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# Prediction of weaning weight of grazing beef by machine learning

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## ABSTRACT

**Objective**: To develop and validate models using the variables available at calving to predict the weaning weight (WW) of grazing beef calves.

**Design/Methodology/Approach**: The WW was modelled using machine learning (ML) algorithms and ordinary least squares (OLS). The model included three variable availability scenarios and the best fit was identified using the coefficient of determination ($r^2$), the mean squared error, and the bias.

**Results**: ML algorithms achieved a better fit than OLS in all scenarios. ML had a 0.70, 0.67, and 0.78 $r^2$ when the following modelling variables were available: B) dam age at calving and parity, calf sex and weight, weaning age, and calving date; I) in addition to the previous variables, dams' weight at calving, type of calving, calf and cow racial purity; and A) in addition to the all the previous variables, type of service, cow and sire tags and sire breed.

**Study Limitations/Implications**: The ML and OLS models were representative of a specific database. Modelling based on regional or national data should be studied. Using the lowest number of variables in this study, ML in scenario B provided an acceptable fitting for the prediction modelling of the WW of grazing beef calves.

**Findings/Conclusions**: ML performed better than OLS, without causing an overfitting, based on the suitability of the WW predictions regarding a database that was not used to train the model.

**Keywords**: Alfalfa, artificial intelligence, regression.

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**INTRODUCTION**

Beef production will amount to 75 Mt in 2030 (a 5.8% increase), in response to the growing demand for animal products (OECD/FAO, 2021). Although grazing animal production pollutes the environment (Steinfeld *et al.*, 2006) and there are proposals for human feeding based on meatless meals, beef production has a significant sociocultural aspect and it is also an option in arid ecosystems where foraging of the primary production is the main strategy. In the short term, improving the efficiency of the beef production plans has been visualized as a way to address climate change (Chang *et al.*, 2021).

Weaning weight (WW) is used to evaluate beef production cows. WW is influenced by genetic effects (Koots *et al.*, 1994), as well as the maternal ability and environmental factors (Kennedy and Henderson, 1975). The role of WW is not limited to genetic improvement and production planning and projection; WW is also a parameter that defines the cows' contribution to the profitability of the commercial operation (Harris and Newman, 1994). Studies on milk yield, early weaning, and other cow-calf production aspects are still under study (Mulliniks *et al.*, 2020) and are needed to identify optimization parameters (Thompson *et al.*, 2020; Greenwood, 2021).

The relation of WW with other production variables defines the nature of production records and, therefore, enough data must be collected. Weaning age, calf sex, dam age at calving, and other variables are used to standardize WW; however, local or temporal conditions also impact its modelling (Harris and Newman, 1994). Achieving the target weaning weight is fundamental for grazing production, because pasture supply is restricted. Consequently, WW prediction models based on specific changes to predictor variables (such as weaning age) are important, once other effects have been adjusted. Once the production projection has been determined, the plan can be modified to suit the environmental resources available and their uncertainty. Coupling animal production plans with environmental limiting factors is fundamental to adapt to certain conditions (such as climate change) and to promote sustainability (Taylor *et al.*, 2020; Greenwood, 2021).

Statistical modelling traditionally uses linear or non-linear regression, likely including polynomial expressions with one or more explanatory variables. The best fitting for these models is achieved with the minimization of the error variance or the maximization of a likelihood function. Bayesian methods are another alternative, particularly regarding the meta-analysis of the data or in those cases in which statistics assumptions are not fulfilled (McElreath, 2020). Recently, as a result of advances in computing power, machine learning (ML) algorithms have proven to be relevant for predictive modelling and data exploration. Both ML models and models solved through ordinary least squares (OLS) have their advantages, but they also have limitations. Therefore, comparing methodologies is important to select the best tool; at the same time, a simple model capable of providing a faithful representation of reality must be established. Interpretability is still a pending task in ML and, overall, they are a black box model: a solution is achieved, but exactly how it was achieved is unknown.

In this study, WW predictive models were trained and validated based on the variables available at the calving. Variables that became available after the calving were not used for predictive purposes. The following hypothesis was set forth: a ML algorithm would predict WW better than OLS regression. A database of Limousin beef cows and their grazing calves was used to achieve the objective of this study.

## MATERIALS AND METHODS

A beef herd grazing mixed pasture was studied at Centro de Enseñanza, Investigación y Extensión en Producción Animal en Altiplano, Facultad de Medicina Veterinaria y Zootecnia, Universidad Nacional Autónoma de México (UNAM). The site is located at 20° 36' 13.88" N and 99° 55' 02.91" W, at an altitude of 1,913 m. The weather is temperate, with a 512 mm average annual rainfall and a 17.5 °C average temperature, with frost from October to February, warm summers, and mild winters.

Cows and their calves grazed on a paddock divided with an electric fence and with center-pivot irrigation. The pasture was established in 2004 with a mixture of species: alfalfa (*Medicago sativa*), cocksfoot grass (*Dactylis glomerata*), fescue (*Festuca* sp.), and perennial ryegrass (*Lolium perenne*); alfalfa was dominant by 50%. Average grazing and rest periods were 2.7 and 37.5 d, respectively. The cows were sporadically fed with good quality hay when handled on yards. At the beginning and during the weaning, the calves were supplied variable amounts of hay and concentrated feed. Cow feeding was exclusively on grazing. The productive model included year-round-calving. Weaning groups were established and the calves were kept apart from the grazing group; however, heifers were returned to the grazing group a few days later, until mating and becoming pregnant. Once a positive pregnancy diagnosis was obtained, they remained in the grazing group until they gave birth and considered cows and so forth.

This study included the 2004-2010 records of an 88-Limousin cow herd, with 159 births (up to 5 calvings per cow). The Limousin calves were the result of artificial insemination (AI) and natural mating (NM); additionally, eleven crossbred calves were born from artificial insemination. The response variable was the weaning weight (WW) of calves. The following predictor variables were recorded: cow and sire tags (representing ancestry), age and weight of dams at calving, type of calving, dam parity, type of service and sire breed, calf sex, calf weight and calnving date, weaning age, and racial purity of the calf and the cow. Weaning age is a variable defined after calving, but it was included as a WW predictor variable, since it determines weaning management.

The R language was used to develop the codes (R Core Team, 2013). Eighty-percent of the records were randomly chosen and OLS and ML models were developed, combined with three modelling variable availability scenarios: basic (B), intermediate (I), and wide (A), according to Table 1. In order to prove the hypothesis, the ML model should have a better performance than OLS in all these scenarios.

The OLS models were developed with a stepwise procedure in the R software, using the lm, stepAIC, and VIF functions. The stepAIC function of the MASS package chooses the best model using the Akaike information criterion. The VIF function of the car package determines the variance inflation factor (VIF); a VIF=10 threshold was used to eliminate variables from the model and to avoid multicollinearity (Fox and Weisberg, 2018). Using the Pratt index, the calc.yhat function of the yhat package determined the importance of

**Table 1**. Predictor variable used for machine learning or ordinary least squares modelling with three variable availability scenarios: Basic (B), Intermediate (I), and Wide (A).

| Predictor variable | Abbreviation | B | I | A |
|---|---|---|---|---|
| Cow tag | cow | | | x |
| Sire tag | sire_tag | | | x |
| Sire breed | sire_br | | | x |
| Dam age at calving (months) | dam_age_cal | x | x | x |
| Dam weight at calving (kg) | dam_ weight_cal | | x | x |
| Type of calving [1] | type_calving | | x | x |
| Type of service [2] | type_service | | | x |
| Calf sex | calf_sex | x | x | x |
| Calf weight (kg) | calf_weight | x | x | x |
| Calving date (month) | calving_date | x | x | x |
| Weaning age (days) | weaning_age | x | x | x |
| Race purity of the calf (%) | purity_calf | | x | x |
| Race purity of the cow (%) | purity_cow | | x | x |
| Dam parity | parity | x | x | x |

[1]Normal or difficult calving. [2]Normal mating (NM) or artificial insemination (AI).

the explanatory variables in the variance portioning. The models were validated with the remaining 20% of the records. The goodness of fit between observed and predicted values was measured using the coefficient of determination ($r^2$); the square root of the mean squared error (RMSE) was calculated using the RMSE function of the Metrics package; and the bias was measured following Bland and Altman (2010) with the blandr package.

The same records selected for the OLS training were used to build the ML models. A stack of models based on ML algorithms was generated with the AutoML function of the H20 package v.2.32.14 (Hall *et al.*, 2019). The ML approach takes into consideration several algorithm realizations: deep learning (DL), feedforward artificial neural network (DL), general linear models (GLMs), gradient-boosting machine (GBM), extreme gradient boosting (XGBoost), default distributed random forest (DRF), and extremely randomized trees (XRT). The AutoML function trains individual models, as well as two model assembles: the first assemble is developed from all the algorithms used in the generated models; the second assemble only takes into consideration the best model of each class or family of algorithms. Often, both assembles achieve better predictions than individual algorithms. The deviance was used as a goodness of fit statistic in order to sort the models within the ML model stack, as well as a criterion to stop the model optimization. The best model assemble or the best individual model were used to predict WW in the records reserved for validation (20%). The h2o.explain function of the H2O package was used to determine the importance of the variables of the individual models; however, it cannot be applied to a model assemble (Hall *et al.*, 2019). The same goodness of fit measurements was used to compare the OLS and ML models; the best modelling method would have the highest $r^2$, the lowest RMSE, and the lowest bias. In order to interpret the contribution of each ML model variable, its SHAP (Shapley Additive exPlanations) values were estimated, using the h2o.explain function.

## RESULTS AND DISCUSSION

The training data base was comprised of 127 records (118 Limousin and 9 Angus-Limousin calves). The validation database included 32 records (29 Limousin and one of each Angus, Belgian Blue, and Blonde D'Aquitaine crosses). Both databases had similar average values for the calf quantitative variables (Table 2). Both databases showed a 3% occurrence of difficult calving. The percentage of IA services was 34 and 40 for training and validation data, respectively. The only major correlation between the predictor variables was recorded between parity and dam_age_cal (r=0.82); the correlations for all the other variables were lower than r=0.23, except for purity_calf and purity_cow, which had a r=0.26 correlation.

ML obtained a better validation than OLS in all scenarios (Table 3). All the goodness of fit measurements favored ML, although bias should be chosen before the coefficient of determination as a goodness of fit criterion (Bland and Altman, 2010). The ML of scenario A obtained the best validation, according to the goodness of fit measurements; likewise, the OLS performed better in this scenario than the OLS of other scenarios. In scenario A, the highest OLS error was also detected in the graphic representation of the observed versus the model-estimated WW values (Figure 1a and Figure 1b). The estimated data showed less dispersion in the ML model, both during the training and the validation phases (Figure 1c and Figure 1d); a similar phenomenon was recorded in the other scenarios (data not shown).

In all three scenarios, the best representation with the ML always was the model assemble; additionally, the best individual models always were of the XGBoost type —a decision tree type algorithm. In scenario A, the deviance of all the model assembles was 472.87 and the deviance for the best individual model was 494.21. In scenario I, the assemble for the best family was 649.53 and the deviance for the best individual model was

**Table 2**. Average ($\overline{y}$) and standard deviation (s) of the variables in the weaning weight (WW) model training and validation databases.

| Variable | | Training | | | | Validation | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Female | | Male | | Female | | Male | |
| | | $\overline{y}$ | s | $\overline{y}$ | s | $\overline{y}$ | s | $\overline{y}$ | s |
| dam_ weight_cal[1] | (kg) | 637 | 57.2 | 654 | 54.9 | 627 | 76.3 | 676 | 52.0 |
| Dam _wean_we[2] | (kg) | 654 | 48.7 | 602 | 50.6 | 509 | 49.2 | 615 | 52.3 |
| dam_age_cal | (months) | 58 | 26.9 | 64 | 29.2 | 65 | 36.2 | 65 | 26.6 |
| calving_weight | (kg) | 37 | 3.6 | 39 | 4.1 | 36 | 3.2 | 39 | 3.9 |
| weaning weight | (kg) | 241 | 34.6 | 244 | 46.2 | 230 | 42.9 | 242 | 50.9 |
| weaning age | (days) | 201 | 20.9 | 198 | 18.8 | 205 | 22.4 | 194 | 25.6 |
| GDP[3] | (kg) | 1.02 | 0.18 | 1.03 | 0.21 | 0.96 | 0.26 | 1.05 | 0.21 |
| n | | 62 | | 65 | | 17 | | 15 | |

[1]Weaing weight, [2]Dam_wean_we: dam weight at weaning, [3]GDP: daily weight gain of the calf; these three variables were not used in the modelling.

**Table 3**. Goodness of fit statistics between predicted and observed weaning weight (WW) values, using the training database, with internal and external validation: root of the mean square error (RMSE), residual standard error (RSE), coefficient of determination ($r^2$), bias, and interval of confidence (IC). The models used were machine learning (ML) algorithms and multiple regression least squares (OLS). The scenarios refer to the availability of explanatory variables for the modelling: Basic (B), Intermediate (I), and Wide (A).

| | | RMSE | $r^2$ | Bias | IC | |
|---|---|---|---|---|---|---|
| **Scenario B** | | | | | | |
| ML | Training | 13.88 | 0.93 | 7.51 | 5.49 | 9.53 |
| ML | Validation | 23.20 | 0.70 | −0.98 | −10.32 | 8.37 |
| OLS | Training | 34.26 | 0.32 | 0.00 | −5.92 | 5.92 |
| OLS | Validation | 32.88 | 0.39 | −4.90 | −18.01 | 8.20 |
| **Scenario I** | | | | | | |
| ML | Training | 17.39 | 0.82 | 0.27 | −2.73 | 3.28 |
| ML | Validation | 25.49 | 0.67 | −9.36 | −18.92 | 0.19 |
| OLS | Training | 33.53 | 0.35 | 0.00 | −5.79 | 5.79 |
| OLS | Validation | 32.54 | 0.41 | −5.89 | −18.79 | 7.01 |
| **Scenario A** | | | | | | |
| ML | Training | 5.20 | 0.99 | 3.97 | 3.38 | 4.56 |
| ML | Validation | 21.75 | 0.78 | −0.50 | −8.46 | 7.46 |
| OLS | Training | 32.61 | 0.35 | 0.00 | −5.75 | 5.75 |
| OLS | Validation | 36.28 | 0.36 | −5.67 | −18.79 | 7.46 |

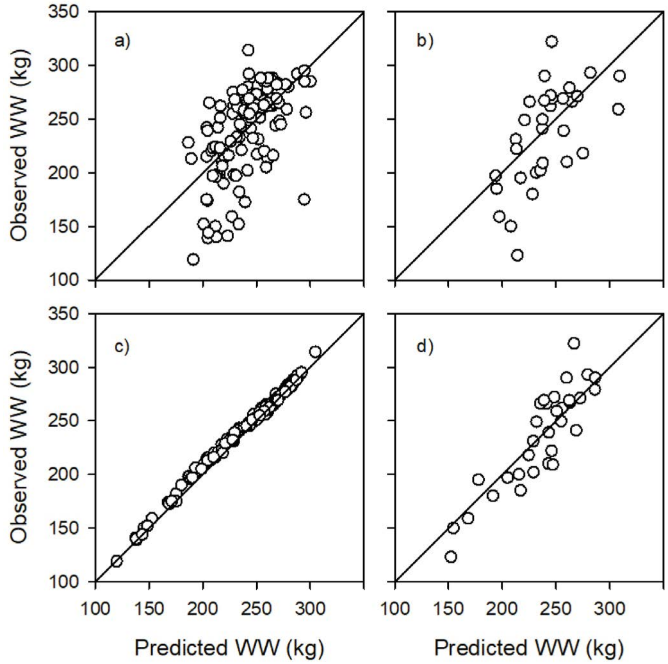


**Figure 1**. Ratio of the recorded and predicted WW values in scenario A, according to the fit of a multiple regression model with ordinary least squares (OLS) for the training (a) and validation (b) databases. Figures c and d belong to the machine learning (ML) model. The diagonal line stands for the 1:1 ratio.

678.30. In scenario B, the assemble for the best family was 538.06 and the deviance for the best individual model was 670.14. The lowest deviance values indicate a better model.

The most important variables for all ML and OLS models were: weaning_age, calf_weight, dam parity, and dam_age_cal (Table 4). Racial purity variables were important for ML in scenarios I and A. Ancestry variables were only important for ML in scenario A. By itself, calf sex was not significant in any model. In the ML model, the importance of breeding bulls was significant; this phenomenon is discussed later on.

Scenario A was better than I for ML, because the ancestry variables were taken into account; r2 improved by 0.11 and both the bias and the interval of confidence were lower (Table 3). In the ML of scenario A, the sires with more progeny were important, particularly Ambition, whose offspring were light; meanwhile, Vet Mosco's offspring were also light, but it did not have the same importance (Table 5). The importance of breeding bulls for ML was closely linked to this database. Consequently, the WW dependence on the variables of scenario I was analyzed. Scenario I is an overall model with greater potential application, although it had a greater bias.

Management decisions are based on the weaning age variable and the dependency of WW on this variable showed a sigmoid shape in various ML models; however, a GLM model (such as OLS) had a linear and proportional dependency (Figure 2a). Therefore, there must be a window of opportunity where weaning age (≈200 to 225 d) had a significant influence and then, other factors determined WW. In the case of ML, Figure 2 shows similar dependency relationships between other variables of importance for the models, which were different in the case of the GLM. The vertical bars show the frequency of the

**Table 4**. Importance of the explanatory variables included in the machine learning (ML) or ordinary least squares (OLS) models in three explanatory variable availability scenarios, according to Table 1. The importance of the category variables is associated with a specific variable value.

| Predictor variable | ML | | | OLS | | |
|---|---|---|---|---|---|---|
| | B | I | A | B | I | A |
| dam_age_cal | 0.15 | 0.12 | 0.02 | 0.08 | 0.06 | 0.07 |
| dam_ weight_cal | | | 0.08 | | | |
| calving_weight | 0.28 | 0.17 | 0.10 | 0.06 | 0.07 | 0.08 |
| calving_date | 0.20 | 0.10 | 0.04 | | | |
| weaning_age | 0.25 | 0.39 | 0.18 | 0.38 | 0.38 | 0.34 |
| purity_calf | | 0.07 | 0.01 | | | |
| purity_cow | | 0.03 | 0.03 | | | |
| parity | 0.11 | 0.10 | 2.17E-03 | 0.48 | 0.40 | 0.40 |
| calf_sex: Female | | | 0.02 | | | |
| type_service: NM | | | 4.59E-05 | | 0.09 | 0.11 |
| calf_sex: Male[1] | | | | | | |
| Sire: AMBITION | | | 0.48 | | | |
| Sire: VET_MOSCO | | | 0.02 | | | |
| Sire: ROBLE | | | 0.01 | | | |

[1]The breedings bulls were only important in the case of male calves. B: Basic, I: Intermediate, A: Wide.

**Table 5**. Weaning weight adjusted to 205 d (kg) of female (H) and male (M) descendants of the breeding bulls included in Table 4. Number of calves (n), average ($\bar{y}$), and standard deviation (s) for the complete database under study. Other breeding sires are not included.

| Sire | Race | F | | | M | | |
|---|---|---|---|---|---|---|---|
| | | n | $\bar{y}$ | s | n | $\bar{y}$ | s |
| Ambition | Limousin | 11 | 138.2 | 25.9 | 19 | 147.4 | 23.3 |
| Vet Mosco | Limousin | 13 | 151.1 | 31.4 | 14 | 145.9 | 35.8 |
| Memin | Angus | 3 | 155.6 | 26.5 | 6 | 153.2 | 19.8 |
| Turcio | Limousin | 7 | 154.2 | 21.3 | 8 | 156.5 | 18.8 |
| Sucha | Limousin | 16 | 169.6 | 21.2 | 13 | 157.3 | 32.1 |
| Roble | Limousin | 6 | 174.6 | 32.8 | 3 | 152.4 | 51.2 |
| Highlander | Limousin | 4 | 162.5 | 27.9 | 6 | 179.6 | 15.4 |
| Hato | | 79 | 161.6 | 28.9 | 80 | 154.8 | 30.9 |

observations, together with the dependency graph, they point out how the WW prediction per model changes according to the accumulated evidence. Consequently, ML did not have a strong dependency on the increase of dam_age_cal (dam age at calving), because few older cows were recorded (Figure 2c).

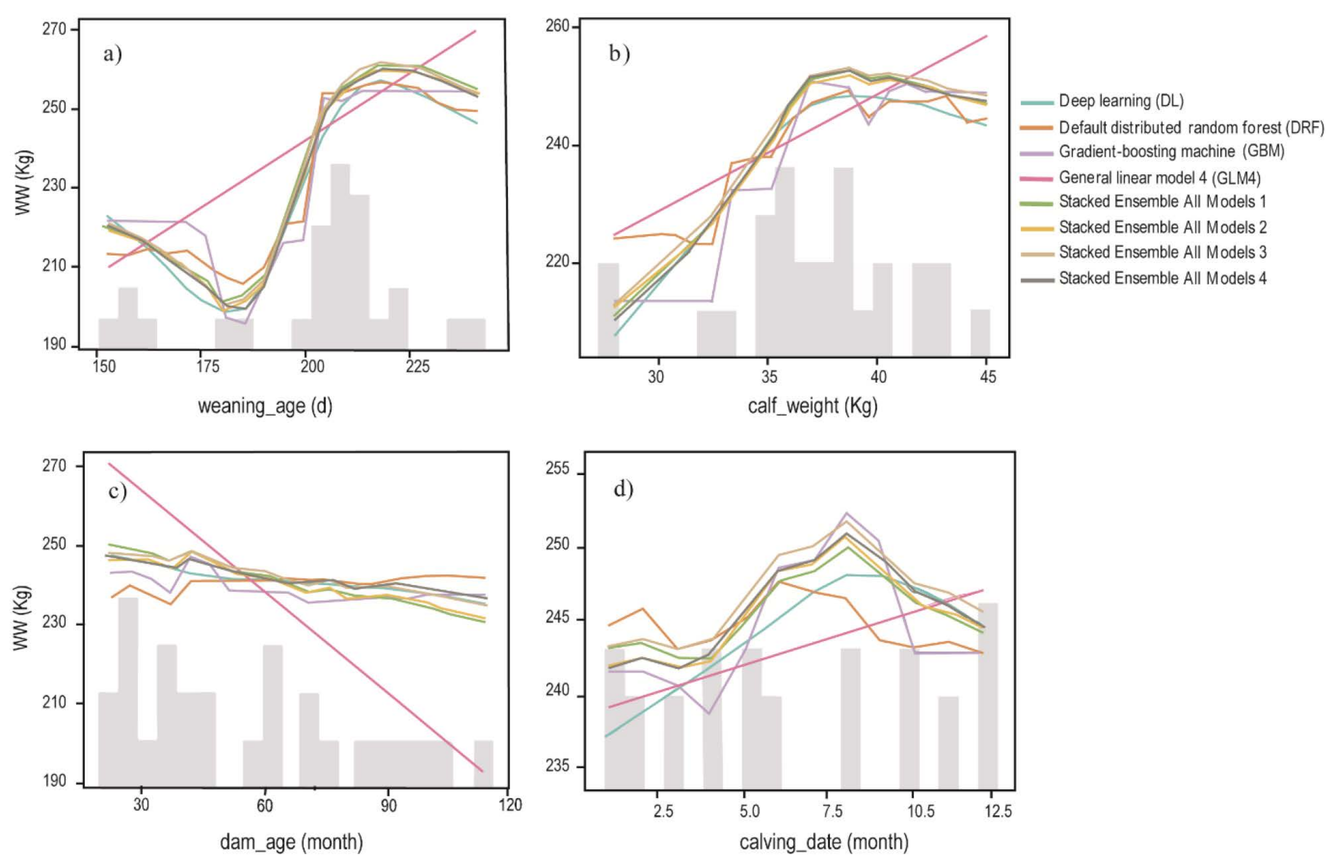


**Figure 2**. Partial dependency in scenario I for weaning weight (WW) according to: a) weaning age, b) calf weight, c) dam age at calving, and d) calving date. All the other variables remained fixed, assuming a lack of correlation with other explanatory variables. The bar graph points out the frequency of the data in the model validation database.

WW depended on calving_date during the summer. The uniform data frequency throughout the year was remarkable and therefore, ML algorithms do not simply depend on a greater number of data (Figure 2d). A potential increase in food quality and quantity during the summer suggested a greater milk yield and, consequently, a greater WW. Greater attention should be paid to these variables along with the changes in the weight of the dam during lactation. Nevertheless, measuring them in commercial operations is a difficult task. The ML models presented can be part of a reproductive planning and pasture budgeting strategy contributing to the optimization of the production plan, based on several important variables: seasonal variation of the production, longevity of the cows, and use of chosen breeding bulls.

## CONCLUSION

The ML model assemble predicted the WW with a lower error and bias. It is an alternative tool to the traditional OLS, regardless of the number of variables available to train the model, even when only production variables that are essential for any cattle-raising operation are available. The best machine learning algorithm was XGBoost.

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