

Forecasting the black Sigatoka development rate: A comparison of machine learning techniques

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Abstract

Pending.

Keywords: Machine learning, Black Sigatoka, Support vector regression,
Banana disease prediction, Biological warning system

1. Introduction

The black Sigatoka disease caused by the fungus *Mycosphaerella fijiensis* Morelet is the major pathological problem of banana and plantain crops in Central America, Panama, Colombia and Ecuador, as well as in many parts of Africa and Asia (Marín Vargas and Romero Calderón, 1995).

This disease attacks the plant leaves producing a rapid deterioration of the leaf area. It affects the growth and productivity of the plants due to the impairment of the photosynthetic process. Furthermore, it causes a reduction in the quality of the fruit, and promotes premature ripening of bunches, which is the major cause of product losses associated with the black Sigatoka.

For these reasons, warning systems have been developed to detect the disease and monitor its progress. For instance, the early warning system developed by Ganry and Meyer (1983) and modified by Ganry and Laville (1972) for the

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14 control of the yellow Sigatoka in Cameroon, was later adapted by Ternesien
 15 (1985) and Fouré (1988) for the black Sigatoka.

16 This biological warning system is based on weekly observations of the disease
 17 progression on young leaves of the plant. Figure 1 shows an example of three
 progressive stages of the black Sigatoka.

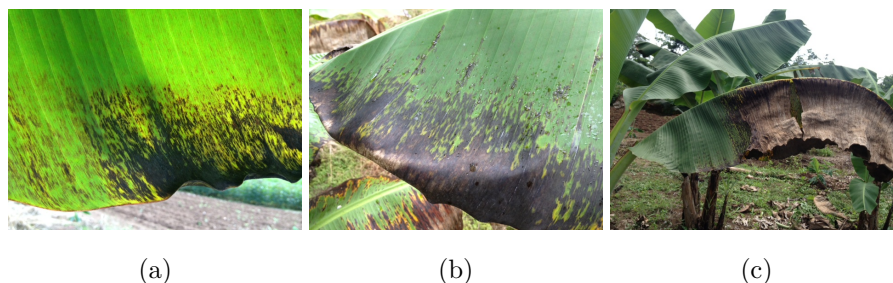


Figure 1: Examples of three disease stages of the black Sigatoka. (a) Initial stage. (b) Intermediate stage, and (c) Advanced stage.

18
 19 The disease progression is then quantified according to Fouré’s scale of the
 20 symptom stages (Fouré, 1988) by means of numeric coefficients that describe
 21 the degree of incidence and the severity of the disease development. These
 22 coefficients are then used to calculate two variables: gross sum and state of
 23 evolution.

24 The gross sum is based on the present disease progression stage and the
 25 numeric coefficients, which increase with the progression of the symptoms and
 26 the juvenility of the leaf. The state of evolution is calculated using the gross sum
 27 and the foliar emission period. Decades ago threshold levels on these variables
 28 were used as a guide to plan the spray schedules. Nowadays the fluctuation of
 29 these two variables seems to better suggest appropriate times to spray (Marín
 30 et al., 2003).

31 In Costa Rica the black Sigatoka is frequently treated with chemical fungi-
 32 cides. Depending on the zone of production and the weather conditions, 45–
 33 55 cycles/year of fungicide applications are required to keep this disease under
 34 control and to produce the expected fruit quality for the international mar-

35 kets. This represents a cost per hectare per year in the range from US\$1600
36 to US\$2000; about 0.64–0.80 cents of the production costs for a 18.14 kg box,
37 which overall corresponds to 10%–12% of the total production costs.

38 The past and present rates of disease development can in principle be used
39 to predict its future behavior and to determine if a particular fungicide spray
40 program will be able to effectively treat the disease in an economically affordable
41 way (Chuang and Jeger, 1987). Phytopathological studies point out that climate
42 has a major effect on the development of the black Sigatoka, where the main
43 variables affecting it are precipitation, temperature, relative humidity and wind
44 (Marín Vargas and Romero Calderón, 1995). It can be expected that patterns in
45 these variables correlate with the disease development and hence its automated
46 discovery can support decision-making in the control of crop diseases.

47 In this work, we compare four machine learning techniques to predict the
48 development rate of the black Sigatoka disease: support vector regression (SVR),
49 echo state networks (ESN), elastic net regression and ordinary least squares
50 linear regression, using input variables: maximal air temperature, minimal air
51 temperature, mean air temperature, mean relative humidity, minimal relative
52 humidity, maximal relative humidity, mean solar radiation, sum of precipitation,
53 maximal wind speed and mean speed wind, to predict the evolution stage in the
54 biological warning system.

55 The main findings were: 1) The highest R2 was 60% 2) The highest R2 were
56 reached with linear models like support vector regression with linear kernel, 3)
57 As little as three meteorological variables can be used because of the correlations
58 detected among variables.

59 The outline of the paper is as follows: Section 2 presents related works and
60 Section 3 summarizes the machine learning techniques selected for the analy-
61 sis. In Section 4 we present the methodology used in this study and describe
62 data used for its verification. The results and their discussion are presented
63 in section 5. The Section 6 concludes this article and presents lines for future
64 works.

65 2. Related works

66 Several efforts have been made to apply machine learning techniques in the
67 automated discovery of relationships between environmental variables and quan-
68 tified descriptors for variables of agricultural interest such as the progress of
69 diseases. Huang et al. (2010) summarize in their survey the development of soft
70 computing techniques in agricultural and biological engineering, especially in the
71 soil and water context for crop management and decision support in precision
72 agriculture, including fuzzy logic, artificial neural networks, genetic algorithms,
73 Bayesian inference and decision trees. They do not present numeric results of
74 each paper, only mention the main idea. Similarly, Kim et al. (2014) survey
75 more recent prediction methods for crop pests using regression and machine
76 learning approaches. Nor do they provide numerical results of each paper. In
77 general, the machine learning methods applied to predict the evolution of plant
78 diseases, can be classified in two main approaches: 1) those whose main inputs
79 are images, and 2) Those whose main inputs are environmental and biological
80 variables. Our study focuses in the second case. Romero Calderón (1995) re-
81 lied on regression models using a stepwise procedure to predict incubation and
82 disease latency periods for the black Sigatoka. He collected environmental data
83 from two different farms in Costa Rica between December 1993 and August
84 1995. The prediction models reached coefficients of determination R^2 of 69%
85 or 78% on the observed data for the incubation and disease latency periods,
86 respectively; however, the cross validation on independent data sets failed. In
87 contrast, our proposal presents a model that can be generalizable to other farms
88 that have data.

89 More recently, Glezakos et al. (2010) used genetic algorithms (GA) and neu-
90 ral networks (NN) to identify the Tobacco Rattle Virus (TRV) and the Cu-
91 cumber Green Mottle Mosaic Virus (CGMMV). The method was tested against
92 some of the most commonly used classifiers in machine learning (Bayes clas-
93 sifiers, decision trees and k -nearest neighbors) via cross-validation and proved
94 their applicability in these kind of problems. These authors do not prove their

95 methods in Sigatoka disease and they do classification. Instead we do regression.

96 Alves et al. (2011) used geoinformation techniques to develop predictive
97 models in the study of risk areas to soybean rust, coffee leaf rust, and banana
98 black Sigatoka, under consideration of Brazil’s climatic characteristics and the
99 distribution of soybean, coffee and banana crops. Temperature and rainfall
100 data were acquired for the period from 1950 to 2000, and simulated data were
101 generated for 2020, 2050 and 2080 using the SRES A2 climate change scenarios.
102 Using principal components analysis, a single variable was generated as a linear
103 combination of 57 input variables, in order to determine an index explaining
104 87%, 88% and 90% of the data variability of soybean, coffee and banana crops,
105 respectively, in municipal districts across Brazil. The climatic model was used
106 to generate the zoning of the three plant diseases, using temperature and leaf
107 wetness as input. This methodology enabled the visualization of the changes in
108 areas favorable for epidemics under possible future scenarios of climate change.
109 How intermediate result, they characterized the monocyclic process of the black
110 Sigatoka using nonlinear regression. Although they do not present the detailed
111 results, it no seem that they wanted to predict the progression of the black
112 Sigatoka in one, two or more periods ahead, how we do.

113 Other applications of machine learning methods in precision agriculture in-
114 clude the use of support vector regression to predict carcass weight in beef cattle
115 in advance to the slaughter (Alonso et al., 2013), machine learning assessments
116 of soil drying for agricultural planning (Coopersmith et al., 2014), and early de-
117 tection and classification of plant diseases with support vector machines based
118 on hyperspectral reflectance (Rumpf et al., 2010).

119 Furthermore, there have been attempts to generate software tools. Camargo
120 et al. (2012) presented an information system for the assessment of plant disor-
121 ders (Isacrodi). They showed that human experts will attain a much accurate
122 assessment than the Isacrodi classifier, particularly when provided with sam-
123 ples from the affected crop. However, in those cases where such expertise is not
124 available, the authors suggest that Isacrodi can still provide valuable support to
125 farmers. Isacordi includes 15 crop disorders, but the black Sigatoka is none of

126 them. The prediction process is based on multi-class support vector machines.

127 Regarding the prediction of the black Sigatoka disease development with
128 machine learning methods, Bendini et al. (2013) presented a study on the risk
129 analysis of its occurrence based on polynomial models. A case study was de-
130 veloped in a commercial banana plantation located in Jacupiranga, Brazil. It
131 was monitored weekly from February to December 2005. The data included the
132 weekly monitoring of the disease’s evolution stage, time series of meteorological
133 data and remote sensing data. They obtained a model to estimate the evolution
134 of the disease from satellite imagery. This model relates gray levels (NC) of
135 the band 2 images of the Landsat-5 satellite, with the progress status or disease
136 severity (EE). The authors claim to reach an R^2 of 90%.

137 There are also works related to the banana fruit. Soares et al. (2014) apply
138 two techniques: artificial neural networks (ANNs) and multiple linear regression
139 (MLR) in banana plant to predict the yield. Their results show that the neural
140 network is more accurate in forecasting the weight of the bunch in comparison
141 to the multiple linear regressors in terms of the mean prediction-error ($MPE =$
142 1.40), mean square deviation ($MSD = 2.29$) and coefficient of determination
143 ($R^2 = 91\%$).

144 Although these studies have their contribution, none proposed the kind of
145 preprocessing that we present, nor pose how to predict more than one period
146 ahead without trying to predict climate.

147 **3. Compared regression techniques**

148 In the prediction of the development rate of the black Sigatoka, we compare
149 techniques such as least squares regression and elastic-net regression, commonly
150 encountered in the agricultural literature with machine learning methods such
151 as support vector regression and echo state networks, where the parameter space
152 of each technique is also taken into account.

153 *3.1. Ordinary least squares regression*

Given a data set

$$D = \{(\mathbf{x}_i, y_i) \mid i = 1 \dots n\} \quad (1)$$

composed of the d -dimensional² feature vectors $\mathbf{x}_i \in \mathbb{R}^d$ and the corresponding responses y_i . The ordinary least squares regression (OLSR) fits a linear model $\tilde{y}_i = f(\mathbf{x}_i) = \langle \mathbf{w}, \mathbf{x}_i \rangle$ such that the sum of squares of the residuals $(\tilde{y}_i - y_i)$ is minimized. Let \mathbf{X} be the $n \times d$ feature matrix containing the i -th data sample \mathbf{x}_i^T in its i -th row and \mathbf{y} contain all the responses y_i corresponding to each row, then the least squares regression finds

$$\hat{\mathbf{w}} = \arg \min_{\mathbf{w}} E(\mathbf{w}) \quad (2)$$

with the error function

$$E(\mathbf{w}) = \|\mathbf{X}\mathbf{w} - \mathbf{y}\|_2^2$$

154 The solution is found by means of the pseudoinverse $\hat{\mathbf{w}} = \mathbf{X}^+ \mathbf{y} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$
 155 or equivalently by the singular value decomposition of \mathbf{X} (Press et al., 2007).

156 *3.2. Elastic net regression*

157 Instead of L_2 regularization prior ($\alpha \|\mathbf{w}\|_2^2$) included in the ridge regression
 158 (RR), Tibshirani (1996) used an L_1 term ($\lambda \|\mathbf{w}\|_1$) for his lasso estimator, which
 159 permits to select a subset of the available features by zeroing the weights of the
 160 deselected features. If the dimension d of the data is larger than the number n
 161 of data samples, lasso will select a maximum of d variables.

The elastic net regression (ENR) of Zou and Hastie (2005) combines both L_1 and L_2 priors of the ridge and lasso estimators such that the error function is now

$$E(\mathbf{w}) = \|\mathbf{X}\mathbf{w} - \mathbf{y}\|_2^2 + \alpha \|\mathbf{w}\|_2^2 + \lambda \|\mathbf{w}\|_1$$

162 This combination of priors still allows to learn a sparse model with only a
 163 few weights being non-zero like in the case of lasso, but still maintaining the
 164 regularization properties of the ridge regression (Pedregosa et al., 2011).

²Without loss of generality assume that the first component of every vector \mathbf{x}_i is always 1.

165 The elastic net is useful when multiple features are correlated: lasso will
 166 likely pick one of these at random, while the elastic net will still likely pick
 167 both.

168 3.3. Support Vector Regression (SVR)

From the perspective of Support Vector Regression (SVR) the regression function is usually formulated as

$$\tilde{y} = f(\mathbf{x}) = \langle \mathbf{w}, \mathbf{x} \rangle + b \quad (3)$$

The weights are selected in a convex optimization problem (Smola and Schölkopf, 2004):

$$\begin{aligned} & \text{minimize} \quad \frac{1}{2} \|\mathbf{w}\|^2 + C \sum_{i=1}^n (\xi_i + \xi_i^*) \\ & \text{subject to} \quad \begin{cases} y_i - \langle \mathbf{w}, \mathbf{x}_i \rangle - b & \leq \epsilon + \xi_i \\ \langle \mathbf{w}, \mathbf{x}_i \rangle + b - y_i & \leq \epsilon + \xi_i^* \\ \xi_i, \xi_i^* & \geq 0 \end{cases} \end{aligned}$$

169 where ϵ is the maximal allowed deviation of the targets \tilde{y}_i from the responses y_i ,
 170 the slack variables ξ_i and ξ_i^* allow to cope with otherwise unfeasible constraints
 171 for the optimization problem, and the constant $C > 0$ controls the trade-off
 172 between the flatness of f and the tolerance to deviations larger than ϵ .

173 Note that since OLSR, RR and ENR use a squared error function, data
 174 outliers will have a strong influence on the resulting weights \mathbf{w} . On the SVR
 175 formulation, however, the usage of the L_1 norm and the slack variables consid-
 176 erably restrict or completely block the influence of those outliers.

The SVR problem is reformulated by means of the dual optimization problem into (Smola and Schölkopf, 2004)

$$\mathbf{w} = \sum_{i=1}^n (\alpha_i - \alpha_i^*) \mathbf{x}_i \quad (4)$$

where $\alpha_i, \alpha_i^* \in [0, C]$ are Lagrange multipliers subject to $\sum_{i=1}^n (\alpha_i - \alpha_i^*) = 0$. In this so-called *Support Vector expansion* the weights are expressed as a linear

combination of the data set patterns \mathbf{x}_i . Inserting (4) in (3) leads to

$$f(\mathbf{x}) = \sum_{i=1}^n (\alpha_i - \alpha_i^*) \langle \mathbf{x}_i, \mathbf{x} \rangle + b \quad (5)$$

177 The Lagrange multipliers α_i, α_i^* are both non-zero only for those data points
 178 where $|f(\mathbf{x}_i) - y_i| \geq \epsilon$. Hence, the expansion of \mathbf{w} in terms of \mathbf{x}_i is sparse.
 179 Those data points with non-vanishing coefficients are called *Support Vectors*
 180 (Wei et al., 2013).

181 Additionally, in (5) it is possible to employ the *kernel trick* and replace the
 182 terms $\langle \mathbf{x}_i, \mathbf{x} \rangle$ with the evaluation of any Mercer kernel $k(\mathbf{x}_i, \mathbf{x}) = \langle \phi(\mathbf{x}_i), \phi(\mathbf{x}) \rangle$,
 183 where $\phi(\mathbf{x})$ is a non-linear mapping of the input space onto a higher (even
 184 infinite) dimensional feature space. The kernel evaluation draws unnecessary
 185 the explicit evaluation of the non-linear mapping, and it allows to solve non-
 186 linear regressions in the input space by implicitly mapping the samples through
 187 the kernel into the higher dimensional space, where the linear regression occurs
 188 (Alonso et al., 2013).

189 Kernels used in this work were:

Linear kernel:

$$K(\mathbf{x}_i, \mathbf{x}_j) = \mathbf{x}_i^T \mathbf{x}_j$$

Radial basis function (RBF):

$$K(\mathbf{x}_i, \mathbf{x}_j) = \exp\left(-\frac{\|\mathbf{x}_i - \mathbf{x}_j\|^2}{2\sigma^2}\right)$$

190 where σ is the parameter of gaussian model.

Sigmoid:

$$K(\mathbf{x}_i, \mathbf{x}_j) = \tanh\left[-c + \frac{\mathbf{x}_i \mathbf{x}_j}{\sigma^2}\right]$$

191 with $c \geq 0$ and σ^2 is the scaling vector.

192 3.4. Echo State Networks (ESN)

193 Recurrent neural networks (RNN) are capable of learning temporal patterns
 194 by feeding neuron outputs back into lower layers. Their training (usually by
 195 means of error backpropagation) is in general slow. Echo state networks (ESN)

are a particular type of recurrent neural network with a sparsely connected random hidden layer where only the weights of the output neurons are changed at training. The randomly selected weights at the input and middle layers (called *reservoir*) reproduce temporal patterns (*echoes*) that the output layer learns to select during the training (Lukoševičius and Jaeger, 2009).

For a given training input signal $u(n) \in \mathbb{R}^{N_u}$ a desired target output signal $y^{target}(n) \in \mathbb{R}^{N_y}$ is known. Here $n = 1, \dots, T$ is the discrete time and T is the number of data points in the training dataset.

The training seeks to learn a model with output $y(n) \in \mathbb{R}^{N_y}$, where $y(n)$ matches $y^{target}(n)$ as close as possible, by means of the minimization of an error measure $E(y, y^{target})$ such that it also generalizes well to unseen data (Lukoševičius, 2012).

4. Specification of data and methodology

Since the suitability of a machine learning technique to a particular problem is entirely depend on the nature of the data, we describe in this section, first, the data set employed in the study, followed by the methodology to compare the chosen techniques under consideration of their parameter space.

4.1. Data

The data used for the current study was acquired in two research farms of Corbana in Costa Rica³ : *28 Millas* located in the region of Matina, and *La Rita* located in Pococí, both in the province of Limón, Costa Rica. Both farms produce banana fruit *Musa* sp. AAA group ‘Grande Naine’ (Cavendish subgroup).

The available input and output variables are summarized in Table 1.

The data was captured for La Rita between the 48th week of 2002 to the 17th week of 2015 (647 weeks); for 28 Miles the data was captured between the

³Both farms were also use in the study of Romero Calderón (1995). Back then, *La Rita* was referred to as *Waldeck*.

Symbol	Description	Units
$T_{a_{max}}$	Maximal air temperature	[°C]
$T_{a_{min}}$	Minimal air temperature	[°C]
\bar{T}_a	Mean air temperature	[°C]
\bar{H}	Mean relative humidity	[0 – 100]
H_{min}	Minimal relative humidity	[0 – 100]
H_{max}	Maximal relative humidity	[0 – 100]
\bar{R}	Mean solar radiation	[W/m ²]
P	Precipitation	[mm]
W_{max}	Maximal wind speed	[m/s]
\bar{W}	Mean speed wind	[m/s]
E_s	Biological warning system – Evolution Stage	> 0

Table 1: Variables available for the learning algorithms

37th week of 2003 and the 18th week of 2015 (605 weeks). The data on the biological warning system were collected once a week.

The meteorological stations of Corbana acquire data every five minutes. computed on the data collected by nearby stations in each farm. Experiments were carry out with daily periodicity in meteorological variables and the results proved do not improve the prediction. Besides, weekly data pretend to diminish noise due sensor accuracy, missing values and outliers no detected.

The value to be predicted in all cases is the evolution stage E_s , which is a measure of the level of disease progression.

4.2. Data preprocessing

Data taken on real farms during more than a decade is expected to contain outliers, noise and missing samples. These problems are caused by human errors or by technical defects on the instruments used. In the preprocessing step described in this section these problems need to be detected and fixed before moving them to the next processing stages.

237 In the farm 28 Miles 1% and in La Rita 2.25% of the data were missing. To
 238 fill-in the missing values spline interpolation was used ALGLIB® (2017). The
 239 data collected did not exhibit outliers.

240 Each variable $x \in [x_{\min}, x_{\max}]$ was normalized into the interval $[0, 1]$ with
 241 the linear map $x_n = mx + b$ with $m = 1/(x_{\max} - x_{\min})$ and $b = -mx_{\min}$.

242 The variable E_s to be predicted was not normalized. This normalization step
 243 was made because learning schemes, like regression methods, deals only with
 244 ratio scales because they calculate the distance between two instances based on
 245 the values of their attributes Witten et al. (2011).

246 4.3. Evaluation criteria

247 Although there are many types of indicators to assess the quality of the
 248 prediction, here the coefficient of determination (R^2) and the Root Mean Square
 249 Error ($RMSE$). This decision is supported by the widespread use of the former
 250 indicator in the agriculture and the latter in machine learning (Soares et al.,
 251 2013, 2014; Ibrahim and Wibowo, 2014; Demir and Bruzzone, 2014).

Given n records $y_i, i = 1 \dots n$ of the actual outcome of a process. The mean
 \bar{y} of the observed data is given by

$$\bar{y} = \frac{1}{n} \sum_{i=1}^n y_i$$

Let \hat{y}_i be the predicted value for y_i . Then, the mean square error (MSE) S_e^2
 and the unexplained variance S_R^2 are estimated as University (2017)

$$S_e^2 = \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n} \quad S_R^2 = \frac{\sum_{i=1}^n (\hat{y}_i - \bar{y})^2}{n}$$

The root mean square error is defined as $RMSE = \sqrt{S_e^2}$ and the coefficient of
 determination is

$$R^2 = \frac{S_R^2}{S_R^2 + S_e^2}$$

252 4.4. Programming environment

253 We use Python programming language in its interpreted 3.5.2 version, partic-
 254 ularly with the libraries; Pandas (0.18.1 version) (McKinney, 2010) and Numpy
 255 (1.11.1 version) (van der Walt et al., 2011).

256 The implementation for SVR, elastic net and ordinary least squares regres-
 257 sions in scikit-learn (Pedregosa et al., 2011) were used. Adjustments to the
 258 ESN implementation code of Lukoševičius (2012) were necessary to allow its
 259 integration into our experimental framework.

260 4.5. Methodology

261 When the amount of data for training and testing is limited, is recommended
 262 to use cross-validation (Witten et al., 2011). We used ten-fold-cross-validation
 263 on the total set. El diseño experimental combinó los siguientes factores:

- 264 • Patrones de semanas: Se formaron patrones desde tres semanas continuas
 265 de observación para predecir una semana adelante, hasta doce semanas
 266 de observación para predecir tres semanas adelante. Por tanto, $n \times m$
 267 combinations, with $n = 1 \dots 12$ and $m = 1 \dots 3$.
- 268 • Techniques: Se utilizaron las siguientes técnicas, revisando el espacio
 269 paramétrico especificado a continuación:
 - 270 – SVR with linear kernel: C [0.001, 1, 10, 100, 1000], $epsilon$ [0.0, 0.4, 0.9].
 - 271 – SVR with gaussian kernel: C [0.001, 1, 10, 100, 1000], $epsilon$ [0.0, 0.4, 0.9],
 272 $gamma$ [0.0, 0.4, 0.9].
 - 273 – SVR with sigmoid kernel: C [0.001, 1, 10, 100, 1000], $epsilon$ [0.0, 0.4, 0.9],
 274 $gamma$ [0.0, 0.4, 0.9], $coef0$ [0.0, 0.5, 5, 10].
 - 275 – Echo state networks: $LeakingRate$ [0.02..0.9], $neurons$ [1%..90%] de
 276 la cardinalidad del training set, $InitLen$ [0.1..0.8].
 - 277 – Ordinary least squares linear regression: No parameters.
 - 278 – Elastic-net regression: $alpha$ [0..0.9], $l1_ratio$ [0..1.0].
- 279 • Variables included in the model:
 - 280 – All variables.
 - 281 – From the set $\{\overline{T}_a, \overline{H}, P, \overline{W}\}$ use the subsets with one, two, three or
 282 four elements. These variables have the largest impact on the disease
 283 development (Marín Vargas and Romero Calderón, 1995).

284 5. Results and discussion

285 Realizados los experimentos, la Table.2 muestra los $RMSE$ obtenidos, en la
 286 cual se puede observar que las ESN obtienen un resultado muy diferente a las
 287 demás técnicas. El $RMSE$ promedio obtenido por las ESN 11085.47 es cercano
 288 a 20 veces el de las otras técnicas. Este resultado de las ESN se explica debido
 289 a que estas redes neuronales recurrentes parten de estados aleatorios para irse
 290 ajustando en el proceso de entrenamiento, y por tanto, los valores obtenidos
 291 son reflejo de que la cantidad de datos disponibles no logra que la red neuronal
 se ajuste. Adicionalmente, la Figure 2 muestra los box plots con respecto a los

Table 2: Promedio y desviación estándar de los RMSE obtenidos por Finca

Farm	Technique	$RMSE_{mean}$	$RMSE_{std}$
28 Millas	Elastic net	463.56	82.39
	SVR with linear kernel	465.92	85.70
	SVR with Gaussian kernel	466.63	89.53
	Linear regression	468.25	83.57
	SVR with sigmoid kernel	552.81	123.82
	ESN	11085.47	7965.66
La Rita	SVR with linear kernel	816.29	216.43
	Elastic net	817.98	211.14
	SVR with Gaussian kernel	820.92	231.21
	Linear regression	823.55	213.24
	SVR with sigmoid kernel	1070.58	331.89
	ESN	8329.72	5435.54

292 $RMSE$ obtenidos. Se grafica ESN por separado debido a la diferencia de escala.
 293 Con respecto a las otras técnicas, la regresión lineal, Elastic net, SVR with gaussian
 294 kernel y SVR with linear kernel presentan compartamientos muy similares
 295 y aunque el promedio del $RMSE$ es diferente entre las fincas, La Rica cercano
 296 a 450 y 28 Millas cercano a 820, el comportamiento relativo de las técnicas es el
 297

298 mismo. Por su parte, SVR with sigmoid kernel presenta un promedio de $RMSE$
 299 muy inferior a ESN, pero superior a las otras cuatro técnicas.

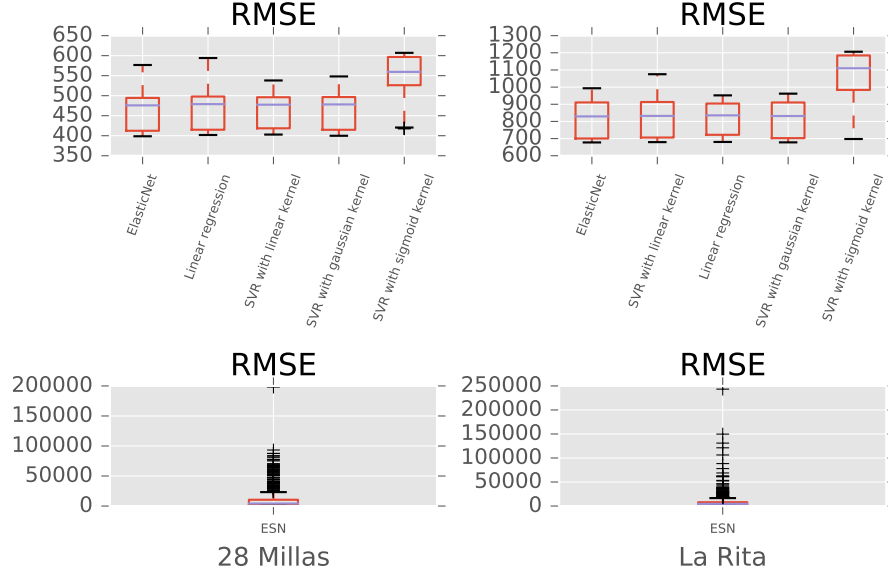


Figure 2: Box plots de los RMSE para cada una de las Fincas

300 Figure 3 shows the Pareto frontier for each farm with respect to R^2 and
 301 $RMSE$. La Rita obtains upper R^2 with respect to 28 Millas, but 28 Millas
 302 obtains better $RMSE$ than La Rita. This situation arise because $RMSE$ con-
 303 siders errors only with respect the prediction and in 28 Millas the average of
 304 Stage of Evolution is 4316.16, unlike, in La Rita the average is 5507.30. So,
 305 in La Rita we obtains higher errors in absolute values. R^2 is a relative metric
 306 between 0 thru 1 and it is less sensitive to absolute values.

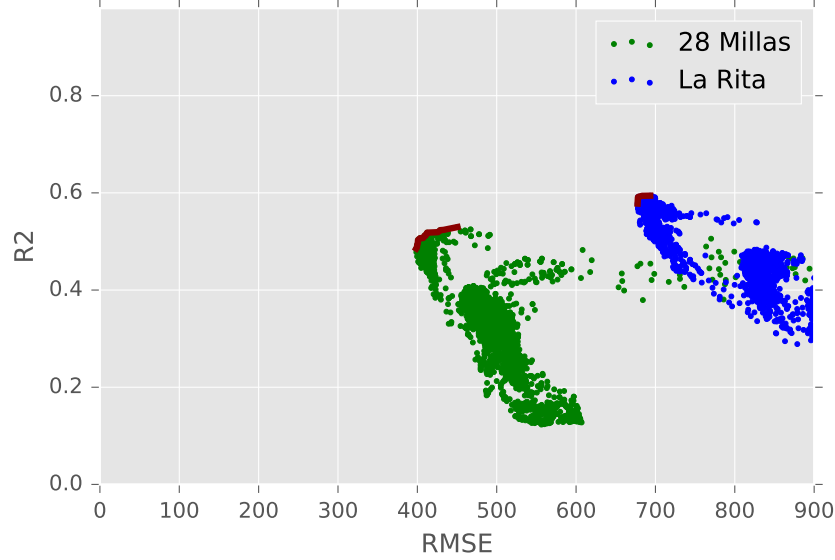


Figure 3: Pareto frontier for R^2 and $RMSE$

307 The Pareto frontier for the La Rita farm is composed by 5 elements. The
 308 Table.3 shows the composition about variables, observation ranges, techniques
 309 and weeks ahead.

Table 3: Composition of the Pareto frontier - La Rita

Variable	Observation range	Weeks ahead	Technique	R^2	$RMSE$
$\bar{T}_a \bar{W}$	1	1	SVR with linear kernel	693.39	59.4%
	2	1	SVR with linear kernel	683.22	59.4%
\bar{T}_a	5	1	SVR with linear kernel	679.25	59.2%
$\bar{T}_a \bar{H}$	5	1	Elastic net	677.49	57.8%
	5	1	SVR with linear kernel	677.37	59.1%

310 Similarly, the Pareto frontier for the 28 Millas farm is composed by 15 el-
 311 ements. The Table.4 shows the composition about variables and observation
 312 ranges.

313 Now, the Figure 4 compares the mean of the $RMSE$ for each technique in

Table 4: Composition of the Pareto frontier - 28 Millas

Variable	Observation range	Weeks ahead	Technique	R^2	$RMSE$
$\overline{T}_a \ \overline{H} \ \overline{W} \ P$	9	1	Elastic net	398.65	48.5%
	8	1	Elastic net	399.57	48.8%
	7	1	Elastic net	399.65	49.1%
$\overline{T}_a \ \overline{H} \ \overline{W}$	9	1	SVR with linear kernel	399.86	49.3%
	7	1	SVR with linear kernel	400.87	50.3%
	6	1	SVR with linear kernel	403.40	50.7%
	3	1	SVR with gaussian kernel	407.25	90.7%
$\overline{T}_a \ \overline{H}$	4	1	Elastic net	400.65	49.6%
	1	1	SVR with linear kernel	412.26	51.8%
	2	1	SVR with linear kernel	409.18	51.2%
$\overline{T}_a \ \overline{H} \ P$	2	1	SVR with linear kernel	410.71	51.2%
All	7	1	SVR with linear kernel	426.19	51.9%
	5	1	SVR with linear kernel	428.66	52.3%
	5	1	Elastic net	433.03	52.4%
	5	1	Linear regression	450.48	53.0%

314 the experiment. Se muestra el $RMSE$ para la predicción de 1, 2 ó 3 semanas
 315 adelante con respecto a la información de las variables climatológicas y del
 316 preaviso biológico observadas. Se aprecia que to predict one week ahead obtiene
 317 un $RMSE$ más bajo que two weeks ahead, and this is better than three weeks
 318 ahead, lo cual es lo esperado pues entre más semanas adelante se desee predecir,
 319 hay más incertidumbre.

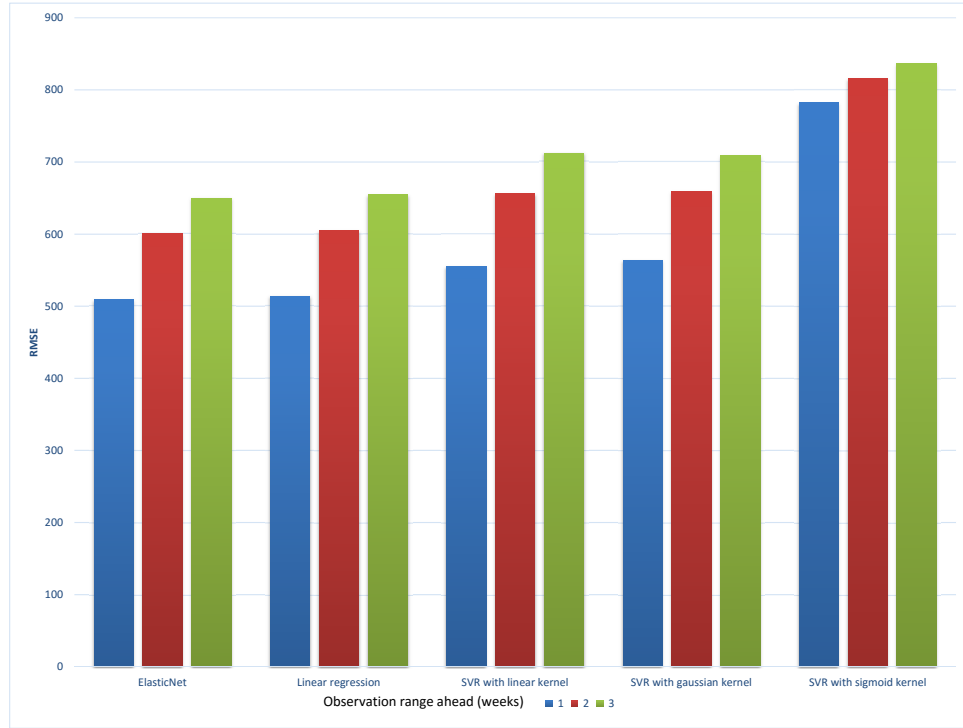


Figure 4: $RMSE$ for each algorithm

320 Figure 5 shows the the mean $RMSE$ for each variables combination. The
321 better results are obtained with \overline{T}_a , \overline{W} and P . Incluir más variables en el
322 modelo no asegura mejorar la métrica, lo cual es importante pues este resultado
323 sugiere que the use of more sensors do not assure a better result of prediction.

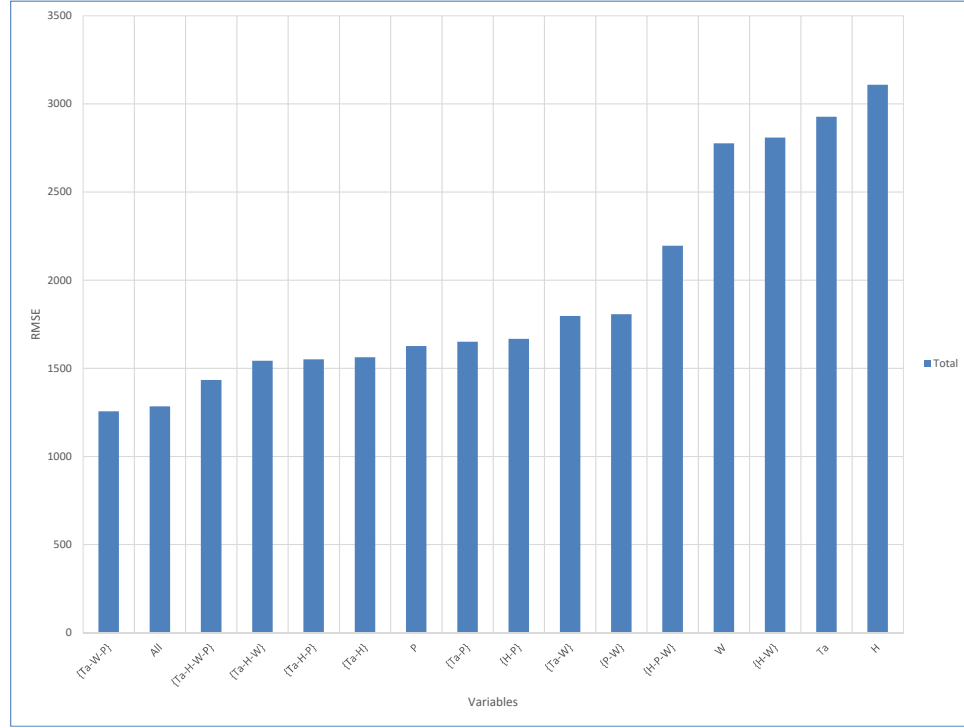


Figure 5: *RMSE* for each variable combination

324 6. Conclusions

325 The main findings were: 1) The highest R^2 was 60% 2) The highest R^2 were
 326 reached with linear models like support vector regression with linear kernel, 3)
 327 As little as three meteorological variables can be used because of the correlations
 328 detected among variables.

329 6.1. Future work

330 Currently this research is focused on the extension of these findings to other
 331 farms and the extension of the model to be applied in an early warning system,
 332 which does not require the regression task.

333 Acknowledgements

334 The authors would like to thank Corbana S.A. for providing the data for
335 this research.

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