Using Non-linear mixed models and artificial neural network in the fitting growth pattern in pears cv. 'Williams' to predict final sizes at harvest.

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Abstract

The diameter of the fruit growth in pear cv. 'Williams' reflects a sigmoid pattern. Growth patterns make predictions of fruit's sizes to harvest at some point in the cycle. The mixed nonlinear models is fitted, since are suited for analyzing correlated and modeling the stochastic variability of fruit development.This models have a high prediction ability. Another way to describe it is using an artificial neural network.They are not able to capture the effects of covariates and the variability of the distribution in fruits predictions.

Keywords: Sigmoid pattern-mixed models-artificial neural network.

1. Introduction

In fruits production, it's extremeley important to know, in advance, the final size of the fruit. Having this information, not only the size but also the distribution, it enables the management strategies preparation in the packaging,storage and marketing logistics.In marketing, few millimeters in the fruit determine significant returns of money. The diameter of the fruit grows throughout the production cycle, which goes, from moments after flowering (days after full bloom or DDPF) to the harvest. It reflects a sigmoid pattern of growth. The figure sigmoid shapes an 's', which is characterized by an upper asymptote, a turning point and a lower asymptote. The upper asymptote indicates the maximum size attained by fruit, the tipping point is the point where the acceleration changes from increasing to decreasing, when the fruit sets the lower asymptote shows it's size. The adjusted model to describe the growth pattern of pears cv. *Williams y Packahms Triumph* is the third parameter logistic like was proposed by Bramardi et al [1]. This model and its great prediction ability comes across the best properties in measures of nonlinearity (Equation 1).

$$Y = \frac{1}{\beta_1 + \beta_2 * \beta_3^{DDPF}} \tag{1}$$

There are usually factors of stochastic variability that are no directly seen, such as site or plot, genetics and climate among others. Moreover, the monitoring of the fruits in constant periods of time causes correlations between measurements generating longitudinal measures during data recording. That why we propose the adjustment of mixed nonlinear models (MNLM). Since they are well suited for analyzing correlated data, which common in various disciplines such as pharmacokinetics, agriculture and medicine hierarchical data. In addition, MNLM allows modeling the stochastic variability of fruit development in its various sources through fixed parameters and random. The random effects in any parameter are useful not only to consider the variability in a population, but also for Empirical Bayesian estimators (EBE). In this context covariates are explained through the fixed parameters and the nonlinear regression models while the traditional sources of heterogeneity and correlation coud be considered through the inclusion of a mixed random effects model. EBEs has been used to examine groups of subpopulations that might be interesting to reveal the existence of quantifiable without considering fixed effects like environmental covariates. From this point of view the MNLM coud be used to predict the final diameter of the fruit from the EBEs, and to estimates the fixed effects and environmental covariates.

Another way to describe the growth pattern is using the artificial neural network (RNAr). This method coud be applied to aproximate any complex functional relationship, and it is not neccesary to specify the type of relationship between covariates and response variables. They represent an innovative technique for model fitting that doesn't rely on conventional assumptions, which is necessary for standard models and they can also be quite effectively to handle multivariate response data. A neural network model is very similar to a non-linear regression model, with an exception that the former can handle a large amount of model parameters. The RNAr consist of a group neurons organized in layers, which are usually fully conected by synapses. The input layer consist of all covariates in separate neurons and the output layer consist of the response variable[4].To each of the synapses a weight is attached indicating the effect of the corresponding neuron, and all data pass the neural network as signal.The signals are processed firts by the so-called integration function and then by the activation function transforming de output of the neuron. The inclution of the hidden layer increase the modelling flexibility one hidden layers is sufficient to model any piecewise continuous function.

In both MNLM like RNAr, they use different metrics to compared the validation in their settings and prediction ability.For example, the root mean square of the prediction,the standard error, the bias means and relative bias means.

2. Materials And Methods

The data collected in this work are intended to carry out the fruit production forecast in the provinces of Neuquén and Río Negro (Argentina). Whose objective is to estimate the potential volume of plantes. The information available consists of the diameters of the fruits of the main varieties of apples and pears, in different productive plots of the Upper Valley dating, from the years 1999-2000 until today. However, the afterwards analysis were used only to measure equatorial diameter of cultivar Williams pears. We analyzed the data which was collected for 16 seasons where 1451 fruits which correlates 16911 records individualized diameters. In each plot, five trees were selected pear cv. Williams, with 5 fruits per stratum size, small, medium and large they were labeled, completing a total of 15 fruits per plant- These fruits were measured weekly equatorial diameter to at least the time of harvest. The times of measurement are referenced as the days after full bloom (DDPF). The climate information related to temperature was relieved during 16 seasons to consider a possible environmental covariate. 976 termoacumulatives indexes were calculated from daily temperature in spring and another 594 for the month of December. These indexes were obtained from the various criteria such as from initial time of daily accumulation temperature, end time of daily accumulation and temperatures accumulation base. 30 models were adjusted, considering the different combinations of random, fixed and the most important climatic effects covariates . The models were evaluated and compared by standard methods such as likelihood ratio and information criteria (Akaike Information Criterion and Bayesian). Regarding the RNAr, to describe the individual growth of the fruits architecture it was used with two input neurons and one hidden layer with 10 neurons with two output neurons.The activation function was the logistic function by default. To describe the effects of site, size and major environmental covariates, we configure an architecture with 5 input neurons, 15 neurons in the hidden layer and 5 output neurons. The validation of the models used in MNLM as RNAr, included two stages: a first stage of calibration or training (depending on model used) and a second step of predicting the response variable. To sum up, the database is separated in a traninig database with 1374 fruits and other fruit validation 150. The R software environment[5] was used to fit the models and neural networks. The MNLM were fitted using the functions nlme and nlmer from packages nlme and lme4 respectively. Neural networks were applied through the nnet packages, neuralnet and NeuralNetTools.

3. Results and discussion

Taking into account the fixed and random effects models and pattern of fruit growth, model is written as follows:

$$Y_{jklmn} = \frac{1}{\beta_{1,size_k} + b_{1,jklm} * 0.01 + ((\beta_{2,size} + b_{2,jklm}) * 0.01)((\beta_{3,jklm}) * 0.1)^{DDPF}} + \varepsilon_{jklm} \quad (2)$$

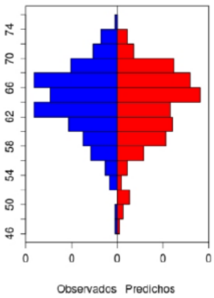
$$b_{i,jklm} = b_{i,plot_j} + b_{i,size(plot)_{k(j)}} + b_{i,tree(plot)_{l(j)}} + b_{i,size*tree(plot)_{kl(j)}} + b_{i,fruit_{m(jkl)}}$$

Although, it is important to clarify that the random effects they were only significant at the plot level and at the level of fruit. Environmental covariates were incorporated to the previous model(2) and they were also selected based on correlations of EBE. Based on 2 covariates temperature calculated from the accumulated respectively in September and December. Two models were built with each of them. Each one of this models were evaluated based on their prediction ability (Table 1). Both models (at temperatures register in September A and temperature register in December

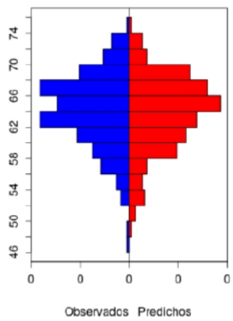
Models	**Diam**	**pred.diam**	$\overline{e}$	$\overline{e}\%$	**SD**
A)	63.89	63.60	0.29	0.40%	2.67
B)	64.42	64.29	0.13	0.14%	2.72

Table 1: Table with prediction metrics for two MNLM with diferent environmental covariates

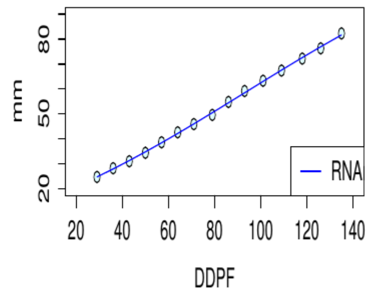
B) have a high predictive ability. Model B has a lower average error and relative error than the model A. However, it has a higher standard error.[7] A very important aspect in the prediction is the size distribution. As is shown in figures 3 both models have a similar prediction the observed distribution, extremely important aspects to production forecasts.



a)



b)



c)

With the architecture considered in this work,t he result that we obtained using the RNAr method they didn't have the production ability that we have with the mixed nonlinear models.

The neural networks able to copy the behaviour of individual fruits, but they couldn't capture the effects of covariates and the variability of the distribution in fruits forecast. Other authors[6] observed that the prediction ability of neural networks shows growth curves wich were superior than the classical nonlinear models except not mixed nonlinear models. The RNAr coudn't offer a complexity of the intervening random effects, variability in individual years over temperatures and evaluated plots. We require more time to monitore the fruits, to improve training on neural networks.

4. Bibliography

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