

# 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

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## 1. Introduction

The black Sigatoka disease caused by the fungus *Mycosphaerella fijiensis* La bibliografía *Morelet* is the major pathological problem of banana and plantain crops in debe ser Central America, Panama, Colombia and Ecuador, as in many parts of Africa autor, anno and Asia [5].

This disease attacks the plant leaves producing a rapid deterioration of the leaf area, affects the growth and productivity of the plants due to the impairment of their photosynthetic ability causes a reduction in the quality of the fruit, and promotes premature maturation of bunches, which is the major cause of product losses associated with the black Sigatoka. Figure.1 shows three stages of this disease.

Phytopathological studies point out that precipitation, temperature, relative humidity and wind are the main climatic variables that affect its development

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14 [5].

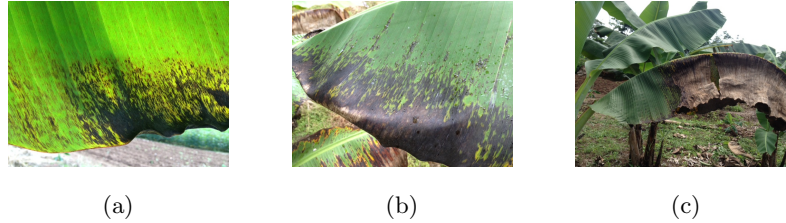


Figure 1: Examples of three disease stages of the black Sigatoka. (a) Initial stage. (b) Intermediate stage, and (c) Advanced stage.

15 In Costa Rica for the control of black Sigatoka is necessary the application  
16 of chemical fungicides. Depending of the zone of production and the weather  
17 conditions 45 - 55 cycles/year of fungicides is needed to keep this disease under  
18 control and to produce fruit with quality for exportation. This represent a cost  
19 per hectare per year ranged between \$1600 USD and \$2000 USD, about 0,64 -  
20 0.80 cents of the cost of production of a box of 18.14 kilograms. Overall, this  
21 represents 10% to 12% of the total production cost.

22 The past and present rates of disease development can in principle be used  
23 to predict its future behavior and to determine whether particular fungicide  
24 spray schedules will be able to effectively and economically control the disease  
25 Chuang and Jeger [2].

26 There are efforts to apply machine learning methods for decision-making in  
27 agriculture, including the control of crop diseases. For example, [Camargo et al.,2012]  
28 present an intelligent system for the assessment of crop disorders, [3] introduce  
29 a plant virus identification method based on neural networks with an evolu-  
30 tionary preprocessing stage, [4] summarize in their survey crop pests prediction  
31 methods using regression and machine learning approaches, while [7] present an  
32 intelligent agricultural forecasting system based on wireless sensor networks.

33 In this work, we compare four machine learning techniques (support vector  
34 regression (SVR), echo state networks (ESN), ridge regression and ordinary least  
35 squares linear regression) to predict the development rate of the black Sigatoka  
36 disease.

37 The main contribution of this work is a comparison between machine learning  
38 methods to forecast black Sigatoka development rate.

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## 39 **2. Materials and methods**

### 40 *2.1. Concepts*

#### 41 *2.1.1. Black Sigatoka disease*

42 Black Sigatoka, disease caused by the fungus *Mycosphaerella fijiensis* Morelet,  
43 is the main problem phytopathologic of banana and plantain crops in Central  
44 America [5].

45 This disease attacks the leaves of plants producing a rapid deterioration of  
46 the leaf area. It affects the growth and productivity of plants by decreasing  
47 photosynthetic capacity. Also causes a reduction in quality of the fruit [5].

48 The climate has a major effect on the behavior of the black Sigatoka. Precip-  
49 itation, temperature, relative humidity and wind are the main climatic variables  
50 affecting the development of this disease [5].

#### 51 *2.1.2. Biological warning system*

52 The early warning system for black Sigatoka is an adaptation of the yellow  
53 Sigatoka warning system developed by Ganry and Meyer and modified by Ganry  
54 and Laville to use for controlling yellow Sigatoka in Cameroon. Ternesien and  
55 Four later improved Ganry and Laville's system. The latter system is based on  
56 weekly observations of disease symptoms on young leaves of the plant, according  
57 to Four's symptom (stages) descriptions. Arbitrary coefficients, based on inci-  
58 dence and severity of disease development, are used to calculate two variables:  
59 gross sum and state of evolution. Gross sum is based on the stage present and  
60 an arbitrary coefficient, which increases with the advance of the symptoms and  
61 the juvenility of the leaf. The state of evolution is calculated using the gross  
62 sum and the foliar emission period. Although threshold levels were initially  
63 suggested as a guide to spray timing, the fluctuation of these two variables was  
64 found to better define appropriate times to spray [6].

65 2.1.3. Support Vector Regression (SVR)

From the perspective of Support Vector Regression (SVR) the regression function  $y = f(s)$  for a given dataset  $D = \{(s_i, y_i)\}_{i=1}^n$ , is represented as a linear function of the form [8]:

$$f(s) = w^T s + b$$

66 where  $w$  and  $b$  are respectively the weight vector and the intercept of the model,  
67 and they are selected to find an optimal fit to the data available in  $D$ .

68 For nonlinear cases, one proceeds by mapping the input  $p$ -dimensional vec-  
69 tors via a nonlinear function  $\phi : R^p \rightarrow F$ , onto the feature space  $F$ . After  
70 nonlinear mapping, the regression function evolves to a pervasive form:

$$f(s) = w^T \phi(s) + b$$

71 SVR uses the  $\epsilon$  - insensitive loss function:

$$l = |y - f(s)|_{\epsilon} = \begin{cases} 0 & |y - f(s)| \leq \epsilon \\ |y - f(s)| - \epsilon & else \end{cases}$$

72 which ignores the error if the difference between the prediction value and  
73 the actual value is smaller than  $\epsilon$ . The  $\epsilon$  - insensitive loss function allows to  
74 find the coefficients  $w$  and  $b$  by solving a convex optimization problem, which  
75 balances the empirical error and the generalization ability. In SVR, the empirical  
76 error is measured by the loss function -insensitive and the generalization ability  
77 is measured by the Euclidean norm of  $w$  [9]. Then, the optimization problem  
78 to identify the regression model can be formulated by [8]:

$$\begin{aligned} \text{miimize} \quad & J(w, \xi_i, \xi_i^*) = \frac{1}{2} \|w\|^2 + C \sum_{i=1}^n (\xi_i, \xi_i^*) \\ & y_i - w^T \phi(s) - b \leq \epsilon + \xi_i \\ \text{subject to} \quad & w^T \phi(s) + b - y_i \leq \epsilon + \xi_i^* \quad i = 1, 2, \dots, n \\ & \xi_i, \xi_i^* \geq 0 \end{aligned} \tag{1}$$

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79 where  $C$  denotes the penalty parameter between empirical and generalization  
 80 errors, and  $\xi_i, \xi_i^*$  are slack variables. Figure.2 shows this situation.

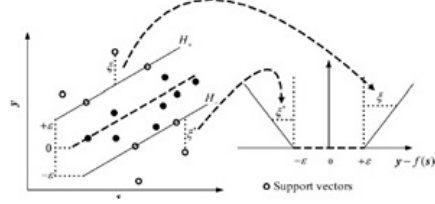


Figure 2:  $\epsilon$  - insensitive loss function[8].

The solution of this optimization problem by the Lagrange method is given by:

$$f(s) = w^T \phi(s) + b = \sum_{i=1}^n (\alpha_i - \alpha_i^*) K(s, s_i) + b$$

where  $\alpha_i - \alpha_i^*$  are the Lagrange multipliers of the optimization problems dual form and  $K(s_i, s_j)$  is the kernel function satisfying the Mercer condition, and holds:

$$K(s_i, s_j) = \langle \phi(s_i), \phi(s_j) \rangle$$

81 Operations in the kernel function  $K(s, s_i)$  are performed in the input space  
 82 rather than in the potentially high dimensional feature space of  $\phi$  [10].

#### 83 2.1.4. Ordinary least squares regression

84 This method fits a linear model with coefficients  $w = (w_1, \dots, w_p)$  to minimize  
 85 the residual sum of squares between the observed responses in the dataset, and  
 86 the responses predicted by the linear approximation. Mathematically it solves  
 87 a problem of the form [? ]:

$$\min_w \left\| Xw - y \right\|_2^2$$

88 where  $X$  denotes the features matrix.

89 According Pedregosa et al. [11] the coefficient estimates for Ordinary Least  
 90 Squares rely on the independence of the model terms. When terms are correlated

91 and the columns of the design matrix  $X$  have an approximate linear dependence,  
 92 the design matrix becomes close to singular and as a result, the least-squares  
 93 estimate becomes highly sensitive to random errors in the observed response,  
 94 producing a large variance. This situation of multicollinearity can arise, for  
 95 example, when data are collected without an experimental design

#### 96 2.1.5. Ridge regression

The ridge regression addresses some of the problems of ordinary least squares regression by imposing a penalty on the size of the coefficients. The ridge coefficients minimize a penalized residual sum of squares [11]:

$$\min_w \left\| Xw - y \right\|_2^2 + \alpha \left\| w \right\|_2^2$$

97 Here,  $\alpha > 0$  is a complexity parameter that controls the amount of shrinkage:  
 98 the larger the value of  $\alpha$ , the greater the amount of shrinkage and thus the  
 99 coefficients become more robust to collinearity.

#### 100 2.1.6. Echo State Networks (ESN)

101 Recurrent Neural Networks (RNN) are useful for temporal patterns, but  
 102 when they are trained with backpropagation methods, they are very slow. Echo  
 103 State Network (ESN) is an alternative training method to solve that problem.  
 104 ESN is based on the observation that if a random RNN possesses certain al-  
 105 gebraic properties, training only a linear readout from it is often sufficient to  
 106 achieve excellent performance in practical applications [12]. For a given train-  
 107 ing input signal  $u(n) \in R^{N_u}$  a desired target output signal  $y^{target}(n) \in R^{N_y}$  is  
 108 known. Here  $n = 1, \dots, T$  is the discrete time and  $T$  is the number of data points  
 109 in the training dataset. The task is to learn a model with output  $y(n) \in R^{N_y}$ ,  
 110 where  $y(n)$  matches  $y^{target}(n)$  as well as possible, minimizing an error measure  
 111  $E(y, y^{target})$ , and, more importantly, generalizes well to unseen data. The un-  
 112 trained RNN part of an ESN is called a dynamical reservoir, and the resulting  
 113 states  $x(n)$  are termed echoes of its input history [13]. Finally, these signals are  
 114 sent to an output layer as shown in the Figure.3.

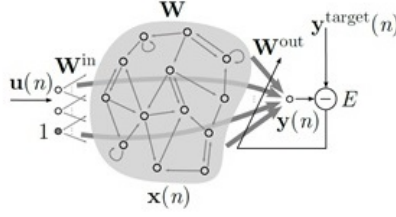


Figure 3: An echo state network [13].

115 The connections between the different elements of an Echo State Network  
 116 have weights randomly generated. The weights of the internal connections of  
 117 the reservoir ( $W$ ) as well as the weights of the input layer ( $W_{in}$ ), after being  
 118 generated are set statically during all stages of implementation of the algorithm.  
 119 The weights between the reservoir and the output layer ( $W_{out}$ ) are subject  
 120 to changes of a supervised learning algorithm to correct the degree of error  
 121 generated by the entire system [13].

#### 122 2.1.7. Related works

123 Huang et al. [3] surveyed the development of soft computing techniques in  
 124 agricultural and biological engineering, including fuzzy logic, artificial neural  
 125 networks, genetic algorithms, bayesian inference and decision trees.

126 A related work, proposed by Romero [14] relies on regression models using  
 127 a stepwise procedure to predict incubation and latency times of black Sigatoka.  
 128 The author performed experiments on two farms located in Costa Rica (La Rita  
 129 and Waldeck, the same as those used in this study but with different names).  
 130 The study used data from: December 1993 to August 1995. Romero concluded  
 131 that the model to predict the incubation period accounted a  $R^2$  of 69% in his  
 132 observed data but it was not a good predictor when it was validated against an  
 133 independent dataset (cross validation). For latency, he developed two models  
 134 that accounted a  $R^2$  of 78% PONER EL VALOR OBTENIDO in the observed  
 135 data, however, when validated against an independent dataset (cross validation),  
 136 the model was incorrect PONER EL VALOR OBTENIDO for Weldeck, and for  
 137 Rita obtained an adjusted  $R^2$  of 82%.

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138 Glezakos et al. [15] proposed to use Genetic Algorithms (GA) and Neu-  
 139 ral Networks (NN) to identify plant virus (Tobacco Rattle Virus (TRV) and  
 140 the Cucumber Green Mottle Mosaic Virus (CGMMV)). This is achieved by  
 141 the development of ana- lytical tools of evolutionary adaptive width, propelled  
 142 by Genetic Algorithms (GAs) and Neural Networks (NNs). The method was  
 143 tested against some of the most commonly used classifiers in machine learning  
 144 (Bayes, Trees and k-NN) via cross-validation and proved its potential towards  
 145 the identification.

146 In the agricultural context, Alves et al. [16] used geoinformation techniques  
 147 to develop predictive models to study the areas of risk to soybean rust in soy-  
 148 bean, coffee leaf rust in coffee, and black Sigatoka in banana, considering Brazils  
 149 climatic characterization and the distribution of soybean, coffee and banana  
 150 crops. Temperature and rainfall data were obtained for the period from 1950  
 151 to 2000, and of simulations for 2020, 2050 and 2080 using the SRES A2 cli-  
 152 mate change scenarios. Using principal components analysis, a single variable  
 153 was generated based on 57 variables, in order to determine an index explain-  
 154 ing 87%, 88% and 90% of the variability of soybean, coffee and banana crops,  
 155 respectively, in municipal districts across Brazil. The climatic model was used  
 156 to generate the zoning of the three plant diseases, using temperature and leaf  
 157 wetness as input. Areas of favorability for the diseases were plotted against the  
 158 main coffee, soybean and banana growing areas in Brazil. This methodology  
 159 enabled the visualization of the changes in areas favorable for epidemics under  
 160 possible future scenarios of climate change.

161 Other applications of machine learning methods in precision agriculture in-  
 162 clude the use of support vector regression to predict carcass weight in beef cattle  
 163 in advance to the slaughter [10], machine learning assessments of soil drying for  
 164 agricultural planning [17], and early detection and classification of plant diseases  
 165 with support vector machines based on hyperspectral reflectance [18].

166 Furthermore, there have been attempts to generate software tools. Camargo  
 167 et al. [Camargo et al.,2012] presented an information system for the assessment  
 168 of plant disorders (Isacrodi). They proposed that experts will attain a much



169 better accuracy than the Isacrodi classifier, particularly when provided with  
 170 samples from the affected crop. However, those cases where such expertise is  
 171 not available, they suggest that Isacrodi can provide valuable support to farmers.  
 172 Isacordi includes 15 crop disorders, but the black Sigatoka no is one of them.  
 173 The prediction process is based on multi-class support vector machines.

174 Regarding the prediction of the development of the black Sigatoka with ma-  
 175 chine learning methods, Bendini et al. [19] presented a study about the risk  
 176 analysis of black Sigatoka occurrence based on polynomial models. A case study  
 177 was developed in a commercial banana plantation located in Jacupiranga, Brazil.  
 178 It was monitored weekly during the period from February to December 2005.  
 179 Data included the weekly monitoring of the diseases evolution stage, time series  
 180 of meteorological data and remote sensing data. They obtained a model to esti-  
 181 mate the evolution of the disease from satellite imagery. This model relates gray  
 182 levels (NC) of the band 2 images of the Landsat-5 satellite, with the progress  
 183 status or disease severity (EE). The authors claim to reach an  $R^2$  of 90%.

184 Also there are works related to banana fruit. Soares et al. [20] apply two  
 185 techniques: artificial neural networks (ANNs) and multiple linear regression  
 186 (MLR) in banana plant to predict the yield, their results show that the neural  
 187 network proved to be more accurate in forecasting the weight of the bunch in  
 188 comparison to the multiple linear regressions in terms of the mean prediction-  
 189 error ( $MPE = 1.40$ ), mean square deviation ( $MSD = 2.29$ ) and coefficient of  
 190 determination ( $R^2 = 91\%$ ).

191 In general, the machine learning methods applied to predict the evolution  
 192 of plant diseases, can be classified in two main approaches: 1) Those whose  
 193 main inputs are images, and 2) Those whose main inputs are environmental  
 194 and biological variables. Our study focuses in the second case.

#### 195 2.1.8. Data

196 In this work we use data acquired in two research farms of Corbana in Costa  
 197 Rica: 1) 28 Millas (previously called Waldeck and located at Matina) and La  
 198 Rita (located at Pococ), both in the province of Limn, Costa Rica. The banana

199 type is Musa AAA, subgroup Cavendish, cv. Grande Naine. The Table.1 shows  
200 the variables available.

Table 1: Variables used in the study

| Variable    | Meaning                                   |
|-------------|---|
| $T_{max}$   | Max air temperature                       |
| $T_{min}$   | Min air temperature                       |
| $\bar{T}_a$ | Mean air temperature                      |
| $H$         | Humidity                                  |
| $H_{min}$   | Min humidity                              |
| $H_{max}$   | Max humidity                              |
| $R$         | Solar radiation                           |
| $\bar{P}$   | Mean precipitation                        |
| $W_{max}$   | Max speed wind                            |
| $\bar{W}$   | Mean speed wind                           |
| $L_2$       | Biological warning system Leaf 2          |
| $L_3$       | Biological warning system Leaf 3          |
| $L_4$       | Biological warning system Leaf 4          |
| $E_s$       | Biological warning system Evolution Stage |

201 The value to be predicted in all cases was  $E_s$ , that is the total measure of  
202 the biological warning system.

203 The data on the biological warning system are collected once a week. Al-  
204 though Corbana has meteorological stations that take data every five minutes,  
205 for these experiments, weekly averages generated by nearby stations to each of  
206 the farms were used.

207 The time intervals used for this study were: La Rita, week 48 of 2002 to  
208 week 17 of the 2015 (647 weeks) and for 28 Miles, week 37 of 2003 to week 18  
209 of 2015 (605 weeks).

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210 *2.1.9. Data preprocessing*

211 In 28 Miles farm, 1% of the data were missing, while in La Rita was 2.25%.  
 212 To fill-in the missing values we use spline interpolation. The data collected did  
 213 not exhibit outliers.

Due the fact that the variables measure meteorological or biological process, they are discretized in order to reflect trends in the data, i.e. the continuous values are not directly used. The coefficient of variation  $C_v(x)$  of each variable  $x$  was used to determine the number  $n$  of discretization levels.

$$n = \lfloor 100 C_v(x) \rfloor$$

214 where  $\lfloor \cdot \rfloor$  is the round operator.

215 Each discretization range was uniformly partitioned. Besides enabling the  
 216 capture of tendencies, the discretization removes the effect of small variations  
 217 in the data collection, either by inaccuracies of the instruments (meteorological  
 218 variables) or by subjective bias introduced by the human who collects the data  
 219 (biological warning system). ESTO DEBE ESTAR DESCRITO EN ALGUNA  
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221 Each feature was scaled to fit in a range between 0 and 1. The variable to  
 222 be predicted was not scaled.

223 *2.2. Evaluation criteria*

224 Although there are many types of indicators to assess the quality of the pre-  
 225 diction, we selected the root mean square error ( $RMSE$ ) and the determination  
 226 coefficient ( $R^2$ ).

Given  $n$  records, let be  $y$  the actual value of the series,  $\hat{y}$  the predicted value and  $\bar{y}$  the mean of the observed data.

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (y - \hat{y})^2}{n}}$$

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

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

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

$$S_y^2 = S_R^2 + S_e^2$$

$$R^2 = \frac{S_R^2}{S_y^2}$$

227 This decision is supported by the widespread use in machine learning and  
228 agriculture areas [20], [21], [22] and [23].

### 229 2.3. Methodology

230 The selection of methods and their parametrisation was performed in two  
231 stages.

#### 232 **Phase one**

233 In the phase one, we did ten-fold-cross-validation on a set of machine learning  
234 methods and different configurations:

- 235 • Patterns: n by m, where n from 1 to 8 and m from 1 to 3.
- 236 • Methods: support vector regression with the kernels functions: linear,  
237 RBF (Gaussian) and sigmoid; echo state networks; ordinary least squares  
238 linear regression and ridge regression.
- 239 • Variables included in the model:
  - 240 – All variables.
  - 241 – from the set  $\{\overline{T}_a, H, \overline{P}, \overline{W}\}$  use the subsets with one, two or four  
242 elements. These variables are according to experts the ones having  
243 most impact on the disease development [5].

244     **Phase two**

245     In the second phase, the best configurations obtained in phase one are used  
246 to validate with the last 52 and 102 weeks.

247     This second phase intends to expose how these methods behave on a consid-  
248 erable climate in the years 2014 and 2015.

249     *2.4. Programming environment*

250     We use the python programming language with the Integrated Development  
251 Environment (IDE) Spyder [24], particularly with the libraries pandas [25] and  
252 numpy [26]. For SVR, ridge and ordinary least squares regressions, we used  
253 sklearn [11] and for ESN the python-based code of Dr. *Lukoševičius* [13] on  
254 which the necessary were done for adjustments for the experiments of this work.  
255 The computer used a processor Intel(R) Core i7-4800MQ CPU @ 2.70GHz, 16.0  
256 GB RAM, running Windows 8 Pro.

257     **3. Results**

258     **4. Discussion and conclusions**

259     **5. References**

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