Simulation model to assess the efficacy of host partial resistance: case of black leaf streak disease on banana

Clara Landry^{1*}, François Bonnot², Virginie Ravigné², Jean Carlier², Jean Vaillant³, Catherine Abadie¹



1: CIRAD, UMR BGPI, 97130 Capesterre B-E, Guadeloupe (FWI) 2: CIRAD, UMR BGPI, F-34398 Montpellier, France

3: University of Antilles-Guyane, LAMIA, 97100 Pointe-à-Pitre, Guadeloupe (FWI) * clara.landry@cirad.fr





INTRODUCTION

- Few epidemiological models exist combining plant and epidemic development and integrating two (asexual and sexual) modes of pathogen reproduction. None exists for the Black leaf streak disease (BLSD), the most severe foliar disease of bananas, due to the heterothallic ascomycete fungus Mycosphaerella fijiensis.
- Previous studies have shown that partial resistance of banana may act on the 3 of the 4 main steps of the BLSD infectious cycle (*Figure 1*): infection, lesion growth and sporulations.
- The aims of this study are to propose a simulation model of banana/M.fijiensis pathosystem at plant scale, to evaluate the impact of partial resistance components on the BLSD severity and to estimate epidemic cycle parameters with dynamical experimental data.

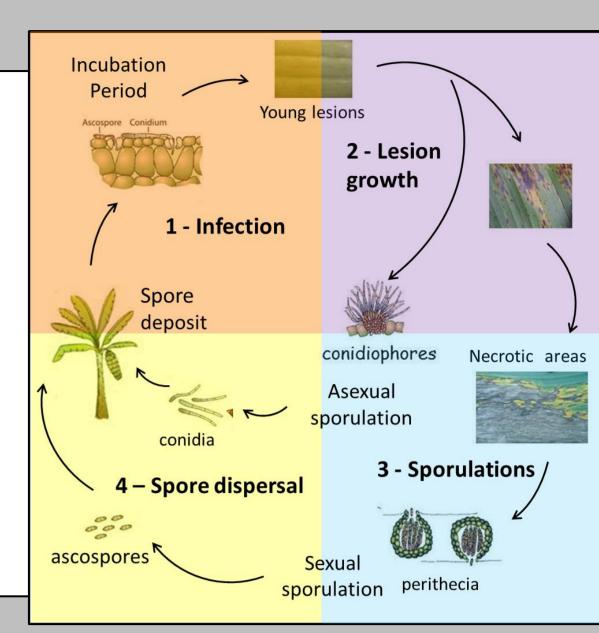


Figure 1. BLSD epidemic cycle

THE MODEL

- A mechanistic model was developed in discrete time (1 day step) at plant scale. It describes both banana development and BLSD process over several crop cycles and under optimal epidemiological conditions. The spatial unit of the model is 1mm² of lesions.
- Two submodels (Figure 2):
 - a deterministic model of banana growth with simplified architecture; 10 parameters are implied.
 - the complete detailed epidemic cycle integrating stochasticity into the reproductive process of the pathogen; 19 parameters are implied. Maximum number of

Example of formalization:

[1] Number of infections on the part of leaf (c) of leaf (l) in t:

$$Infection_{l,c}(t) = \frac{vacant_area_{l,c}(t)}{total_area_{l,c}(t)} IE. exp^{-b.l} (A_{l,c}(t) + S_{l,c}(t))$$

The main output of this model is the BLSD severity (i.e.% necrotic area).

Primary inoculum **Epidemic cycle submodel** Plant submodel (asexual and sexual spores) Infection **Lesions growth** Banana growth Incubation period (IP) - Number of asexual and sexual spores - 2 stages: juvenile and lesion growth (LG) deposited (resp. A and S). adult (SJ, SA) Infection efficiency (IE) Leaf surface (LF) Leaf receptivity (b) Leaf emission rate (LER) Maximum number of leaves (MNL) - Harvest time (HT) **Spores dispersal Sporulations** - Asexual spores dispersal $(\alpha_a, \beta_a, \gamma_a, \delta_a)$ - Sporulating lesions sizes (θ_{inf} , θ_{sup} for leaves at HT (MNLH) Sexual spores dispersal $(\alpha_s, \beta_s, \gamma_s, \delta_s)$ sexual and asexual reproduction) - Flowering time (FT) (air, plant and sucker leaves, ground) Sporulations capacities (asexual Spores lifetime (LT) ASC and sexual SSC) **OUTPUT:** $severity_{l,c}(t)$, $severity_l(t)$, severity(t)

Figure 2. Overview of the banana/M.fijiensis model and the articulation of different submodels

SIMULATIONS

 The prior knowledge of parameters based on available data issued from field and controlled experiments, expert opinion and literature, were used to realize simulations over several crop cycles (Figure 3).

Difference of variety susceptibility = different values of IE, IP, LG, ASC and SSC epidemic parameters

partial resistant variety Flowering time: severity is on the susceptible Simulation time (days)

Figure 3. Simulated BLSD severity kinetic on 3 different varieties differing on epidemic cycle parameters during one crop cycle

SENSITIVITY ANALYSIS

- We performed a sensitivity analysis to quantify the impact of 5 epidemic parameters and their interactions on the decomposition of the disease severity variance (Figure 4).
- We used FAST method to calculate the global sensitivity indices (Saltelli et al., 2000) from 200 simulations for each parameter.

Main effect = First order index, influence of one parameter independently of the others.

Interactions= Total index, influence of the parameter in combination with the others

 LG and IE parameters have the highest first order indexes (resp. 0,41 and 0,18), explaining the largest part of severity variance.

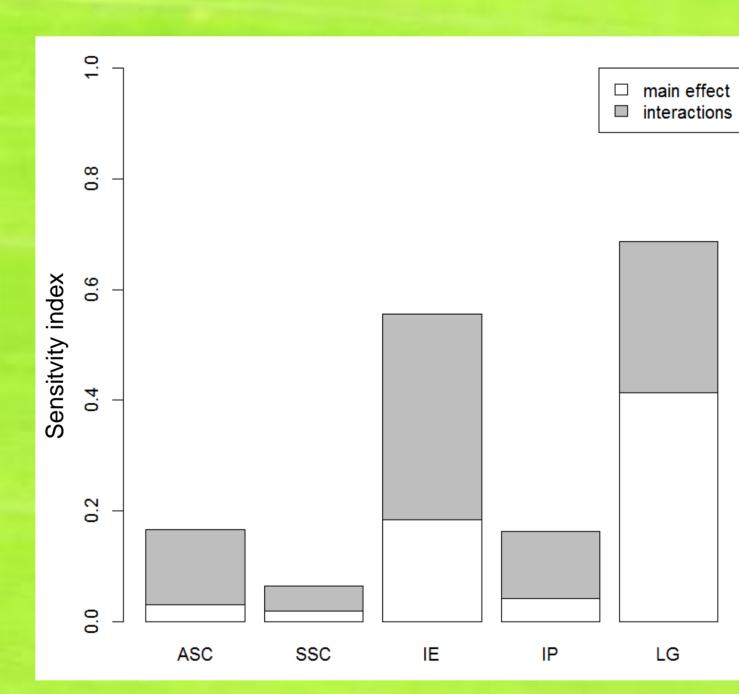


Figure 4. Evaluation of first order and total sensitivity indices on 5 epidemic cycle parameters.

ASC, SSC and IP have no significant influence (index < 0,1)

MODEL CALIBRATION

the highest level of BLSD

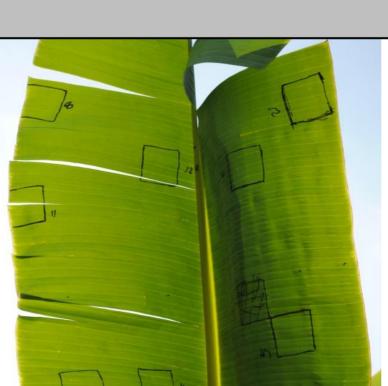
variety with the highest LG.

the lowest level is on the partial

resistant variety with the lowest IE.

Results show that:

- Inference on the epidemic parameters is being performed by Bayesian methods using available and newly collected data.
- Newly collected data: Kinetics of number and size of lesions on 3 leaves during their complete life. Leaves were divided in zones and BLSD spots were drawn during 3 months and analyzed using image analysis software



Bayesian framework: MCMC methods such as Metropolis within Gibbs algorithm (Robert and Casella, 2010)

$$\pi_m(\theta_m|data) \propto L(data|\theta_m).\pi^0(\theta_m)$$

$$L(data|\theta_m) = \prod_{t} \prod_{l} \frac{\exp(-(severity_{l,c}(t) - severity_{l,c}(t)^*)^2/2\sigma^2)}{\sqrt{2\pi\sigma^2}}$$

Where $severity_{l,c}(t)^*$ are the severity values predicted by the model and $\pi^0(\Theta_m)$ are priors, based on available data.

CONCLUSION / PERSPECTIVES

• We built a specific simulation model combining the banana growth and the complex epidemic cycle of M.fijiensis.

First sensitivity analyses suggest that lesions growth has the main effect on BLSD severity. Experimental field data and the use of a Bayesian framework will enable us to estimate epidemic cycle parameters and their uncertainties. This model will be helpful both for geneticists by allowing to test the efficacy of partial resistance and for agronomists by identifying the most efficient cultural practice in disease control.

Robert C. and Casella G., 2010, Mote Carlo Statistical Methods, second ed. Springer.; Saltelli A., Tarantola S., and Campolongo F., 2000, Sensitivity analysis as an ingredient of modeling, Stat. Science, 15(4):377-395.