

# Forecasting the black Sigatoka development rate: A machine learning methods comparison

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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* Morelet is the major pathological problem of banana and plantain crops in Central America, Panama, Colombia and Ecuador, as in many parts of Africa and Asia [6].

This disease attacks the plant leaves producing a rapid deterioration of the leaf area, affects the growth and productivity of plants as the ability of photosynthesis decreases, causes a reduction in the quality of the fruit, and promotes premature maturation of bunches, which is the major cause of product losses due to this disease. 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 the development of this disease [6].

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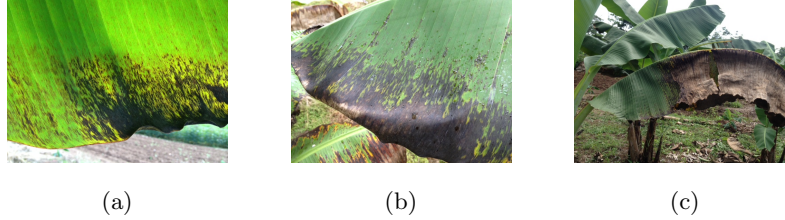


Figure 1: Examples of three disease stages of the black Sigatoka. (a) Initial stage. (b) Intermediate stage, and (c) Advanced stage.

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15 According to studies by the National Banana Corporation of Costa Rica (Cor-  
 16 bana) made in 2013, considering on average between 53 thru 57 cycles of fungi-  
 17 cide applications per farm, the cost per hectare per year ranged between \$1800  
 18 USD and thru \$1900 USD. This represents about 0.76 cents of the price of a box  
 19 of 18.14 kilograms. Overall, this represents 10% to 12% of the total production  
 20 cost Brescani [1].

21 The past and present disease development rate can in principle be used to predict  
 22 its future behavior, tendencies and to determine whether particular fungicide  
 23 spray schedules will be able to effectively and economically control the disease  
 24 Chuang and Jeger [3].

25 There are efforts to apply machine learning methods for decision-making in agri-  
 26 culture, including the control of crop diseases. For example, [Camargo et al.,2012]  
 27 present an intelligent systems for the assessment of crop disorders, [4] introduce  
 28 a plant virus identification method based on neural networks with an evolu-  
 29 tionary preprocessing stage, [5] summarize in their survey crop pests prediction  
 30 methods using regression and machine learning approaches, while [7] present an  
 31 intelligent agricultural forecasting system based on wireless sensor networks.

32 In this work, we compare four machine learning methods: support vector re-  
 33 gression (SVR), echo state networks (ESN), ridge regression, and ordinary least  
 34 squares linear regression, to predict the black Sigatoka disease development rate.  
 35 The main contribution of this work is a comparison between machine learning  
 36 methods to forecast black Sigatoka development rate.

## 38 **2. Materials and methods**

### 39 *2.1. Concepts*

#### 40 *2.1.1. Biological warning system*

41 The system measures the disease development state to determine when to  
 42 apply fungicides [6]. This system is based on two components: a climate com-  
 43 ponent, which is given by the Piche evaporation and a biological component,  
 44 given by the stage of progress or the rate of disease development. Originally,  
 45 this system was designed to work with young plants. One selected plant must  
 46 exhibit a normal growth and be in a place that enforces a healthy development.  
 47 The plant must start with 5 to 6 true leaves. The assessments are made at  
 48 fixed intervals of seven days as long as possible, on the same plant. The first  
 49 observations should consider the leaf emission, also the level of infection on the  
 50 leaves should be evaluated considering the stages of development [6].

#### 51 *2.1.2. Support Vector Regression (SVR)*

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## 53 **3. Results**

## 54 **4. Discussion and conclusions**

## 55 **5. References**

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