ARTICLE

Prediction of grain yield, adaptability, and stability in landrace varieties of lima bean (*Phaseolus lunatus* L.)

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Abstract: *The aim of this study was to compare the Multiple Linear Regression and Artificial Neural Network models in prediction of grain yield of ten landrace varieties of lima bean and evaluate adaptability and stability through the Lin and Binns method for identification of the best performing variety. Trials were conducted in the municipalities of Teresina, PI, and São Domingos do Maranhão, MA, through measurement of 12 traits, except for grain yield in São Domingos do Maranhão. The parameters of Pearson and Spearman correlation, root mean square error, mean absolute error, and coefficient of determination were used to compare the models. The Artificial Neural Network proved to be more adequate for prediction of grain yield. Adaptability and stability analyses indicated that the environments are discriminant for selection of promising genotypes, and that the landrace variety Mulatinha can be recommended for planting in the municipalities.*

Keywords: *Genotype × environment interaction, prediction model, artificial neural network, multiple linear regression*

INTRODUCTION

The development and application of modeling in agriculture is an important tool that can serve to guide research, technological management, and decision-making (Corrêa et al. 2011). In this context, the use of mathematical models such as multiple linear regression and artificial neural networks allows correlation of agronomic traits with genotype performance in the field.

Regression analysis models and investigates the relationship among variables, studying the dependence of the trait of interest in relation to one or more independent variables (Gujarati 2000). For their part, artificial neural networks are computational techniques inspired by the neural architecture of the human brain, which acquires knowledge through experience (Braga et al. 2012). Thus, it is able to recognize patterns, i.e., it has the ability to learn through examples and generalize information learned, generating a non-linear model (Soares et al. 2015).

In recent years, artificial intelligence has repeatedly been used to predict the phenotypic expression of agronomic traits in economically important species, or even in species with high economic potential. Torkashvand et al. (2017) used Multilayer perceptrons (MLPs) to predict fruit firmness in kiwi varieties

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through contents of nutrients such as nitrogen, potassium, calcium, and others as predictors. Niedbała et al. (2019) used quantitative and qualitative predictor traits to evaluate the efficiency of three MLP architectures and predict wheat yield. They stressed the potential of this tool in pre-harvest stages.

Lima bean (*Phaseolus lunatus* L.) is the second most socio-economically important species of the genus (Ormeño-Orrillo et al. 2015); however, few studies have been conducted to determine the yield of the crop in Brazil (Freitas et al. 2015, Lopes et al. 2017). Lack of information combined with fierce competition to obtain resources for research justify the use of mathematical modeling to predict yield. For Soares et al. (2015), prominent advantages of use of models are savings in time, work, and volume of resources for planning and decision-making in the agricultural sector.

In plant breeding, a detailed study of the interaction between genotypes and environments (G × E) is fundamental when the purpose is selecting or recommending genotypes for planting (Streck et al. 2019). To attenuate the effects of the G × E interaction, Cruz and Carneiro (2006) advocate recommendation of cultivars based on the adaptability and stability of the genotypes.

Numerous methods have been proposed to estimate adaptability and stability parameters in multienvironment trials. These methods use concepts of univariate parametric (Eberhart and Russell 1966), multivariate (Zobel et al. 1988), mixed (Resende 2016), and non-parametric models. Among them, the Lin and Binns method (Lin and Binns 1988) stands out through its wide use and for combining the concepts of stability and adaptability in one parameter.

Thus, the aim of the present study was to compare the Multiple Linear Regression (MLR) and Artificial Neural Network (ANN) models in prediction of grain yield of lima bean grains and subsequent analysis of adaptability and stability for identification of the best performing landrace variety.

MATERIAL AND METHODS

Data were collected in experiments conducted in the Plant Science Department of the Agrarian Science Center of the Universidade Federal do Piauí (UFPI) in the municipality of Teresina, PI (lat 05° 05' 21" S, long 42° 48' 07" W, alt 72 m asl); and in a rural area in the municipality of São Domingos do Maranhão, MA (lat 05° 34' 33" S, long 44° 23' 07" W, alt 191 m asl) (Figure 1).

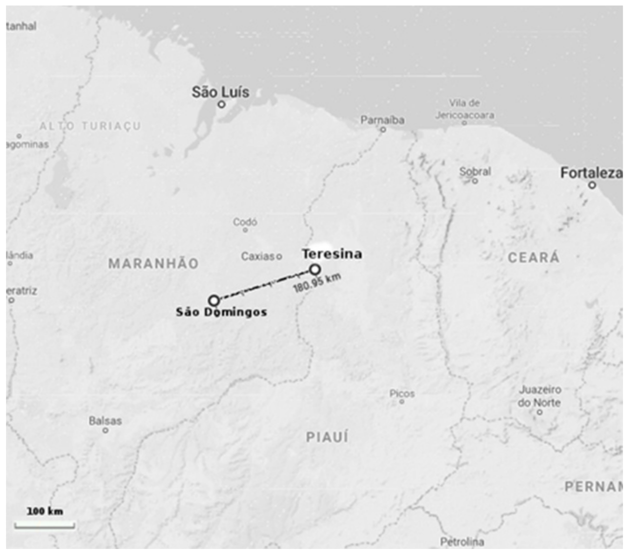

Figure 1. Teresina, PI and São Domingos do Maranhão, MA. Experimental stations where ten landrace varieties of lima bean were evaluated in a randomized block experimental design with four replications, in the Northeast region of Brazil.

A randomized block experimental design was used with four replications. Plots consisted of four 3.5-m rows at a spacing of 0.80 m between rows and 0.70 m between plants. The ten landrace varieties of lima bean evaluated are grown in the Northeast region of Brazil and have potential for commercialization (Table 1). The varieties evaluated have an indeterminate growth habit, and were therefore intercropped with late maturity landrace maize, which served as a trellis or support.

Table 1. Listing of the ten landrace varieties of lima bean coming from the Active Germplasm Bank of *Phaseolus* of the Universidade Federal do Piauí (AGB-UFPI), with the common names and places of origin

AGB-UFPI Code	Common name	Origin
UFPI 944	Boca-de-Moça	Várzea Grande – PI
UFPI 979	Fígado de Galinha	Pedra Branca – CE
UFPI 1235	Fava Branca	Buriti Bravo – MA
UFPI 1237	Fava Amarela	Farias Brito – CE
UFPI 1241	Fava Raio de Sol	Farias Brito – CE
UFPI 1246	Rajada	Balsas – MA
UFPI 1247	Chumbinho	Miguel Alves – MA
UFPI 1248	Fava Branca	Tianguá – CE
UFPI 1249	Fava Branquinha	Tianguá – CE
UFPI 1299	Mulatinha	Bom Jesus – PI

The following traits were measured in both experiments, according to the descriptors for *Phaseolus lunatus* L. (IPGRI 2001): number of days to flowering (NDF), number of days to pod maturity (NDM), pod length (PL), pod width (PW), pod thickness (PT), number of seeds per pod (NSP), number of locules per pod (NLP), seed length (SL), seed width (SW), seed thickness (ST), and 100 grain weight (100GW). Grain yield was measured only in the municipality of Teresina, PI.

The data (ten varieties and twelve traits measured) were separated in distinct samples for development (75% for training and 25% for testing), and they were standardized by subtracting each observation by the mean and dividing by the standard deviation of each trait.

To estimate grain yield in lima bean through multiple linear regression, the following linear model was adopted: $Y = \beta_0 + \beta_1 X_1 + ... + \beta_i X_i$; where Y represents grain yield; β_0 is the intercept of the regression; and β_i are the regression coefficients associated with the X_i predictor traits, with respect to i, with i = 1 ... n, where n is the total number of predictor traits.

Multilayer Perceptron (MLP) networks were trained considering the variation from one to three hidden layers plus the respective input and output layers. For the hidden layer, the number of neurons ranged from 25 to 100. The input layers of all the networks tested consisted of 11 neurons (number corresponding to the number of predictor traits). In all the layers, except for the last, the Rectified Linear Unit (ReLU) activation function was used, given by the relation: $f(x) = 0$, for $x < 0$, and $f(x) = x$, for $x \geq 0$. In the last layer, the identity function, $f(x) = x$ was used.

To train and validate the ANNs, the data obtained in the experiment developed in the municipality of Teresina, PI, were used. The networks were trained through the supervised learning process, for which the true output values (grain yield of each genotype) were provided in addition to the training data (predictor variables).

To adjust the weights, the backpropagation algorithm was considered. In order to avoid memorization of the data, a validation procedure was performed in each training epoch, in which 20% of the training data were sampled and used for model testing. The stopping point of the training algorithm was determined when the value of the mean absolute error (MAE) remained unchanged for five epochs. The architecture that had the lowest mean absolute error (MAE) and root mean square error (RMSE) values was selected as the predictor model.

The values of mean absolute error (MAE), the root mean square error (RMSE), the coefficient of determination (R^2), the mean absolute percentage error (MAPE), and the Pearson and Spearman correlation coefficients were used as criteria for comparison between the MLR and ANN models regarding the values predicted by the models and the true values:

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |O_i - P_i|$$

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

$$R^2 = \frac{\sum_{i=1}^{n} (O_i - \bar{O})^2 (P_i - \bar{P})}{\sqrt{\sum_{i=1}^{n} (O_i - \bar{O})^2 \sum_{i=1}^{n} (P_i - \bar{P})^2}}$$

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{O_i - P_i}{O_{-i}} \right| \times 100$$

where n is the number of data, O_i is the observed value, P_i is the predicted value, and the bar denotes the mean of the variable.

The prediction model selected was used to predict grain yield in São Domingos do Maranhão, MA. To do so, the data of the 11 traits collected in São Domingos do Maranhão, MA, were standardized (by subtracting each observation from the mean and dividing the results by the standard deviation of each trait) and used as predictor variables.

A sign of the effects of the G × E interaction was obtained based on the significance of the mean square of the interaction of the traits correlated with grain yield. Initially, the Pearson correlation coefficient was obtained between predictor traits and true yield in Teresina, PI, and then the traits that showed significant correlations with yield were selected. Combined analysis was conducted on these traits considering the two environments, which served to confirm the G × E interaction between the two locations.

Adaptability and stability were estimated based on the Lin and Binns method, described in the following manner (Lin and Binns 1988):

$$P_i = \frac{(X_{ij} - M_j)^2}{2n}$$

where:

P_i = superior index of the *i*th genotype;

X_{ij} = productivity of the *i*th genotype planted in the *j*th local;

M_j = maximum response obtained among all *n*th local genotype;

n = number of locations.

All the analyses described in this study were performed with the assistance of the keras package and functions implemented in the R software (R Core Team 2018).

RESULTS AND DISCUSSION

One hundred training epochs were necessary to obtain the optimum values of mean absolute error (MAE) and loss (Figure 2A). Reduction in loss values indicates that the learning process of the neural network was efficient during the training, considering that this parameter evaluates the difference between the output value and the expected value. For Ponti and Costa (2017), loss is a parameter that calculates the quality of the prediction.

Considering that at the beginning of the training the free parameters are generated at random, the instability of the data in the first epochs is noteworthy. Stability only occurs beginning in epoch 20, indicating an increase in the learning rate by means of adjustment of outputs. For Silva et al. (2010), after the network is trained and the error is at a satisfactory level, it can be used as a tool for evaluation of new data.

Based on training, the architecture that best combined good stability over the epochs and effective reduction in errors was that composed of three hidden layers, with 50, 100, and 50 neurons, respectively (Figure 2B). This ANN architecture was used for comparison with the predictive power of grain yield in Teresina obtained by the MLR method.

Between the two models evaluated, that which exhibited higher values of correlation and R^2, as well as lower values of root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE), was the ANN (Table 2). The performance of the ANN was found to be significantly superior to MLR when the correlation coefficients between the true data and the data predicted by the two models were compared. The magnitude of the RMSE and MAE parameters obtained by the ANN was around 40% less in relation to those obtained when the MLR model was considered, and the MAPE value obtained for ANN was six times lower than that obtained for the MLR model, indicating lower typical magnitude of the errors of the first model.

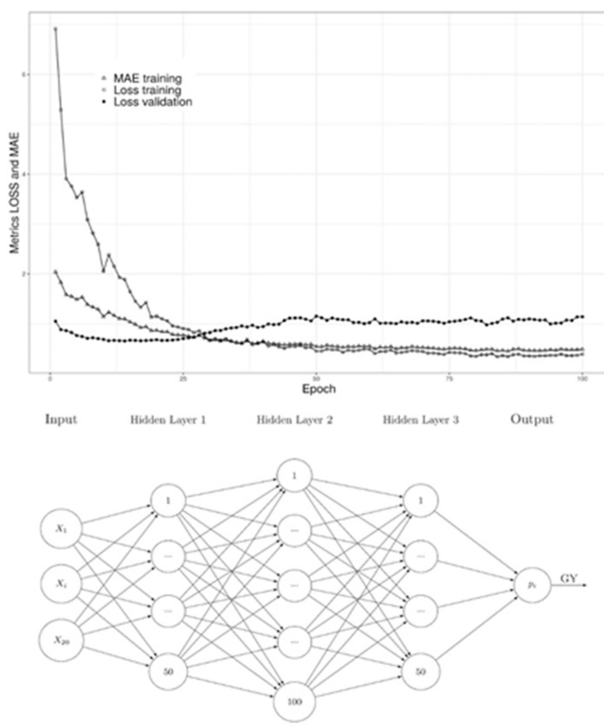

Figure 2. Training and architecture of the neural network. 2A - Average loss and MAE estimation curves for the calibration process of the ten best artificial neural network architectures, with training and validation data measured in Teresina, PI, Brazil. The iterative process ran 100 epochs, with reduction in the average of the loss and mean absolute error (MAE) parameters; 2B – Neural network consisting of three hidden layers, with 50, 100, and 50 neurons, used for prediction of grain yield in lima bean, with the data measured in Teresina, PI, Brazil, in 2018.

Table 2. Comparison of efficiency between the Multiple Linear Regression and Artificial Neural Network models for prediction of grain yield in lima bean in the municipality of Teresina, PI, Brazil

Parameter	Multiple Linear Regression	Artificial Neural Network
Spearman correlation	0.557	0.784
Pearson Correlation	0.559	0.806
Coefficient of determination (R^2)	0.312	0.650
Root mean square error (RMSE)	0.828	0.595
Mean absolute error (MAE)	0.690	0.426
Mean absolute percentage error (MAPE) - %	6.458	1.701

The coefficient of determination between the true data and data predicted by the ANN for grain yield in Teresina, PI, was 0.65, around 50% greater in relation to the multiple linear regression model, indicating that the values predicted by the ANN had lower quadratic deviations in relation to the experimental data. Such results show the suitability of use of neural networks for yield prediction in lima bean. Niazian et al. (2018), using metrics similar to those presented here, observed the efficiency of the ANN tool compared to the MLR model to predict seed yield of ajowan, and Torkashvand et al. (2017) observed the superiority of MLR models over ANNs using the RMSE and correlation measures applied to observed and predicted data. Niedbała et al. (2019) used the MAE and MAPE measures to evaluate the relative efficiency of three artificial neural network architectures.

In a study to evaluate the efficacy of the artificial neural network and of multiple linear regression for grain yield in wheat, Mehnatkesh et al. (2012) found that the ANN and MLR prediction models resulted in R^2 values of 0.84 and 0.53 and RMSE of 0.033 and 0.055, respectively, showing better suitability of the ANN, similar to that observed for lima bean. Thus, the model based on the ANN was used for prediction of grain yield in São Domingos do Maranhão, MA (Table 3).

The traits 100GW, PL, PT, NSP, NLP, SL, SW, and ST measured in Teresina showed significant correlation with grain yield. Thus, to confirm the G × E interaction, combined analysis among these traits measured in Teresina, PI, and São Domingos do Maranhão, MA, was performed. Significant values of the mean square of the G × E interaction were obtained only for the traits 100GW and SL (Table 4). Based on that premise, analysis of adaptability and stability considering the yields measured in Teresina, PI, and predicted in São Domingos do Maranhão, MA, was performed.

According to their average yield, the landrace varieties were classified in the following decreasing order: Mulatinha > Fava Branca MA > Amarela > Boca-de-Moça > Raio de Sol > Fava Branquinha > Fígado de Galinha > Rajada > Fava Branca > Chumbinho.

According to Cruz and Carneiro (2006), the nonparametric method proposed by Lin and Binns (1988) does not have the limitations observed with the use of regression-based methods and allows one or more genotypes to be identified with near-maximum performance in the environments evaluated through estimates of only one parameter (*Pi*). The most stable genotype has the smallest deviation in relation to the maximum yield of each environment (*Mj* value), that

Table 3. Grain yields of ten landraces of lima bean with values measured in Teresina, PI, and predicted in São Domingos do Maranhão, MA, Brazil, by Artificial Neural Networks

Variety	Yield measured in Teresina, PI (kg ha^{-1})	Predicted yield in São Domingos do Maranhão, MA (kg ha^{-1})
Mulatinha	1490.05	1381.06
Fava Branca MA	1191.33	973.78
Boca-de-Moça	1011.98	1037.48
Fava Branquinha	939.76	854.51
Raio de Sol	886.34	1116.97
Fava Amarela	851.80	1266.34
Fígado de Galinha	702.82	1056.26
Rajada	692.14	839.37
Fava Branca CE	605.86	600.13
Chumbinho	325.64	589.59

Table 4. Summary of combined analysis of variance for the traits of seed length (SL) and 100 seed weight (100SW) from seeds collected in Teresina, PI, and São Domingos do Maranhão, MA, that showed significant correlation with grain yield in Teresina, PI, Brazil, in 2018

Source of variation	**df**	**SL** (mm)		**100SW** (g)	
		Mean square	F	**Mean square**	**F**
Genotype	9	270.43	141.10**	6309.00	304.48**
Environment	1	29.99	15.64**	8382.10	404.53**
G × E	9	4.22	2.20*	192.40	9.28**
Error	57	1.91		20.70	
Overall mean		13.99		49.13	
CV (%)		9.87		9.25	

* and ** significant at 5% and 1% probability by the F test.

is, the lowest P*i* value. Thus, genotypes with lower *Pi* values respond in a more similar way to the ideal hypothetical genotype, since they have greater general adaptability.

For Mattos (2013), an ideal genotype should have high mean yield and maintain this yield in all the environments. Thus, the variety Mulatinha stood out by exhibiting performance nearest that of a hypothetical "ideal genotype" (Table 5). This genotype had lower *Pi* values and a satisfactory overall average, with higher yield than the others. Oda et al. (2019) states that genotypes identified as more stable and adapted are generally among the highest yielding when evaluated by this method. Melo et al. (2018) obtained similar results when evaluating adaptability and stability of 15 bean (*Phaseolus vulgaris* L.) genotypes in family farming systems in the state of Goiás, Brazil.

Table 5. Adaptability and stability (*Pi*) for grain yield, according to the Lin and Bins (1988) method, obtained from ten landraces of lima bean genotypes in two environments (Teresina, PI, and São Domingos, MA), Brazil

Variety	**Pi**
Mulatinha	< 10E-9
Fava Branca MA	63.77
Boca-de-Moça	86.64
Fava Branquinha	145.01
Raio de Sol	108.55
Fava Amarela	105.13
Fígado de Galinha	181.30
Rajada	232.51
Fava Branca CE	347.90
Chumbinho	495.56

The varieties Fava Branca MA, Boca-de-Moça, Fava Amarela, and Raio de Sol also performed better than the overall average and showed good stability. In contrast, Branquinha, Fígado de Galinha, Rajada, Fava Branca CE, and Chumbino did not have good grain yield, meaning that their relative performance is still far from ideal. In fact, high stability only makes sense when associated with high mean performance for the trait of interest (Yan 2011).

The variety Mulatinha is recommended for growing in São Domingos and Teresina. The landrace varieties Fava Branca CE and Chumbinho are not recommended for growing in these environments. The Lin and Binns method can be recommended for use in phenotypic stability studies of lima bean cultivars since it is simple to use and identifies stable genotypes among the most productive ones.

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