-linear prediction error

Introduction

Cattle in Sub-Saharan Africa play a key role in livelihoods of farmers since they are the main source of drought power, manure, food (6.5 million ton of red meat and 35.6 million ton of milk (FAOSTAT, 2018)) and cash (Rege, Kahi, & Okomo-Adhiambo, 2001). Furthermore, cattle have social and political values that impact the social life of farmers in Africa (Ghaffar & Ahmed, 2014). Majority of cattle in Africa are admixed with unknown breed composition due to uncontrolled crossbreeding and arbitrary mating which resulted in high variability in appearance and body conformation.

Precision in agriculture is now widely regarded as a key route to optimal use of global resources in food production, but often focuses on application of modern technologies (Fuglie, 2016). This focus overlooks the importance of generating simpler data such as correct estimates of livestock weight in developing countries to ensure livestock are optimally maintained and used.

Live weight (LW) of cattle is closely related to nutrient requirements (Kearl, 1982), milk production (Kanuya et al., 2006), potential drought power (Fall, Pearson, & Fernández-Rivera, 1997), dosage of veterinary medications and market price (Lesosky et al., 2013). However, live weight determination of cattle among African cattlemen is a challenge because they do not use scales due to their high cost and continuous demand for maintenance and calibration. Development of alternative means of accurate determination LW of cattle in African countries would increase the efficiency of resources use associated with this key animal in African food production.

Some studies have reported a close correlation between LW of zebu cattle and morphological body measurements which may be used to predict LW using simple models (Goopy, Pelster, Onyango, Marshall, & Lukuyu, 2017). However, accuracy of these equations considerably decreases when they are applied to other cattle breeds (Goopy et al., 2017). It has been reported that a simple linear model could be used to predict LW of Baggara cattle using heart girth (HG) with high R^2 (LW (kg)= 3.54*HG(cm) – 322.63; R^2= 0.9) (Alsiddig, Babiker, Galal, & Mohammed, 2010). However, the model was generated by regressing LW on HG without any validation. Moreover, its prediction error (PE) was not reported. Accordingly, the model by Alsiddig et al. (2010) cannot be confidently used to predict LW of Baggara cattle. Visual estimation of LW of zebu cattle by Kenyan cattlemen was reported to be inaccurate (Lesosky et al., 2013). However, the accuracy of estimating LW of cattle by eyeballing varies due to cattle breed and experience of cattlemen.

Sudan has a large herd of cattle, estimated at 31.2 million head (FAOSTAT, 2018) belonging mainly to Baggara breed (Ghaffar & Ahmed, 2014). Baggara breed belongs to the large East African zebu group and North Sudan zebu subgroup (*Bos taurus indicus*) (DAGRIS, 2018). It is characterized by a compact body and a pyramidal hump, medium horns and variable coat colour (DAGRIS, 2018). The majority of Baggara cattle are kept by nomadic Baggara cattlemen in the west, central and southern Darfur, and in central and southern Kordofan, Nuba mountains and in west of the White Nile Sudan (DAGRIS, 2018). Baggara cattle have common grazing land and migratory routes with small Nilotic and large Fulani cattle (Alsiddig et al., 2010) which resulted in indiscriminate crossbreeding resulting in highly admixed animals with unknown breed composition and high variability in body conformation (Ojango et al., 2014).

To our knowledge, there are no comprehensive studies on the possibility of determining LW of highly admixed zebu cattle by eyeballing or using a HG-based model. Therefore, the objective of this study was to evaluate the accuracy of eyeballing and simple HG-based models to estimate the live weight of admixed shorthorn zebu cattle for production, veterinary and marketing purposes.

Materials and methods

Data

The current study is compliant with ethical standards of Khartoum University.

Data was collected at Mathieu Company for Agricultural and Animal Production Cattle Station in Sheikh Yosif, Khartoum, Sudan during the first week of January 2019. The station is located 10 km north of the capital city of Khartoum, at an altitude of 389 m.a.s.l. A total of 432 Baggara cows, with an age range of 12-48 months were weighed for the purposes of this study after overnight fasting. Cattle that were pregnant and/or sick according to station records were excluded from the study. Live weight was determined by a calibrated weigh scale (Camry, NTB, Camry company, China), with capacity of 1000 kg and sensitivity of 0.1 kg. The scale was calibrated using standard weights, after which 10 cattle were weighed in 3 replicates to confirm reliability of LW measurements. The scale was further calibrated at 50 cattle measurement intervals. Heart girth was determined as body circumference immediately behind the front shoulder at the fourth ribs, posterior to the front leg, using an ordinary measuring tape held with 1kg tension using a light spring balance. The same two investigators carried out all the measurements to ensure continuity in the placement of measuring tools. Immediately after LW and HG measurement, five cattlemen and a breeder, with no previous experience with the cattle of the study were asked to estimate LW of the cattle. They did not meet each other before or after LW estimation. Their experience with cattle production was 23-25 years for the cattlemen and 12 years for the breeder. The breeder was 35 years old and held a PhD in animal breeding and the cattlemen were 40-45 years old with elementary schooling.

Calculations and statistical analysis

Interquartile range method (Zwillinger & Kokoska, 2003) was used to identify the existence of outliers according to the following equation:

Lower bound= Q1 - (IR×1.5)

Upper bound= Q3 + (IR×1.5)

Where Q1 and Q3 are the first and third quartiles of LW respectively and IR is the interquartile range of LW. Observations of LW which fall out of these boundaries were considered outliers.

Data collected was divided into two sets, a calibration set and a validation set using Puchwein (1988) algorithm. Puchwein (1988) algorithm identified 50 cattle which best represent all cattle in the study. These were used as the models' validation set.

Normal Q-Q plot was used to test the normality of LW and box-cox transformed LW. The best power of transformation of LW was identified using box-cox transformation procedure with boundaries of –3 and +3 and a step of 0.1 and a log likelihood value of λ was used to identify the best power of transformation (Box & Cox, 1964).

Live weight was regressed on HG to generate three prediction models: a simple linear model, a simple linear model with box-cox transformed LW and a quadratic model.

Model I regression was used because the error in measuring HG is unimportant and all regression error is attributed to errors related to LW.

Coefficient of determination (R^2), root mean square of prediction error (RMSPE), root mean square of validation error (RMSVE), RMSPE to standard deviation ratio (RSRP), RMSVE to standard deviation ratio (RSRV), mean bias (MB), slope bias (SB), concordance correlation coefficient (CCC), calibration error (CE) and prediction error (PE) were calculated to evaluate the performance of the three models.

The RSR of the models was calculated as follows:

$$RSR = \frac{\sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}}}{S_O}$$

Where O_i is the observed value, P_i is the predicted value and S_O is the standard deviation of observed values (Moriasi et al., 2007). Calibration and validation sets were used to calculate RSRC and RSRV, respectively. Root mean square of error to standard deviation ratio with a value less than 0.7 indicates a satisfactory accuracy of a model (Ibarra-Zavaleta et al., 2017).

The Nash-Sutcliffe efficiency (NSE) is a normalized parameter which identifies the relative magnitude of residual variance compared to measured data variance (Nash & Sutcliffe, 1970).

$$NSE = 1 - \left[\frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})}\right]$$

Where O_i is the observed value, P_i is the predicted value and $\bar{O}$ is mean of observed value. The calibration set was used to calculate NSE of the models. A model with NSE higher than 0.5 was considered to have a satisfactory predictability (Ibarra-Zavaleta et al., 2017). Systematic biases were identified by partitioning mean square prediction error into MB and SB as follows:

$$MB = (\bar{P} - \bar{O})^2$$

$$SB = \left(S_p - r \times S_O\right)^2$$

Where $\bar{P}$ is mean of predicted values, $\bar{O}$ is mean of observed values, S_p is the standard deviation of predicted values, S_o is the standard deviation of observed values and r is coefficient of correlation (Niu et al., 2018). The calibration set was used to calculate both MB and SB. The smaller the value of MB and SB, the smaller the bias of the model. The concordance correlation coefficient which includes bias correction factor (C_b) and *r* as measurements of accuracy and precision, was calculated as follows:

$$CCC = r \times C_b$$

Where:

$$C_b = \left[\frac{\left(V + \frac{1}{V} + U^2\right)}{2}\right]^{-1}$$

$$V = \frac{S_O}{S_P}$$

$$U = \frac{(\bar{P} - \bar{O})}{\sqrt{S_p \times S_O}}$$

Where $\bar{P}$ is mean of predicted values, $\bar{O}$ is mean of observed values, S_p is the standard deviation of predicted values, S_o is the standard deviation of observed values and r is coefficient of correlation (Lin, 1989). The calibration set was used to calculate CCC. The higher the CCC of a model, the better the predictability (Niu et al., 2018). A model with CCC higher than 0.9 was considered to have a satisfactory predictability (McBride, 2005).

The calibration error of a model was calculated as follows:

$$CE\% = 100 \times \left|\frac{O_i - P_i}{O_i}\right|$$

Where O_i and O_i are predicted and observed LW respectively. The equation to calculate CE was applied to the validation set to calculate PE.

Homogeneity of residuals is an important assumption of regression analysis (Kaps & Lamberson, 2004). Calculating correlation between LW and residuals of a given model in addition to positive and negative frequencies are useful to assess the assumption of homogeneity of residuals. Thus, frequencies of residuals as well as the linear correlation between LW and CE and PE were calculated for the constructed models.

Coefficients of Alsiddig et al. (2010) model were used to calculate estimation error (EE) according to the following equation:

$$EE\% = 100 \times \left|\frac{E_i - O_i}{O_i}\right|$$

Where E_i and O_i are estimated and observed LW respectively. Correlation between EE and LW and frequencies of estimation residuals were determined using data of this study. Error of estimation of LW was analysed according to the following model:

$$Y_{ij} = \mu + P_i + LW_j + (P \times LW)_{ij} + \varepsilon_{ij}$$

Where Y_{ij} is the error of estimation, μ is the overall mean, P_i is the effect of the participant (i= breeder, cattlemen 1 to 5 and cattlemen averaged), LW_j is the linear effect of observed live weight, $(P \times LW)_{ij}$ is the effect of the interaction between the participants and observed live weight and ε_{ij} is the residual. Means were separated using least significant difference method at 0.05 level of significance. Data were analysed using R software (R core Team, 2017).

Results

Live weight of the cattle ranged from 165 kg to 520 kg while the minimum and maximum HG was 138 cm and 217 cm, respectively. Fig.1 shows that distribution of both LW and box-cox transformed LW was close to normal with some deviation. All cattle had LW within the boundaries of outliers (122 kg - 530 kg). Box-cox transformation procedure indicated that λ= 0.909 had the highest loglikelihood value.

Fig. 2 presents the linear and nonlinear models which describes the relation between LW and HG. Table 1 presents the performance parameters of linear and nonlinear models used to predict LW using HG. All constructed models had high R^2 ranging from 0.725 to 0.728. All constructed models had almost the same RSR (RSRC and RSRV) ranging from 0.522 to 0.525. All constructed models had very small MB and SB values (<0.001). All constructed models had high NSE values with a minimum of 0.694. The CCC of all models ranged from 0.84 to 0.842.

Only the 75^{th} percentile of CE of all constructed models was less than 20. Calibration errors correlated either moderately or weakly with LW in all constructed models (r<0.42, P<0.001). The frequencies of negative and positive calibration residuals were almost equal (54% - 56). All constructed models had similar RSRV ranging from 0.544 to 0.569. Again, only the 75^{th} percentile of PE of all constructed models was less than 20.

The correlation between PE and LW was moderate and negative in all constructed models (r<0.4, P<0.001). The positive and the negative validation residuals of all constructed models had similar frequencies (~54%).

Fig.3 shows the relation between predicted LW and observed LW in both prediction and validation set.

Alsiddig et al. (2010) model had high EE with values exceeding 20. The correlation between Alsiddig et al. (2010) model's EE and LW was positive and moderate (r= 0.42, P<0.001). Negative residuals dominated positive residuals in Alsiddig et al. (2010) model (~80%). Analysis of variance showed that there was a significant effect of the participants (P<0.001) and linear significant effect of LW (B= -0.028, P<0.001) but there was no significant effect of the interaction between them (P= 0.618).

Table 2 presents performance of the cattlemen and the breeder in estimating LW of Baggara cattle. There was significant effect of the estimator (P<0.001), LW (P<0.001, β= -0.015) but not the estimator*LW on EE (P= 0.618).

Mean of estimations of cattlemen had significantly lower EE than the breeder and 2 of the individual cattlemen. Estimation error of the breeder was not significantly different from the three cattlemen. Negative residuals dominated positive residuals for all cattlemen in addition to the mean of the cattlemen (~70% - ~90%) while the residuals of the breeder were almost symmetrically distributed around zero. The 95th percentile of EE was higher than 20% for all cattlemen and in addition to the breeder (EE= 24.6%-36%). The mean of the estimations of cattlemen had EE less than 20% but higher than 10%.

Discussion

The outliers' boundaries fall within LW range which means that there are no outliers to be excluded from the data (Zwillinger & Kokoska, 2003). The deviation in QQ plot of LW from normal suggests that box-cox transformation might improve predictability of the linear model (Box & Cox, 1964). Box-cox procedure indicated that the best power of transformation was 0.909. This agrees with Goopy et al. (2017) which indicated that there is need for power transformation of LW in cattle to improve accuracy of linear models in predicting LW by HG.

Heart girth explained 70% of the variation in LW in all three constructed models. The similar R^2 value of all models suggests that the three models explained the same proportion of variation in LW using HG. However, R^2 alone does not express the performance of the constructed models (Goopy et al., 2017).

The low values of MB and SB in all models suggest that the symmetric bias in all models was small. The small RSR value and the high NSE (NSE>0.1) is indicates an acceptable predictability of all constructed models. On the other hand, low CCC (CCC<0.9) suggests that the performance of all models in predicting LW is not satisfactory (Moriasi et al., 2007). However, RSR, NSE and CCC do not give sufficient information about the magnitude of deviation of predicted LW from observed LW, therefore, CE and PE were identified.

The moderate correlation between LW and CE and PE, combined with the symmetric distribution of residuals around zero in both prediction and validation set, suggests that residuals of the constructed models were homogenous. The magnitude of CE and PE is the key criteria to conclude if the predictability of a model is accepted for veterinary, nutrition, management and marketing purposes. When HG is used to predict LW, PE of ≤ 20% is adequate to determine dosage rates of veterinary medications (Leach & Roberts, 1981), however, PE of ≤10% is suitable for production traits which demand precise LW determination (Goopy et al., 2017). Accordingly, the models generated by this study cannot be used by nutritionists to determine LW of cattle for feeding purposes as their 95th percentile of CE and PE was considerably higher than 20%.

The relative measurement of LW to HG in Baggara cattle seems to be affected by the unknown mixture of Fulani and Nilotic cattle which results in poor predictability of LW by HG equation. This is in agreement with Goopy et al. (2017) who reported that HG equations are breed specific. Introducing other body measurements to the prediction models may improve the predictability. This option is not valid in the case of zebu cattle which are reported to be aggressive and difficult to handle.

The 95th percentile of PE of Alsiddig et al. (2010) model was higher than 20, therefore, it cannot be used to predict LW of the cattle for production and veterinary practices. The dominance of negative residuals of Alsiddig et al. (2010) model means that the model consistently underestimates LW of the cattle by 33 kg - 104 kg which is practically a considerable loss of 5000-15600 SP (66$-208 $)/head in the market.

Since feed and veterinary medicine are expensive in the developing country, poor determination LW of cattle would lead to wide margin of error in recommending the appropriate ration and medication does which would decline profitability of cattle production. That would decrease the interest of farmers in keeping cattle leading to decrease meat and milk production and consequently the overall food safety. Thus, more research should be carried out to find alternative options to traditional calibrated scales.

All cattlemen tended to underestimate LW of 95% of the cattle by EE more than 20% which agrees with (Lesosky et al., 2013). However, when their estimations were averaged, the 95th percentile of PE ranged between 10% and 20% suggesting that repeating estimations using more than one cattleman could significantly improve accuracy, and consequently, the averaged estimation could be used for veterinary services but not for production purposes.

The error in estimation of LW by the cattlemen was close to 20%. In addition, the estimation of LW by the breeder was significantly better than the estimation of only one cattleman. Accordingly, training cattlemen on estimating LW of cattle could improve their accuracy and consequently their estimation could be used for production and veterinary services.

Conclusion

Heart girth models and eyeballing by individual cattlemen failed to predict LW of highly admixed Sudani short horn zebu cattle for production and veterinary purposes. This inaccuracy decreases the confidence of farmers about cattle LW and weakens their bargaining power in livestock markets. Moreover, it would lead to inaccurate feeding and veterinary treatment which would decrease profitability of cattle production. That would finally debilitate the farmer's propensity in cattle production resulting an incline in the overall food safety. Accordingly, providing an alternative to scales is still required. Error in LW eyeballing was not far from the accepted threshold suggesting that accuracy of determination of highly admixed shorthorn zebu cattle LW by cattlemen could be improved by using appropriate training approaches and by aggregating estimation of LW by more than one cattleman. However, future studies need to use larger number of cattlemen to add more layers of confidence to the current results.

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Compliance with ethical standards

This study has been approved by the ethical committee of International Centre of Agricultural Research in the Dry Areas.

Conflict of interest

The authors declare that they have no conflict of interest.

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Table 1 Performance of linear and nonlinear models in prediction live weight of Baggara cattle using heart girth

	Linear	Box-cox	Quadratic	Published[a]
R^2	0.728	0.725	0.728	
RMSPE	33.2	18.1	33.2	
RSRP	0.522	0.525	0.523	
MB	<0.001	<0.001	<0.001	
SB	<0.001	<0.001	<0.001	
CCC	0.842	0.84	0.842	
NSE	0.728	0.724	0.694	
Percentiles of CE				
75th	12.6	11.6	12.7	31.5
90th	23.1	20.6	22.9	38.8
95th	27	24.8	26.7	44.4
Correlation between LW and CE	-0.381*	-0.374*	-0.251*	0.42*
Negative residuals	55.2	56	54.9	81.1
Model validation				
RMSVE	46.9	25.4	49	
RSRV	0.544	0.547	0.569	
Percentiles of PE				
75th	18.2	16.7	18.3	
90th	28.1	25.4	27.6	
95th	37.4	33.3	37.1	
Correlation between LW and PE	-0.394*	-0.387*	-0.332*	
Negative residuals (%)	54.1	54.2	54	

a, Live weight (kg)=3.54 × heart girth (cm) – 322.63 (Alsiddig et al., 2010); CCC, the concordance correlation coefficient; CE, calibration error; LW, live weight; MB, mean bias; NSE, Nash-Sutcliffe efficiency; PE, prediction error; R^2, coefficient of determination; RSRP, RMSPE to standard deviation ratio; RMSPE, root mean square of prediction error; RSRV, RMSVE to standard deviation ratio; RMSVE, root mean square of validation error; SB, slop bias; *: $P \leq 0.05$

Table 2 Accuracy of a breeder and cattlemen in estimating live weight of Baggara cattle

	Mean	% of negative residuals	Percentiles of EE (%)		
			75^{th}	90^{th}	95^{th}
Breeder	12.5^{a}	43.7	20.4	26.7	31.5
Cattleman 1	10.5^{ab}	72.8	13.8	21.1	29.9
Cattleman 2	10^{ab}	80.6	13.9	18.1	24.6
Cattleman 3	11.9^{a}	69.9	18.4	28.2	31.6
Cattleman 4	10.8^{ab}	63.1	14.3	26.7	30.2
Cattleman 5	16.1^{c}	95.1	22	31.9	36
Mean of cattlemen	8.58^{b}	80.6	12	16.6	19.8
SEM	0.993				

$^{a-c}$, means within a column with a similar superscript are not significantly different at 0.05 level of significance. EE, error of estimation; LW, live weight (kg)

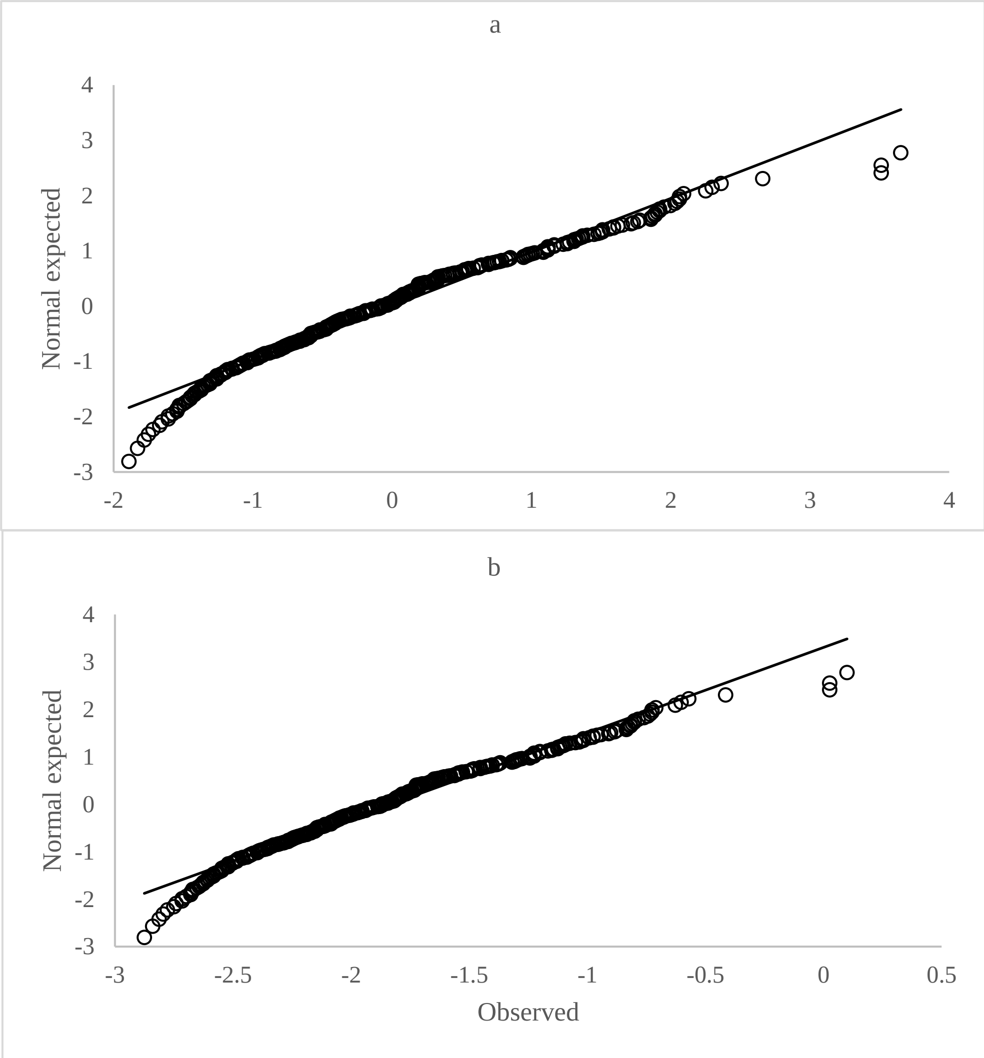

Figure 1 Normal QQ plot of live weight (a) and box-cox transformed live weight (b)

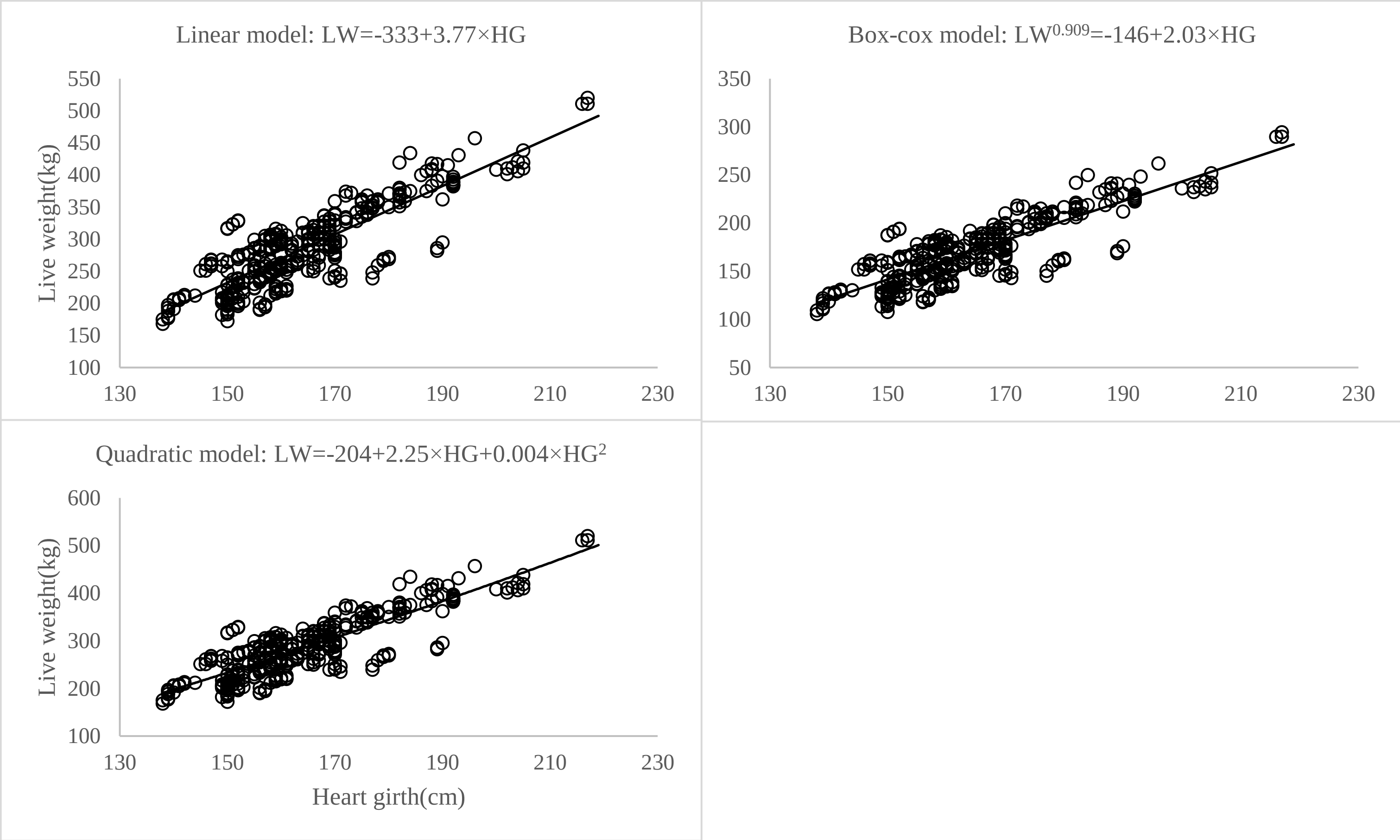

Figure 2 Linear and nonlinear relationship between live weight and heart girth of Baggara cattle. LW, live weigh (kg); HG, heart girth (cm)

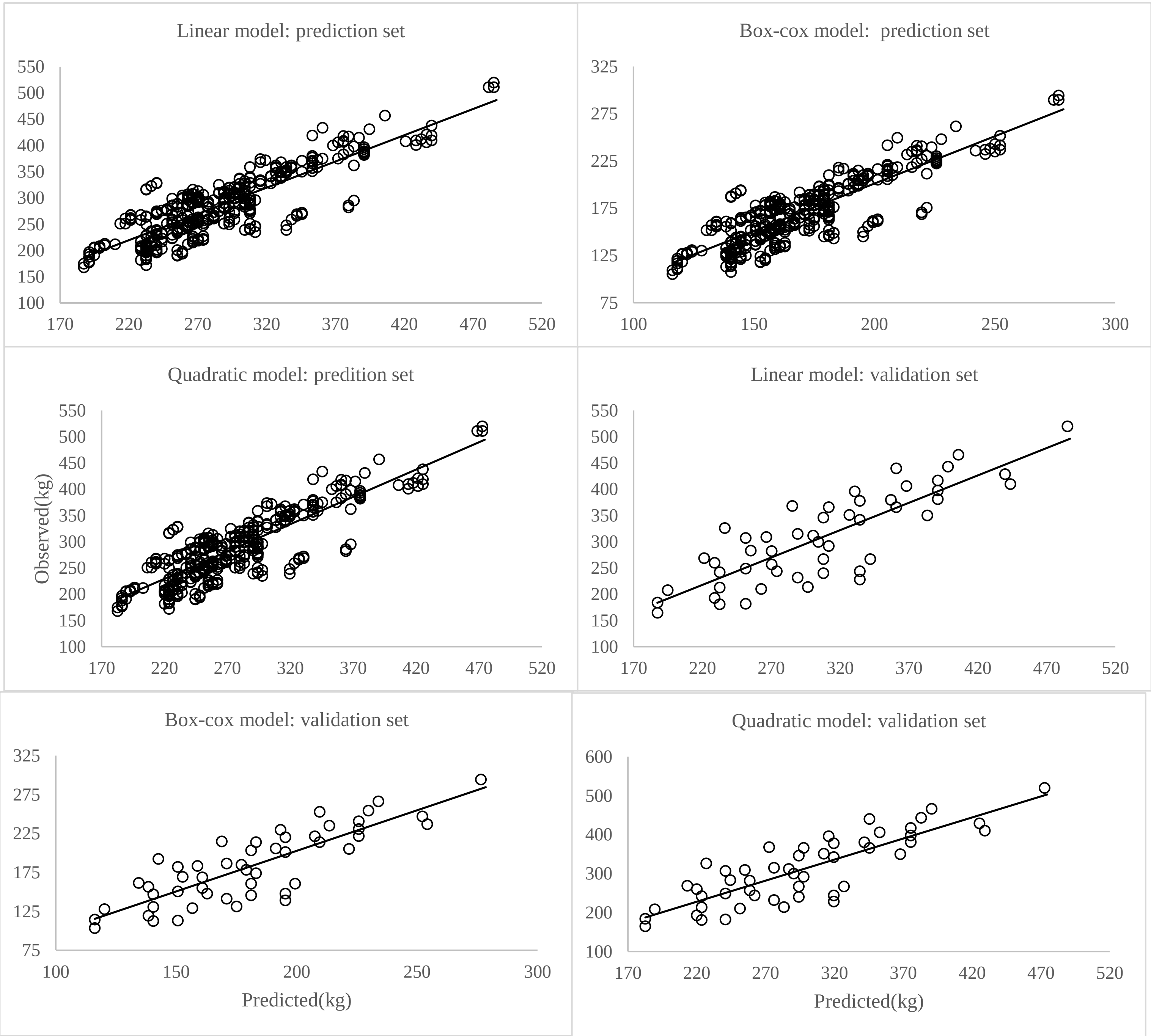

Figure 3 predicted live weight vs observed live weight of Baggara cattle in prediction and validation sets

التخمين اعتمادا على الشكل الخارجي و معادلات محيط الصدر للتقدير بالوزن الحي لأبقار الزيبو السودانية ذات المادة الوراثية عالية الخلط للأغراض البيطرية و الانتاجية

أشرف الخطيب[1]، عبيدة المصري[2]، إيميلي بارتون[1]، جين واماتو[3]

1الهيئة العامة للبحوث العلمية الزراعية، دمشق، سورية

2جامعة ترنت في نوتنغهام، قسم علوم الحيوان، العلوم البيئية و العلوم الريفية، ساوثويل، نوتنغهام، المملكة المتحدة

3المركز الدولي للبحوقث الزراعية في المناطق الجافة، ص ب 5689، أديس أبابا، أثيوبيا

يعتبر إنتاج الماشية ركيزة أساسية للأمن الغذائي في قارة أفريقيا. تمتلك معظم الأبقار الأفريقية بدرجة عالية من الخلط الوراثي المجهول التركيب. سيزيد تقدير الوزن الحي لهذه الأبقار الدقة في التغذية والخدمات البيطرية وتثمين السعر مما يزيد من عائد الإنتاج. تعالج هذه الدراسة موضوع تقدير الوزن الحي لأبقار الزيبو السودانية ذات التركيب الوراثي المختلط و ذلك باستخدام التقيم الشكلي و معادلات التنبؤ المبنية على أساس محيط الصدر.

تم قياس محيط الصدر و الوزن الحي ل 432 رأسا من أبقار البقارة (التي تمثل أبقار الزيبو المختلطة التركيب الوراثي في المنطقة). تم استنباط ثلاث معدلات (خطي بسيط، خطي بسيط بعد تحويل الوزن الحي باستخدام طريقة بوكس-كوكس، تربيعي) باستخدام 382 رأسا بينما تمت التحقق من دقة المعادلات باستخدام 50 رأس. تم التثبت من دقة احدى المعادلات المنشورة و ذلك باستخدام بيانات الدراسة الحالية. تم تسجيل أخطاء تقدير الوزن الحي أثناء تقييمها من قبل خمسة مربي أبقار و باحث في الإنتاج الحيواني.

كانت قيمة R^2 مرتفعة لجميع المعادلات المستنبطة (0.725-0.728). و بالرغم من ذلك، كانت قيمة المئين الخامس و التسعين لخطأ التنبؤ للمعالات المستنبطة و المنشورة أعلى من 20%. كانت قيمة المئين الخامس والتسعين لخطأ التقييم المظهري من قبل كل المقيمين أعلى من 20%.

بناءا على ذلك، لا يمكن تقدير الوزن الحي لأبقار الزيبو العالية الخلط الوراثي لأغراض الإنتاج و العلاج البطري و التسويق سواءا باستخدام المعادلات المبنية على أساس محيط الصدر أو باستخدام التخمين المظهري بسبب خطأ التقييم المرتفع.

الكلمات الدليلية: محلي، أبقار، خطي، غير خطي، خط التنبؤ