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Natacha Motisi[1,2,5*], Pierre Bommel[3,5], Grégoire Leclerc[3,5], Marie-Hélène Robin[4], Jean-Noël Aubertot[4], Andrea Arias Butron[4], Isabelle Merle[1,2,5], Edwin Treminio[5], Jacques Avelino[1,2,5]

[1]CIRAD, UMR PHIM, Turrialba, Costa Rica

[2]PHIM Plant Health Institute, Univ Montpellier, CIRAD, INRAE, Institut Agro, IRD, Montpellier, France

[3]CIRAD, UMR SENS, Université de Montpellier, Montpellier, France

[4]INRAE-INPT-ENSAT-EI-Purpan, University of Toulouse, UMR 1248 AGIR, F-31326, Castanet Tolosan, France

[5]CATIE, Centro Agronómico Tropical de Investigación y Enseñanza, Turrialba, 30501, Costa Rica

* Corresponding author: Natacha Motisi
Email: natacha.motisi@cirad.fr

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1. Introduction

Since 2003, Central America has been the scene of epidemics of coffee leaf rust (CLR) on *Coffea arabica* that have caused severe socio-economic crises, particularly from 2012 on (Avelino et al., 2015). In fact, *C. arabica* is not only the cultivated species of the *Coffea* genus the most susceptible to CLR, but is the main source of income for hundreds of thousands of smallholders and harvesters in the region. The causal fungal pathogen, *Hemileia vastatrix*, is an obligate parasite that infects leaves and causes them to fall prematurely; severe defoliation due to CLR can cause the death of branches. Cerda et al. (2017) showed that CLR epidemics cause not only primary yield losses, i.e. in the current year, but also secondary yield losses, i.e. in the following years, due to the death of branches in the first year. Considering the significant socio-economic stakes, in 2016, the European Union started a project called Procagica (*Programa Centroamericano para la Gestión de la Roya del Café*) aimed at building a regional network of national early warning systems to prevent new severe epidemics at national and regional levels in Central America.

Until now, scattered scientific and empirical knowledge concerning the highly complex CLR-coffee pathosystem has been an obstacle to the development of CLR forecasting models. Most existing models developed to forecast CLR development use linear regressions or semi-mechanistic approaches (before the year 2000) and machine learning (after 2000, Merle, 2019). Predictors used in regression models were mostly linked to meteorology, i.e. temperature, rainfall and relative humidity, but also included the stock of inoculum and number of coffee leaves (Avelino and Rivas, 2013). More recent models use other predictors such as cropping practices, e.g. planting density, use of fungicides, use of fertilizers, use of shade trees (Avelino et al., 2006; Corrales et al., 2016, 2015). Bebber et al. (2016) proposed a mechanistic model to assess the risk of *H. vastatrix* infection based on temperature and relative humidity. This model represents an important advance in our understanding of how CLR epidemics function, but did not account for other processes such as leaf colonization or sporulation, both of which determine the latent period, nor spore dispersal. All these models help understand some of the interactions among the processes at stake by simplifying the relationships, but they are not able to test a large range of possible scenarios with multiple interactions between factors.

Models to forecast the risk of CLR should take advantage of available knowledge on the biophysical functioning of the CLR-coffee pathosystem and in particular empirical knowledge provided by CLR experts to unravel the multiple interactions at play in the pathosystem. One example of multiple interactions leading to mathematical modeling issues when attempting to forecast CLR are the antagonistic effects of shade on CLR: shade can reduce host physiological susceptibility to CLR, but at the same time, shorten the latent period and increase *Lecanicilium lecanii* hyperparasitism. Another example is the dynamics of CLR results from interactions between the population of pathogen and the population of leaves, both of which are influenced in different ways by the environment (notably meteorology and cropping practices; Avelino and Rivas (2013), Fig. 1). On the one hand, coffee leaves have their own dynamics linked to source-sink relationships that are themselves influenced by the environment (de Reffye et al., 2021; Vezy et al., 2020), and by provoking defoliation, CLR further modifies leaf dynamics. On the other hand, the development of CLR is influenced by leaf dynamics. Additionally, fruit phenology influences plant health: a high fruit load increases leaf physiological susceptibility to CLR (Costa et al., 2006; Kushalappa and Eskes, 1989a; López-Bravo et al., 2012), which is a particularity of the CLR-coffee pathosystem. The mutual interactions between the dynamics of the host and the pathogen and modeling become daunting when interactions with the environment and management practices are added.

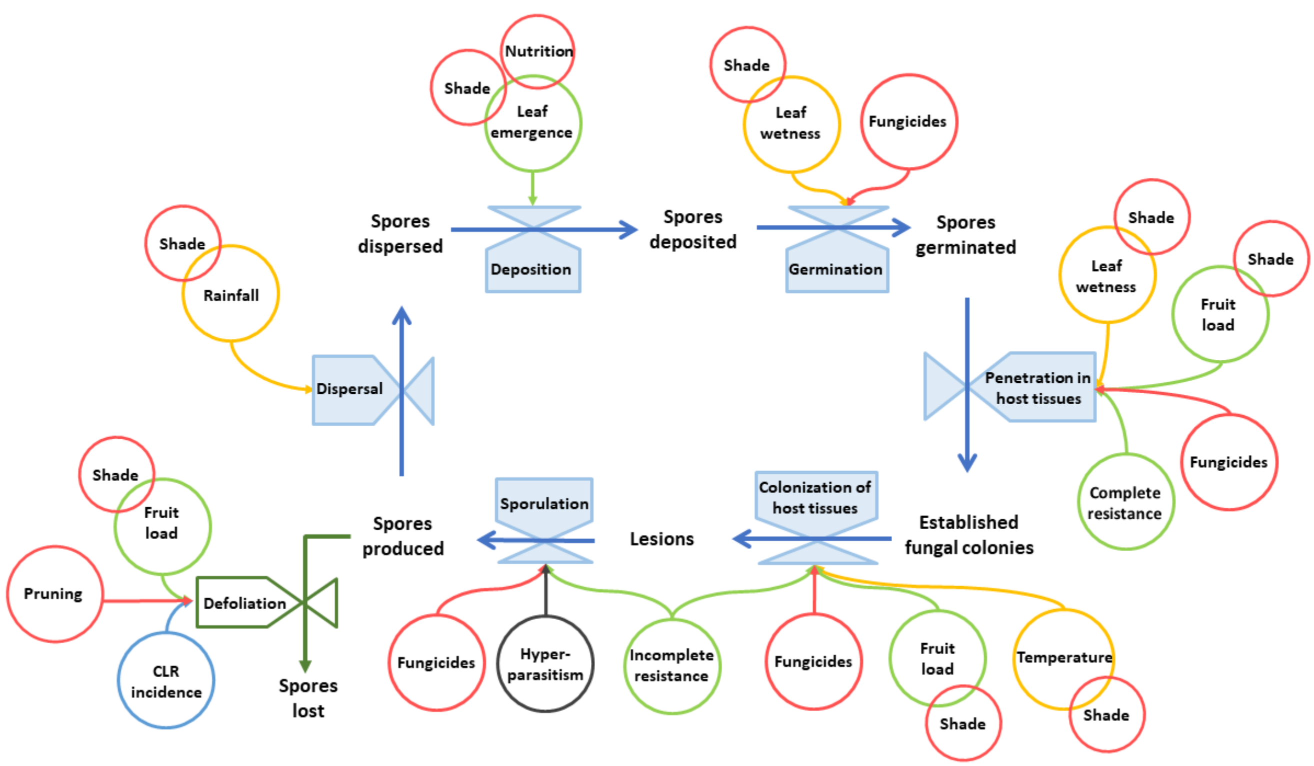

Figure 1. Based on the literature and expert knowledge, the most important factors affecting the life cycle of *Hemileia vastatrix* selected to build the ExpeRoya model. The

circles correspond to the factors that influence the rates of transition (represented by the valve symbols). The yellow circles represent the meteorological variables, the red circles represent factors linked to the cropping practices, the green circles represent factors linked to the host, the blue circle indicates factor linked to the pathogen, and the dark grey circle indicates the action of the hyperparasite *Lecanicillium lecanii*. The blue valve symbols represent the rates of transition linked to fungus life traits and the dark green valve symbol the rate of transition linked to the host dynamics. The effects of shade and nutrition on the epidemiological variables are indirect, by changing meteorological conditions or host status. Adapted from figure 1 in Avelino et al. (2004).

Qualitative modeling can cope with the difficulty of incorporating numerous relationships linking production situations and injury profiles. The IPSIM (Injury Profile SIMulator) framework (Aubertot and Robin, 2013) is a qualitative and aggregative modeling approach that describes the effects of the cropping system and the plot environment on injuries, thereby making it possible to incorporate scattered knowledge on the system and all its complexity in a simplified way. Moreover, the model can be easily understood by the farmers, in our case coffee farmers, as it organizes knowledge in a way that is close to the organization of thought. This modeling approach incorporates different sources of knowledge: scientific and technical literature, expert knowledge, co-design workshops, existing models, etc. Involving experts makes this approach powerful and robust because it builds on empirical knowledge based on a very large number of field observations. In addition, expert knowledge helps design farming models able to account for the complexity of the interactions inherent to the system concerned, particularly when few data are available (Harou et al., 2021). The IPSIM framework has already been shown to be effective in predicting the incidence of eyespot on wheat (Aubertot and Robin, 2013), brown rust on wheat (Robin et al., 2013); fruit fly injuries on chayote crop (Deguine et al., 2021), and infestations of the weed *Cirsium arvense* (Lacroix, 2020).

The aim of the present study was to improve forecast modeling of CLR to enable the provision of information on the monthly risk of an increase of CLR incidence at (i) national scale to help Central American coffee institutes design their alert bulletins and recommendations each month, and at (ii) plot scale to provide farmers with more specific information concerning the risk of CLR on their farms. For this purpose, we adopted the IPSIM modeling framework to account for all the complexity of the coffee-CLR pathosystem and all the major biotic and abiotic variables that drive the system. We named the model *ExpeRoya* because it is based on expert knowledge and on the scientific literature on CLR and because *Roya* is the Spanish word for ‘rust’.

2. Materials and Methods

2.1. Design of the ExpeRoya model

We used the IPSIM framework, which is based on the DEX method, a qualitative and hierarchical multi-attribute method mainly used to evaluate and analyze decision problems, implemented with Dexi software (Bohanec, 2020; https://kt.ijs.si/MarkoBohanec/dexi.html). DEX is based on the decomposition of a complex decision problem into smaller, less complex sub-problems that makes it possible to gather and structure different sources of knowledge in rule-based models. This framework forms the cornerstone of the design of ExpeRoya.

ExpeRoya involves the following components (Fig. 2):

1. *Input attributes*: these are the entry variables in the format of vectors of values that are assessed by ExpeRoya.
2. *Multi-attribute model*: a static and deterministic model that embeds the characteristics of the system in “if-then” deterministic aggregative rules. ExpeRoya is composed of two submodels: the first describes CLR dynamics and the second describes coffee tree dynamics.
3. *Final output*: Assessment of the ultimate response variable, the monthly risk of increase in CLR incidence. For CLR, incidence is usually used as the indicator of the level of infection of a coffee crop population. It is defined by the proportion of leaves affected by CLR. Therefore, we defined the final output as the rate of increased CLR incidence each month.

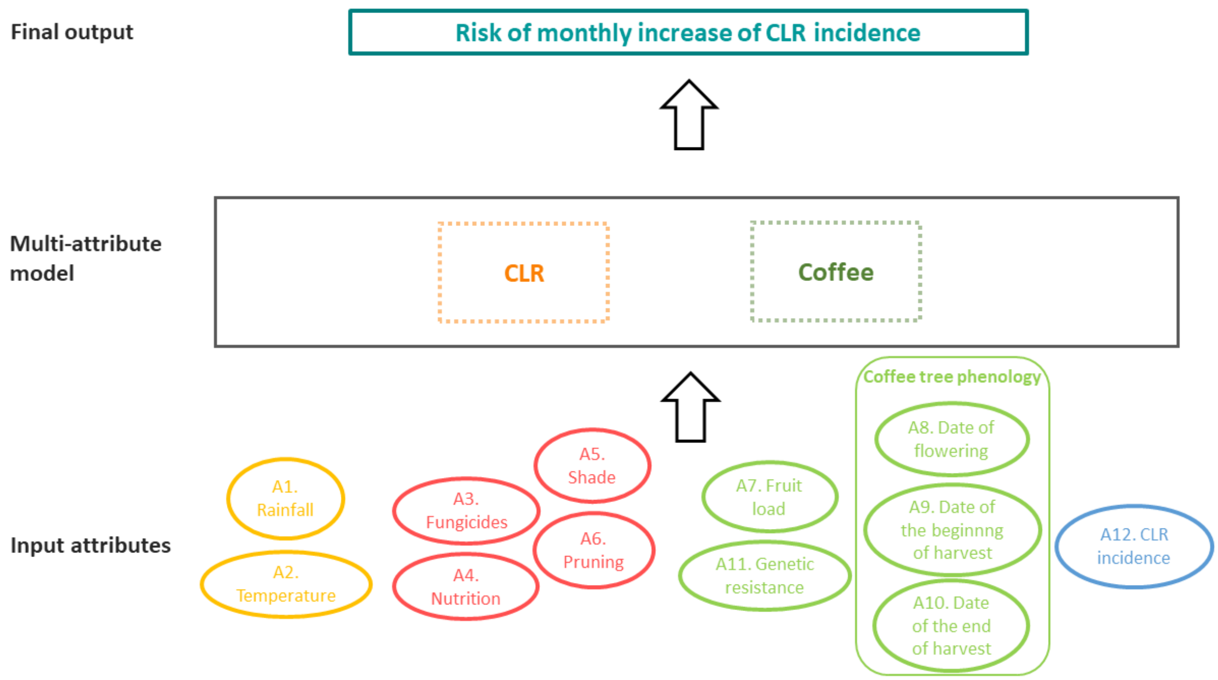

Figure 2. General framework of the multi-attribute model ExpeRoya. The model is composed of (i) 12 input attributes numbered A1 to A12, two meteorological variables shown in yellow, four management variables shown in red, five variables linked to the coffee tree shown in green, and one variable for incidence recorded at the monitoring date, which is a proxy of the stock of inoculum, in blue, (ii) a multi-attribute model composed of two submodels describing coffee leaf rust (CLR) and coffee dynamics, and (iii) the final output, which is the final assessed variable of the model, i.e. the risk of increased incidence of CLR each month.

All ExpeRoya attributes are qualitative, meaning they are described by categories. These categories can be (i) ordinal, meaning that they are organized in a specific order (e.g. non-numeric ranked variables such as “small”, “medium” and “high”, or numeric intervals such as [0-20], [20-50], [50-100]), or (ii) nominal, meaning that the possible names or categories do not follow a natural order (e.g. phenology of the coffee tree, with three periods of phenological development). In the following section, these qualitative attributes are defined based on strictly quantitative explanations that allow automated processing of data.

In ExpeRoya, the temporal scale is the month, and the spatial scales are either the landscape scale (national scale) or the plot scale.

The Dexi version of ExpeRoya is available in the Cirad Dataverse repository (Motisi, 2021).

2.2. Input attributes

The risk of an increase in CLR incidence is based on 12 input attributes (A1 to A12 in Fig. 2 and see the “Input attributes” column in Table 1). The rules for defining each category are also detailed in Table 1. Several processes can be computed from the same input attributes (e.g. rainfall, CLR incidence, fruit phenology and fruit load). For example, daily rainfall is used to calculate three processes: spore loss through rain wash-off, infection of leaves by wetness, and emergence of new leaves. Therefore, at the lowest levels of the multi-attribute tree (Fig. 3), it is possible to describe 21 basic processes (P1 to P21 detailed below and see the “Processes described” column in Table 1) originating from the 12 input attributes.

Table 1. Input attributes of ExpeRoya model. The attributes are numbered from A1 to A12, and the processes they described are numbered from P1 to P21. (*) The model at national scale usually falls in this category.

Type of input attribute	Input attributes	Processes described	Categories	Rules defining the categories	References
Meteorology	A1. Rainfall	P1. Spore loss by rain wash-off	Insufficient wash-off	< 3 days with 10mm of daily rainfall	Avelino et al., 2020; Lasso et al., 2020; Merle et al., 2020
			Regular wash-off	[3-5] days with 10mm of daily rainfall	
			Sufficient wash-off	> 5 days with 10mm of daily rainfall	
		P2. Infection of leaves by	High infection	> 7 days with 5mm of daily	(Guzman and Gomez,

		wetness		rainfall	1987)
			Medium infection	[3-7] days with 5mm of daily rainfall	
			Low infection	< 3 days with 5mm of daily rainfall	
		P3. Leaf emergence	Favorable for leaf emergence	> 10 days with 1mm of daily rainfall	(DaMatta et al., 2007)
			Moderately favorable for leaf emergence	[5-10] days with 1mm of daily rainfall	
			Unfavorable for leaf emergence	< 5 days with 1mm of daily rainfall	
	A2. Temperature	P4. Latent period by temperature	Short latent period	> 10 days with temperature ranging from 22°C to 24°C	Nutman et al, 1963; Kushalappa et al, 1983
			Medium latent period	[5-10] days with temperature ranging from 22°C to 24°C	
			Long latent period	< 5 days with temperature ranging from	

				22°C to 24°C	
Crop management	A3. Fungicide application	Effect of fungicide application on the loss of inoculum of: P5. *Hemileia vastatrix*, and P6. the hyperparasite *Lecanicillium lecanii*	Yes	Fungicide was applied during the month prior to monitoring	(González et al., 2014)
			No	No fungicide was applied	
	A4. Coffee nutrition	P7. Effect of nutrition on leaf emergence	Yes	On average, trees have no deficiencies	Costa el al., 2006, Lopez Bravo et al., (2012)
			No	On average, trees need fertilization	
	A5. Shade	Effect of shade cover on: P8. microclimate, P9. hyperparasitism, and P10. host	High	> 60% of shade	Lopez-Bravo et al. (2012), Boudrot et al. (2016) and Avelino et al. (2020)
			Medium	[40% - 60%] of shade	
			Low	< 40% of shade(*)	
	A6. Pruning	P11. Effect of pruning on the loss of inoculum	Total pruning	Cutting from the tree to the base, 100% of the	Expert knowledge

				leaves are removed	
			50% pruning	Drastic pruning of the tree with 50% of the leaves removed	
			25% pruning	Light pruning, or maintenance pruning of the tree, with 25% of the leaves removed	
			No pruning	0% of leaves removed	
Host	A7. Fruit load	Effect of fruit load on : P12. leaf physiological susceptibility, P13. defoliation, and P14. leaf emergence	High	> 250 fruiting nodes per tree equivalent to > 40q/ha	López-Bravo et al. (2012) (Avelino et al., 1993)
			Medium	[100-250] fruiting nodes equivalent to 17-40q/ha	
			Low	< 100 fruiting nodes	

					equivalent to < 17q/ha	
	Phenology of the coffee tree	A8. Date of flowering	P15. Coffee berry growth	From flowering to the beginning of harvest	Average date of the main flowering	Kushalappa and Eskes, 1989
		A9. Date of the beginning of harvest	P16. Coffee berry maturity	During harvest	Average date of the beginning of harvest	
		A10. Date of the end of harvest	P17. Coffee trees without berry	From the end of harvest to the beginning of flowering	Average date of the end of harvest	
	A11. Genetic resistance		P18. Genetic susceptibility of the cultivar	Susceptible		Expert knowledge
				Moderately susceptible		
				Resistant		
Pathogen	A12. CLR incidence at the date of monitoring		P19. *Hemileia vastatrix* inoculum stock before hyperparasitism (*Lecanicillium*	High inoculum stock	> 30% of incidence	Merle et al, 2020
				Medium inoculum stock	[10-30%] of incidence	

		lecanii)	Low inoculum stock	< 10% of incidence	
		P20. Effect of the inoculum stock on the efficacy of fungicide application	High inoculum stock	> 30% of incidence	Rivillas et al, 2011; Zambolim, 2016
			Medium inoculum stock	[10-30%] of incidence	
			Low inoculum stock	< 10% of incidence	
		P21. Effect of incidence on the rate of defoliation	High defoliation	> 20% of monthly defoliation when incidence is >36%	Avelino (unpublished data, Appendix 1)
			Medium defoliation	[6-20%] of monthly defoliation when incidence is [0-36%]	
			Regular defoliation	<= 6% of monthly defoliation when incidence is equal to 0%	

In section 2.3 below, we detail how the tree attributes were aggregated and provide justifications for the choices made concerning the thresholds of each category.

Rainfall (A1) and Temperature (A2) are the meteorological attributes of the model, they are calculated in a window covering the 15 days that precede the monitoring date. This time window is based on the known length of the CLR incubation period in field conditions, which ranges varies from 29 to 62 days (Kushalappa and Chaves, 1980). Monitored incidence, one of the predictors of incidence one month after the monitoring date, is therefore a reflection of the meteorological conditions that occurred in the two preceding months. To reduce redundancy between predictors, we chose to limit the period of consideration of the meteorological attributes of the model to 15 days. These attributes are calculated as follows:

A1. Rainfall: this attribute contributes to three basic processes:

- *Rainfall, as a proxy of rain wash-off linked to spore loss (P1)*: Beyond 10 mm per day, rain removes the spores from the lesions and carries them to the ground (Avelino et al., 2020; Lasso et al., 2020; Merle et al., 2020). As *H. vastatrix* is an obligate parasite, any spore that reaches the ground is lost for the growth of the epidemic. Hence we classified the number of rainy days with more than 10 mm of rainfall in three ordinal categories for spore loss by rain wash-off: “insufficient” (< 3 days), “regular” ([3-5] days) and “sufficient” (> 5 days) wash-off.
- *Rainfall, as a proxy of leaf wetness linked to infection (P2):* suitable temperatures and leaf wetness are preconditions for CLR infection (Kushalappa et al., 1983). Infection response to temperature is quadratic (convex) with optimal temperatures between 22 °C and 24 °C (Kushalappa et al., 1983; Nutman et al., 1963) while infection increases linearly with an increase in the duration of wetness in the first 24 h (Kushalappa et al., 1983). As the effect of temperature on infection is included in the effect on the latent period (which starts from germination), we considered humidity to be the most influential factor for infection. We thus classified the number of days with more than 5 mm of rainfall (Guzman and Gomez, 1987) in three ordinal categories for infection efficacy: “high” (> 7 days), “medium” ([3-7] days) and “low” (< 3 days) infection.
- *Rainfall linked to leaf emergence (P3):* Meteorological constraints to leaf emergence were analyzed as follows. First, we consider that temperature is not a limiting factor since the average temperature in coffee producing areas is above the 10 °C threshold for coffee tree growth (Pezzopane et al., 2012; Rodríguez et al., 2011). Second, rainfall patterns show intra-annual and inter-annual variability. Coffee producing areas often have marked

rainy and dry seasons, and are exposed to other inter-annual climatic phenomena such as El Niño and La Niña. Assuming that leaves are the last organs in the coffee tree to be allocated carbon and water (Vezy et al., 2020), we chose to use rainfall as a limiting factor for leaf emergence (Table 1). We classified the number of rainy days with more than 1 mm of rainfall (DaMatta et al., 2007) in three ordinal categories of rainfall for leaf emergence: "favorable" (> 10 days), "moderately favorable" ([5-10] days) and "unfavorable" (< 5 days) to leaf emergence.

A2. Temperature linked to the latent period (P4): According to Kushalappa et al. (1980), the latent period is shortened by extreme minimum and maximum temperatures, 22 °C to 24 °C being the optimum range for a short latent period (Kushalappa and Martins, 1980). This range also suffices for germination (with an optimum of about 22-23 °C; Nutman et al. 1963; Kushalappa et al. 1983), which is included in the latent period. We thus classified the number of days with an average temperature of between 22 °C and 24 °C in three ordinal categories for latent period: "short" (> 10 days), "medium" ([5-10] days) and "long" (< 5 days) latent period.

Other attributes are described below:

A3. Fungicide application and its effect on the loss of inoculum (P5): this attribute is updated monthly by two ordinal categories "yes" or "no" in response to the question whether fungicides were applied in the past month. The effect of fungicide on CLR (P5) and on the hyperparasite *Lecanicillium lecanii* (P6) is assumed to last from one to two months after application (Rivillas et al., 2011; Zambolim, 2016).

A4. Coffee nutrition and its effect on leaf emergence (P7): this attribute is defined for the whole coffee growing period by two ordinal categories "yes" or "no" in response to the question whether nutrition is sufficient for the growth and development of coffee tree. The two categories reflect whether the quantity and type of fertilizer applied are sufficient (or not) based on soil analyses and expected yield.

A5. Shade and its effect on microclimate (P8), hyperparasitism (P9) and host (P10): this attribute is defined by the average percentage of shade that has an impact on CLR dynamics, deduced from Avelino et al. (2020), Boudrot et al. (2016) and López-Bravo et al. (2012). Shade is described by three ordinal categories: "high" (> 60%), "medium" ([40-60%]) and "low" (< 40%).

A6. Pruning and its effect on the loss of inoculum (P11): Pruning the coffee tree is applied once a year and is an effective management practice to control CLR dynamics; removing diseased leaves reduces the stock of CLR inoculum. Pruning is described by four ordinal categories according to the degree of pruning commonly applied: “total pruning” (stumping or cutting down the coffee tree), “50% pruning” (removal of 50% of the leaves of the coffee tree by, for example, removing half the branches), “25% pruning” (removal of 25% of the leaves), and “no pruning”.

A7. Fruit load, and its effect on leaf physiological susceptibility (P12), defoliation (P13) and leaf emergence (P14): fruit load affects leaf physiological susceptibility to CLR as described by (López-Bravo et al., 2012). From these authors, we deduced three ordinal categories for fruit load: “high” (> 250 fruiting nodes per tree, equivalent to > 1,840 kg of green coffee/ha), “medium” ([100-250] fruiting nodes per tree, equivalent to 780-1,840 kg of green coffee/ha) and “low” (< 100 fruiting nodes, equivalent to < 780 kg of green coffee/ha). The same fruit load categories are used to describe defoliation and leaf emergence.

A8. Date of flowering, A9. Date of the beginning of harvest and A10. Date of the end of harvest are the three nominal attributes we used to define three categories of the *phenology of the coffee tree*: “between flowering and the beginning of harvest”, “during harvest” and “between the end of harvest and the beginning of flowering”. According to Kushalappa and Eskes (1989b), host predisposition to *H. vastatrix* infection increases with fruit growth. These three categories describe the processes of coffee berry growth (P15), coffee berry maturity (P16) and coffee tree without berries (P17), respectively.

A11. Genetic resistance: this attribute describes the genetic susceptibility (P18) of the cultivar and was defined by three ordinal categories: “susceptible”, “moderately susceptible” and “resistant”. Moderately susceptible varieties are generally those that originate from the Timor hybrid and whose resistance is incomplete after being broken down by CLR (Silva et al., 2006). Another possible reason to be in this category is when resistant varieties are mixed with susceptible ones.

A12. CLR incidence on the monitoring date: CLR incidence on the date the disease is monitored (by farmers or by extension officers) evaluates three different basic processes:

- *CLR incidence as a proxy of the stock of* H. vastatrix *inoculum before hyperparasitism (P19)*, to explain the development of the hyperparasite *L. lecanii*, the higher the CLR incidence, the higher the hyperparasitism (Merle et al., 2019). Here “incidence” describes three ordinal categories, “high” (incidence >30%), “medium” ([10-30%] of incidence) and “low” (<10%) stocks of inoculum.
- *CLR incidence as a proxy of the stock of inoculum (P20)* to determine the efficacy of the fungicide spray, the higher the incidence, the lower the fungicide efficacy. Here “incidence” describes three ordinal categories, “high” (incidence > 30%), “medium” ([10-

30%] of incidence) and “low” (< 10%) inoculum stock (adapted from Rivillas et al., 2011; Zambolim, 2016).

- *CLR incidence as an indicator of leaf defoliation (P21)* (Brown et al., 1995). We use CLR incidence as a predictor of defoliation (Avelino, unpublished data, Appendix 1). Here “defoliation” describes three ordinal categories, “high” (monthly defoliation > 20% when incidence is > 36%), “medium” ([6-20%] of monthly defoliation when incidence is [0-36%]), and “regular” defoliation (monthly defoliation <= 6% when incidence is equal to 0%).

2.3. Aggregate attributes

The aggregate attributes are intermediate variables resulting from the aggregation of each variable of the hierarchical model tree (from the input attributes to the final output, see aggregation tables in Appendix 2 and Cirad Dataverse (Motisi, 2021)) according to the rules defined by a group of experts of the CLR-coffee pathosystem and based on the literature. Aggregate attributes are grouped in two submodels (Fig. 3):

1. The CLR submodel defined by the subtree *Disease increase considering fungicide application*.
2. The coffee submodel defined by three subtrees, *Overall host susceptibility*, *Defoliation* and *Leaf emergence.*

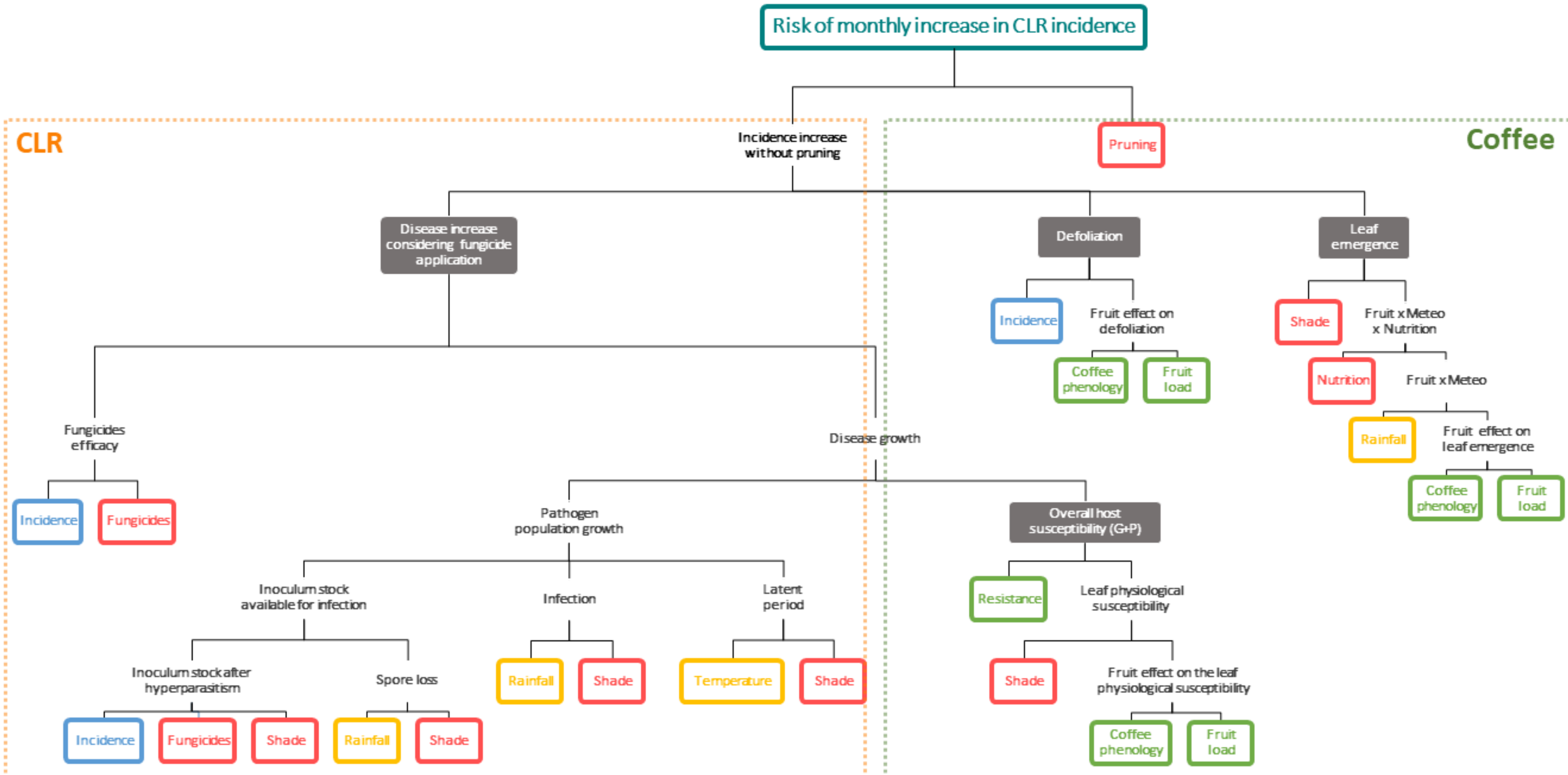
Risk of monthly increase in CLR incidence
CLR
Coffee
Incidence increase without pruning
Pruning
Disease increase considering fungicide application
Defoliation
Leaf emergence
Incidence
Fruit effect on defoliation
Coffee phenology
Fruit load
Shade
Fruit x Meteo x Nutrition
Nutrition
Fruit x Meteo
Rainfall
Fruit effect on leaf emergence
Coffee phenology
Fruit load
Fungicides efficacy
Incidence
Fungicides
Disease growth
Pathogen population growth
Overall host susceptibility (G+P)
Resistance
Leaf physiological susceptibility
Shade
Fruit effect on the leaf physiological susceptibility
Coffee phenology
Fruit load
Inoculum stock available for infection
Infection
Latent period
Inoculum stock after hyperparasitism
Spore loss
Rainfall
Shade
Temperature
Shade
Incidence
Fungicides
Shade
Rainfall
Shade

Figure 3. Hierarchical structure of the ExpeRoya model. The model structure is a tree that aggregates variables in a hierarchical way according to available knowledge on CLR and host dynamics. The CLR submodel (dotted orange frame) is described by a subtree *Disease increase considering fungicide application* and the coffee submodel (dotted green frame) is defined by three subtrees, *Overall host susceptibility (genetic and physiological susceptibility, G+P)*, *Defoliation,* and *Leaf emergence*. Note that this structure shows that some input attributes are used several times for different calculation rules (Table 1). The white and grey boxes represent aggregate attributes, the white boxes represent intermediate aggregate attributes which, by successive aggregations, form the four subtrees represented by the grey boxes.

2.4. The CLR submodel

At the lowest level of aggregation, this submodel describes the main processes of the CLR life cycle, driven by hyperparasitism, loss of spores, infection and the latent period in interaction with *Overall host susceptibility (G+P)* (from the coffee submodel coffee dynamics).

Compared to full sun, shade modifies the effect of each meteorological variable on the processes. We detail the rationale for aggregation of the variables that lead to the growth of the pathogen population in the following subsections.

2.4.1. Stock of *Hemileia vastatrix* inoculum after hyperparasitism by *Lecanicillium lecanii*

L. lecanii is more often present when there are large levels of CLR (Merle et al, 2020), high levels of shade or low light intensities (Galvao and Bettiol, 2014; Perfecto et al., 2014; Staver et al., 2001; Zewdie et al., 2021), while the application of fungicides reduces the inoculum of the hyperparasite *L. lecanii* (González et al., 2014).

We thus classified the aggregate attribute *Inoculum stock after hyperparasitism* in three categories, “high”, “medium” and “low”, as the result of the interaction between the original stock of inoculum of *H. vastatrix* (deduced from the CLR incidence, P14 in Table 1), shade (P9, Table 1) and the applications of fungicide that reduce the effect of *L. lecanii* (P6, Table1).

2.4.2. Spore loss

While rainfall greater than 10 mm leads to spore wash-off (Avelino et al., 2020; Lasso et al., 2020; Merle et al., 2020), dense shade counteracts this effect because the shade tree canopy intercepts the rainwater and limit its wash-off effect, thereby reducing loss of spores in the understorey (Avelino et al., 2020).

We thus classified the aggregate attribute *Spore loss* in three categories, “insufficient”, “regular” and “sufficient” wash-off as a result of the interaction between shade (P8, Table 1) and the number of days with rainfall greater than 10 mm (Spore loss caused by rain wash-off, P1, Table 1) (Fig.3).

2.4.3. Infection

Infection depends on leaf wetness (see section 2 *Rainfall, as a proxy of leaf wetness linked to infection (P2)* and Table 1), and shade was found to increase wetness (López-Bravo et al., 2012). We thus classified the aggregate attribute *Infection* in three categories, “high”, “medium” and “low” as the result of the interaction between shade (P8, Table 1) and the duration of leaf wetness (P2, Table 1).

2.4.4. Latent period

Temperatures between 22 °C and 24 °C favor a short latent period (Kushalappa et al., 1983; Nutman et al., 1963) and shade keeps temperatures at this optimum (López-Bravo et al., 2012). We thus classified the aggregate attribute *Latent period* in three categories, “short”, “medium” and “long” as the result of the interaction between shade (P8, Table 1) and temperature (P4, Table 1).

2.4.5. Efficacy of the fungicide application

The higher the incidence, i.e. the greater the amount of available inoculum, the less effective the fungicides in controlling the disease (Rivillas et al., 2011; Zambolim, 2016).

We thus classified the aggregate attribute *Efficacy of fungicide application* in three categories, “good”, “medium” and “poor” as a result of the interaction between fungicide application (binary response, “yes” or “no”; P5, Table 1) and inoculum stock (P20, Table 1) (Fig.3). This attribute does not include the quality of the fungicide sprays, which depends on the doses used, the pH of the water, and calibration of the equipment. In ExpeRoya we assume all these aspects are adequate.

Thereafter, the higher levels of the CLR submodel were linked to each of the subtrees in the coffee submodel (Fig. 3, Appendix 2): <u>*Overall host susceptibility*</u>, <u>*Defoliation*</u> and <u>*Leaf emergence*</u>*.*

2.5. The coffee submodel

2.5.1. Overall host susceptibility (G+P)

The aggregate attribute *<u>Overall host susceptibility (G+P)</u>*, was defined by the interaction between the physiological susceptibility (P) and the genetic susceptibility (G) of the cultivar.

Host physiological susceptibility to CLR is linked to the phenology of the fruit (Kushalappa and Eskes, 1989b), a high fruit load increases leaf physiological susceptibility to CLR (Costa et al., 2006; López-Bravo et al., 2012).

Zambolim (2016) found no clear relationship between coffee tree nutrition and coffee physiological susceptibility to CLR. This result may be due to opposing effects of leaf nutrition on the physiological susceptibility of the leaf to CLR. In fact, it is known that appropriate coffee nutrition increases fruit load (Van Oijen et al., 2010; Vezy et al., 2020), which can potentially increase host susceptibility to CLR. On the other hand, nutrition is also often mentioned as a way to reduce host physiological susceptibility in different pathosystems (Dordas, 2008; Walters and Bingham, 2007) and particularly in *C. arabica*-*H. vastatrix* (Toniutti et al., 2017). Therefore, the opposing effects of nutrition and leaf susceptibility may offset one another resulting in no clear effect of nutrition on coffee susceptibility at field scale.

However, from an arithmetic point of view, Avelino et al. (2006) proposed a negative effect of nutrition on CLR incidence: by stimulating leaf emergence, nutrition increases the number of new healthy leaves thus diluting the disease ("dilution effect" modeled by Ferrandino (2008), see 2.5.3.).

Finally, shade reduces host physiological susceptibility compared to a coffee tree growing in full sun (Eskes, 1982).

We thus defined the aggregate attribute *Leaf physiological susceptibility* according to the interaction between fruit load (P12, Table 1), coffee tree phenology (P15 to P17, Table 1) and shade (P10, Table 1).

We classified the final aggregate attribute of the subtree "*<u>Overall host susceptibility (G+P)</u>*" in four categories, "high", "medium", "low" and "null" susceptibility as the result of the interaction between *Leaf physiological susceptibility* and genetic susceptibility (P18, Table 1).

2.5.2. Defoliation

High incidence increases the number of fallen leaves (Brown et al., 1995). We used the relationship defined experimentally by Avelino (unpublished data, Appendix 1) to describe the effect of incidence on defoliation. Additionally, a high fruit load (number of fruiting nodes per tree) increases the risk of defoliation of the coffee tree relative to source-sink relationships in the tree (de Reffye et al., 2021; Vezy et al., 2020). From López-Bravo et al. (2012), Zambolim et al. (1992) and Carvalho et al. (2001) it can be deduced that with a high fruit load, on average, the maximum incidence of epidemics is reached faster than with a lower fruit load. This is possibly linked to defoliation, which rapidly reduces the number of susceptible tissues.

Defoliation also depends on the phenology of the coffee tree (Costa et al., 2006). Before harvest, defoliation is positively linked to fruit growth and incidence; the stresses linked to fruit load and CLR incidence are exacerbated during harvest, thereby increasing leaf senescence, while after harvest these stresses decrease.

We thus classified the final aggregate attribute of the subtree *Defoliation* in three categories, “high”, “medium” and “regular” (baseline defoliation level defined when CLR incidence is null, Appendix 1) as the result of the interaction between incidence (P21, Table 1), fruit load (P13, Table 1) and phenology of coffee plant (P15 to P17, Table 1).

2.5.3. Leaf emergence

As CLR incidence is the ratio of infected leaves to the total number of leaves, a variation in incidence may be due to a variation in the numerator due to coffee CLR growth, and in the denominator due to leaf emergence. The coffee submodel characterizes the leaf appearance dynamics to account for the dilution effect (Ferrandino, 2008) caused by leaf emergence that has already been reported for CLR (Kushalappa and Ludwig, 1982; López-Bravo et al., 2012).

Like defoliation, the lowest level of the process of leaf emergence was defined by the interaction between fruit load (P14, Table 1) and fruit phenology (P15 to P17, Table 1) to account for the influence of the source-sink relationship on leaf dynamics (Avelino et al., 1993; Vezy et al., 2020). Fruit load competes with vegetative growth (DaMatta et al., 2007), and possibly to a greater extent during the final stages of fruit development (Taugourdeau et al., 2014). We next aggregated the input attribute rainfall (P3, Table 1) as a limiting factor for leaf emergence, followed by the input attribute nutrition (P7, Table 1) as a stimulating factor for leaf emergence. Finally, the effect of shade, which reduces leaf emergence (DaMatta, 2004; López-Bravo et al., 2012), was introduced at the highest level of the subtree *Leaf emergence*.

We thus classified the final aggregate attribute of the subtree *Leaf emergence* in three categories, “Favorable”, “Moderately favorable” and “Unfavorable” for leaf emergence as the result of the interaction between fruit load, coffee tree phenology, rainfall, coffee nutrition and shade.

The aggregate attribute of the subtree *Defoliation* interacts with the aggregate attribute of the subtree *Leaf emergence* statistically by counterbalancing the "dilution effect" of leaf emergence on disease incidence. In these interactions, we also assume that high defoliation due to rust reduces the stock of inoculum.

2.5.4. Pruning

Like defoliation, pruning the coffee tree reduces the stock of inoculum by removing infected leaves consequently reducing the risk that CLR incidence will increase in the following month. We aggregated pruning (P11, Table 1) to the whole model tree just below the final output of the model, i.e., the risk of an increase in CLR incidence in the following month.

2.6. Aggregation of the two submodels

The aggregation rulesets for submodels *CLR* and *Coffee* are presented in Appendix 2. In all, 20 tables represent the aggregation of 44 attributes. Each attribute is described by either 2, 3, or 4 categories. The model defines a total of 229 possible interactions to describe the final output.

ExpeRoya was computed in R (R Core Team, 2017) and a user-interface was implemented in R shiny, the latter is available on the Pergamino platform (https://www.redpergamino.net/app-experoya).

2.7. Attribute weights

The relative influence of each attribute on the final output was calculated as normalized local and global weights using software Dexi. Calculation was based on a simple sensitivity analysis to input variables for quantitative models. The higher the weight, the greater the contribution of the attribute to the output. Local weights define the relative contribution of each attribute belonging to the same node. Total weights define the contribution of each attribute to the final output relative to all the other attributes.

2.8. Social evaluation of the model

The social evaluation of the model consisted of comparing the formalism developed in the model with the experts' opinions. Two methods were used for the social evaluation, (i) qualitative evaluation with experts and practitioners during workshops organized during the Procagica project, and (ii) quantitative evaluation through a survey of CLR experts selected based on their referenced works on CLR (particularly researchers) and their known level of knowledge on CLR (particularly actors of coffee technical services).

The experts selected for the social evaluation were not the same as the experts who participated in the construction of ExpeRoya.

2.8.1. Qualitative evaluation through workshops held during the design phase of ExpeRoya

During the design phase, incremental versions of ExpeRoya were used in a succession of 19 workshops (regional and national in Central America). Most of the partners (coffee farmers, members of coffee technical institutes and researchers) of the project were consulted several times as the model increased in complexity. During the workshops, exchanges between participants made it possible to evaluate their interest and their willingness to help produce monthly bulletins on CLR risks using the tool.

During the workshops, members of technical services used the model, examined the outputs, and explored various scenarios by modifying the values of the input attributes.

2.8.2. Quantitative evaluation of the final version of ExpeRoya through a survey

The final version of ExpeRoya was quantitatively evaluated through a survey: 17 CLR experts agreed to take part in the survey out of the original 30 experts contacted by email. Seven of the 17 experts who responded to the survey belonged to organizations involved in the Procagica project (Icafé, Costa Rica; Centa-café, El Salvador; Ihcafe, Honduras; IICA, Nicaragua; Indocafé, Dominican Republic; Cirad, France).

The questionnaire (Appendix 3) was designed using Google Form and was available in English (https://forms.gle/xUxn53gEzhSV12GQ9) and in Spanish (https://forms.gle/G98cu23kr47xghd88). The experts came from Latin America, Canada and France. The questions were framed to facilitate elicitation of expert opinion (Morgan, 2014). The questions were either quantitative, to describe the functional responses of the disease processes and host dynamics to their related input attributes (only one biophysical attribute), or qualitative, (i) to describe interactions between multiple attributes and (ii) to enable free-text answers so experts could clarify or add their own comments on the description of the relationships.

The questionnaire comprised 31 questions, in addition, the expert was asked to state the degree of confidence of each of her/his responses on a scale from 1 to 10. The questions were multiple-choice and were designed to compare the formalism incorporated in the model with the experts' knowledge component by component.

Evaluation of the quantitative relationships. The questions concerning the quantitative relationships aimed to enable the experts to quantitatively describe (i) the functional responses of the CLR processes and host dynamics to their related input attributes and (ii) the prevalence of the attributes in the interactions.

The questions were in the form of a double entry table with, row-wise, the categories of the input attribute (the variable to be explained) and column-wise, the explanatory variable discretized over the intervals of values that this variable could take. For example, for the efficacy of fungicides, the variable to be explained "efficacy of fungicides" was described in one row by three categories, "low efficacy", "medium efficacy" and "high efficacy", and the explanatory variable "incidence" was described in one column by seven values [0, 5, 10, 15, 20, 25, > 30%].

To analyze the responses, we fitted a binomial model by transforming the values of the variable to be explained into an interval ranging from 0 to 1. For example, for the efficacy of fungicides, "low efficacy" took the value 0, "medium efficacy" 0.5, and "high efficacy" 1.

For the categories that associate a number of days with a threshold, we computed the variable *number of days*threshold* to account for the different thresholds chosen by the experts.

Evaluation of the qualitative relationships. The questions concerning the qualitative relationships aimed at obtaining experts' descriptions of the interactions between multiple input attributes. These questions were designed to follow a gradient of increasing complexity reflecting the increasing complexity of the relationships within the CLR-coffee pathosystem (depending on the scale of observation of each process, e.g. aggregation of attributes from high-level nodes to lower levels nodes). The questions were either multiple-choice, or in the case multiple attributes, double entry tables.

For the quantitative and qualitative relationships, we averaged the experts' responses by only accounting for answers ranked with a degree of confidence of more than 5 (range 0-10) and computed the average experts' response by weighting each expert's response with her/his degree of confidence.

The results were analyzed using R programming language (R Core Team, 2017).

2.9. The model “in action”

To illustrate the behavior of the model, we simulated the cropping season in 2012, a year that was favorable for CLR (Avelino et al., 2015). We uploaded simulated weather data including daily mean temperature and daily rainfall from the Nasa data access viewer (https://power.larc.nasa.gov/data-access-viewer/) for three locations at increasing altitudes: San Vito, Costa Rica (8.8202, -82.9579; 899 m a.s.l.), Antigua, Guatemala (14.5748, -90.7747; 1,156 m a.s.l.) and Las Margaritas, Mexico (16.456, -91.9022; 1,487 m a.s.l.). We tested effects on the forecasted monthly increase in CLR under (i) High (>60%), Medium ([40-60%]) and Low (<40%) shade cover (see Table 1 for details on the thresholds of the attributes), (ii) High (25%), Medium (10%) and Low (3%) incidence at the first monitoring date of the simulation and (iii) fungicide application (yes/no). To simulate the course of the epidemics, we applied realistic increases in incidence rates using the incidence at the monitoring date and the risk category for an increase in CLR in the following month (Drastic increase, Stable increase, Decrease; Appendix 4). To compare the situations, we applied daily rainfall recorded in Antigua (Guatemala) to San Vito (Costa Rica) and Las Margaritas (Mexico). Finally, for fungicide applications, we used the rules included in the standard recommendations for coffee production systems (Rivillas et al., 2011), i.e., fungicide should only be applied (i) after flowering and before harvest, (ii) if the incidence at the monitoring date is greater than 3%, (iii) if no fungicide was applied in the month preceding the monitoring date, and (iv) with a limit of 4 applications. All the other attributes of the model were fixed: medium fruit load (17-40q/ha), susceptible cultivar, no fertilization and no pruning,

3. Results and Discussion

3.1. Structure of the ExpeRoya model and weights of the attributes

The model is a nested hierarchical model in which the variables are qualitative (ordinal and nominal) and, based on various sources of knowledge (literature, data, and empirical and scientific knowledge accumulated by CLR experts), aggregated in a comprehensive way to systematically describe the pathways and the interactions involved in the dynamics of the CLR-coffee pathosystem.

The weights of each model attribute depends on the arrangement of the attributes in the model architecture. The variables in the lowest parts of the tree contribute less to the value of the final output than those in the highest hierarchical levels of the tree. The overall and local weights of each variable computed to forecast CLR (Fig. 4) are consistent with expert opinion (evaluated by members of the technical services during Procagica workshops).

The risk of a monthly increase in CLR incidence is explained at the highest level by the interaction between *Pruning* and *Incidence increase without pruning* (Fig. 4). They both have the same importance in explaining the final output (each weighs 50% of the final output). *Incidence increase without pruning* is explained by the interaction between <u>*Disease increase considering fungicides*</u> (35% of the total weight), <u>*Defoliation*</u> (8% of the total weight) and <u>*Leaf emergence*</u> (8% of the total weight).

Management practices linked to *Fungicide application* and coffee tree characteristics linked to *Genetic resistance* contribute more (17%) to the risk of monthly increase in CLR incidence than the meteorological variables (10%), after summing the overall weights of rainfall, temperature, and shade (which modify the meteorological variables). This corroborates the general opinion of the experts. It also questions the widespread belief that climate is the main cause of CLR outbursts that led to vast efforts and investments to monitor and forecast climate for CLR risk management, thereby shifting the focus away from coffee growers.

Attribute	Loc.norm.	Glob.norm.
Risk of monthly increase in CLR incidence		
├Pruning	50	50
└**Incidence increase without pruning**	50	50
├**Disease increase considering fungicide application**	69	35
│ ├**Disease increase**	50	17
│ │ ├**Pathogen population growth**	56	10
│ │ │ ├**Inoculum stock available for infection**	32	3
│ │ │ │ ├**Inoculum stock after hyperparasitism**	50	2
│ │ │ │ │ ├***Shade***	8	0
│ │ │ │ │ ├***Incidence related to inoculum***	78	1
│ │ │ │ │ └Fungicides	14	0
│ │ │ │ └**Spore loss**	50	2
│ │ │ │ ├Spore loss by rain wash-off	71	1
│ │ │ │ └***Shade***	29	0
│ │ │ ├**Infection**	32	3
│ │ │ │ ├Infection of leaves by wetness	67	2
│ │ │ │ └***Shade***	33	1
│ │ │ └**Latent period**	36	3
│ │ │ ├Latent period by temperature	67	2
│ │ │ └***Shade***	33	1
│ │ └**Overall host susceptibility (G+P)**	44	8
│ │ ├**Leaf physiological susceptibility**	22	2
│ │ │ ├***Shade***	57	1
│ │ │ └**Fruit effect on leaf physiological susceptibility**	43	1
│ │ │ ├***Coffee phenology***	33	0
│ │ │ └***Fruit load***	67	0
│ │ └Level of genetic resistance	78	6
│ └**Fungicide efficacy**	50	17
│ ├Incidence related to inoculum	43	7
│ └Fungicide application	57	10
├**Defoliation**	15	8
│ ├Incidence on defoliation	50	4
│ └**Fruit effect on defoliation**	50	4
│ ├***Coffee phenology***	57	2
│ └***Fruit load***	43	2
└**Leaf emergence**	15	8
├Shade	33	3
└**Fruit x meteorology x nutrition**	67	5
├**Fruit x meteorology**	63	3
│ ├**Fruit effect on leaf emergence**	33	1
│ │ ├Coffee phenology	33	0
│ │ └Fruit load	67	1
│ └Rainfall	67	2
└Coffee nutrition	37	2

Figure 4. Average normalized weights of each attribute of the ExpeRoya model. Screenshot of Dexi software (Bohanec, 2020). The local weights (Loc. norm.) define the relative contribution of each attribute belonging to the same node. The overall weights (Glob. norm.) define the contribution of each attribute relative to all the other attributes compared with the uppermost node. The same attributes used in different aggregation tables are shown in italics. Note: attributes with low overall weights can nevertheless have a high local weight, meaning they play a role in certain circumstances. For example, *Fungicide application* affecting *L. lecanii* and linked to *Inoculum stock (of H. vastatrix) after hyperparasitism* has a negligible overall weight (less than 1%, which was rounded off to 0%) but nevertheless explains 20% of the attribute *Inoculum stock after hyperparasitism*, meaning it plays a role in certain local interactions.

3.2. Social evaluation of the model

3.2.1. Qualitative evaluation took place at workshops organized during the design stage of ExpeRoya

During the workshops, the participants agreed with the formalism of the model and the results of the model scenarios were in line with what the participants knew about the system. Today, coffee technical services in Honduras and Nicaragua use ExpeRoya to help forecast increases in CLR. As a result, they can take preventative measures instead of basing their decisions on surveillance only, and they can rapidly react to the observed incidence of CLR. Honduras IHCAFE also uses the forecasts in its monthly alerts. Central American coffee institutes have access to the ExpeRoya user-friendly web interface available via https://www.redpergamino.net/app-experoya, hosted by the Pergamino platform (http://www.redpergamino.net/).

3.2.2. Quantitative evaluation of the final version (V1) of ExpeRoya through a survey

Evaluation of the quantitative relationships

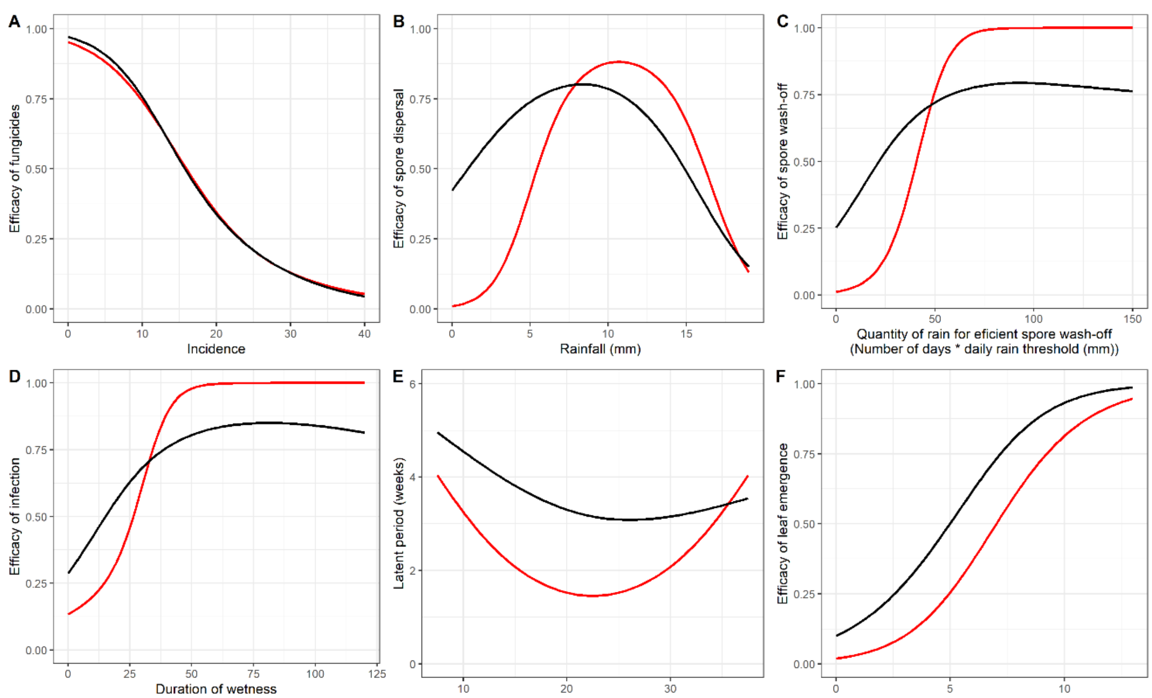

Figure 5. The functional responses of the disease processes (y-axis) to their related input attributes (x-axis) incorporated in the ExpeRoya model (red lines) corroborate expert knowledge (black lines, represent the weighted average of the responses with a degree of confidence greater than 5). A) question 1.4; B) question 2.1; C) question 2.5; D) question 3.3; E) question 4.5 and F) question 6.12 of the survey available in English and in Spanish (Appendix 3).

All the experts were able to quantitatively describe the functional responses of the biophysical processes in the multiple-choice questionnaire. Overall, the patterns described by the experts were consistent with the formalism incorporated in ExpeRoya.

The relationship between incidence and fungicide efficacy described by the experts and the one incorporated in the model are extremely close (Fig. 5A), which is surprising because this relationship is not explicitly described in the literature.

The relationship between rainfall and the efficacy of spore dispersal was on average overestimated by the experts compared to ExpeRoya (Fig. 5B) for low rainfall amounts, but the threshold beyond which spore wash-off occurs was on average around 8 mm, which is close to the 10-mm threshold reported in the literature (Avelino et al., 2020; Lasso et al., 2020; Merle et al., 2020). Indeed, beyond the 10-mm threshold, the reduction in spore dispersal is indicative of spore wash-off. When experts were asked to explicitly define the threshold of rainfall for spore wash-off (question 2.3 of the survey, Appendix 3), only 5% of the experts cited the 10 mm threshold used in ExpeRoya. However, the pattern of the functional response of spore wash-off described by the experts (question 2.5 of the survey, Appendix 3; Fig. 5C) was close to the functional response incorporated in ExpeRoya. These results show that the experts were able to explicitly define different thresholds depending on the processes they took into consideration. Also, in the free-text answer to question 2.9 of the survey, they pointed out that other variables such as rainfall intensity, the size of the raindrops and the duration of the rainfall event must be taken into account when describing spore dispersal and wash-off.

The relationship between infection and leaf wetness described by the experts was on average close to the relationship in ExpeRoya, although it was slightly overestimated by the experts at low duration of wetness and underestimated at high duration of wetness, compared to the model (Fig. 5D). A majority (56%) of the experts selected 5 mm of daily rainfall as a proxy of leaf wetness (question 3.1 of the survey, Appendix 3) as specified in ExpeRoya (Guzman and Gomez, 1987).

The relationship between the latent period and temperature was the most difficult for the experts to assess (question 4.5 of the survey, Appendix 3; Fig. 5E). While the experts' relationship pattern was close to that described in the ExpeRoya, the experts' average curve revealed an optimum of 25 °C corresponding to a latent period of three weeks, versus an optimum ranging between 22 °C and 24 °C for a latent period of one week in ExpeRoya, which corresponds to the literature (Kushalappa et al., 1983; Nutman et al., 1963). The experts also tended to indicate that high temperatures are less limiting to CLR growth than low temperatures, whereas the ExpeRoya considers a symmetric relationship of the latent period as a function of temperature.

Finally, the experts' assessment of the relationship between the number of rainy days (i.e., days with more than 1 mm of rainfall) and leaf emergence was very close to the one incorporated in ExpeRoya (Fig. 5F).

The discrepancies between the experts' answers and the model may be partly due to the difficulty for the experts to describe the shape of a curve based on a table (used in the Google Form) that does not represent a graph.

Evaluation of the qualitative relationships

For each qualitative relationship (interactions between multiple input attributes), the experts were asked to select one response. We evaluated the degree of agreement between the experts' opinions and ExpeRoya by computing the percentage of experts who selected the same response as that specified in ExpeRoya (percentages in red in Figure 6) and the percentage of experts who selected other responses (percentages in grey in Figure 6). Among all the relationships, a majority of experts chose 28 relationships out of the 47 relationships proposed, i.e. we obtained 60% of hits (Fig. 6).

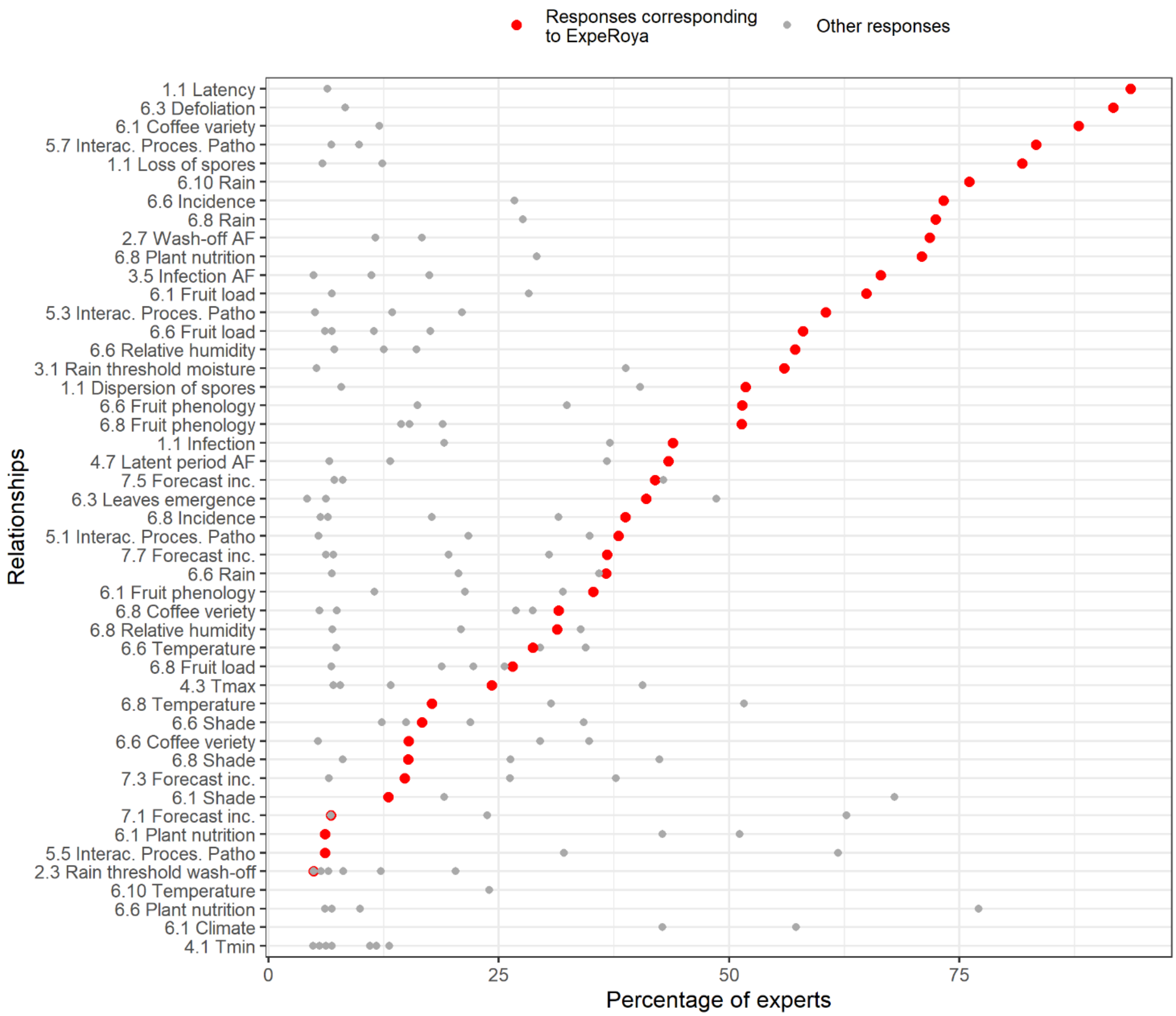

Figure 6. Distribution of the experts' responses to questions involving qualitative relationships (interactions between multiple input attributes). The graph shows the percentage of experts who chose a given relationship between two attributes at least. The dots are in red when they match ExpeRoya and in grey otherwise. We defined hit percentages when the majority of experts chose the ExpeRoya response.

The observed range of experts' responses when dealing with a large number of interactions is indicative of discrepancies between experts' projections based on the same information. The variability of the experts' responses of course depends on the weight that each person gives to each process (Morgan, 2014). However, this variability also depends on the difficulty people have processing a large number of factors when making decisions. Such a process entails a level of conceptual complexity that has been shown to limit human information processing capacity to three- to four-way interactions (Halford et al., 2005).

The experts' responses to question 7.3 (Appendix 3) illustrate this complexity: 38% of the experts estimated that the incidence would be stable or increase slightly in the following month, whereas ExpeRoya forecast a dramatic increase in incidence that was only suggested by 15% of the experts. Figure 7 shows the hierarchy of the combinations of attributes proposed in question 7.3 based on which ExpeRoya forecasts a dramatic increase in incidence.


Risk of monthly increase in CLR incidence
Pruning
Incidence increase without pruning
Disease increase x fungicide
Disease increase
Pathogen population growth
Inoc. stock available for infection
Inoc. stock after hyperparatism
Shade
Inoculum stock
Fungicide application
Spore loss
Spore loss by rain wash-off
Shade
Infection
Infection by wetness
Shade
Latent period
Latent period by temperature
Shade
Overall host suceptibility (G+P)
Physiological suceptibility
Fruit
From Flowering to Harvest
Fruit load
Shade
Genetic resistance
Fungicide efficacy
Inoculum stock
Fungicide application
Leaf emergence
Shade
Fruit x Meteorology x Nutrition
Fruit x Meteorology
Fruit
From Flowering to Harvest
Fruit load
Rainfall
Nutrition
Defoliation
Incidence
Fruit
From Flowering to Harvest
Fruit load

Figure 7. Hierarchical tree representing the output of ExpeRoya with the input attributes proposed in question 7.3 of the survey (Appendix 3)**.** The color code of the nodes indicates the point of view of a coffee farmer: green when his/her opinion is favorable, orange when it is moderately favorable, red when it is unfavorable, dark red when it is drastically unfavorable, and grey when it is a non-ordered attribute. At the time of the survey, the level of defoliation proposed was low, but as ExpeRoya has evolved since then, we show here the results with the latest version of the model (Version 1.3), i.e., medium defoliation (orange node).

One way to compensate for human error in integrating and processing a large number of variables is to automate responses using a well-defined framework. This is the main challenge of system modeling for decision making. Agro-ecological systems, such as coffee farms and coffee producing areas, are made up of countless variables and interactions; we show that a qualitative hierarchical model such as ExpeRoya can integrate this complexity in a simple way and in line with expert opinion, which helps explain its high level of adoption by practitioners.

3.3. Obtaining accurate CLR forecasting with ExpeRoya

The mechanistic and multi-attribute approach used in ExpeRoya allows the production of accurate and realistic scenarios (rather than providing precise quantitative information), especially for monthly alerts on CLR. ExpeRoya can process 229 interactions from only 12 input attributes corresponding to meteorological variables, management practices, host characteristics and the estimated stock of inoculum, that are all easily acquired in the field. The aim of the IPSIM framework (Aubertot and Robin, 2013) from which ExpeRoya is derived, is not to precisely calculate the levels of the output response (e.g. to the nearest percentage incidence) but to obtain accurate levels of the response that enable the identification of trends and, in our case, to predict possible future CLR incidence. This particular feature enables farmers and extension officers to make rapid and appropriate decisions based on the observed on-farm or national incidence of CLR.

3.4. The model “in action”

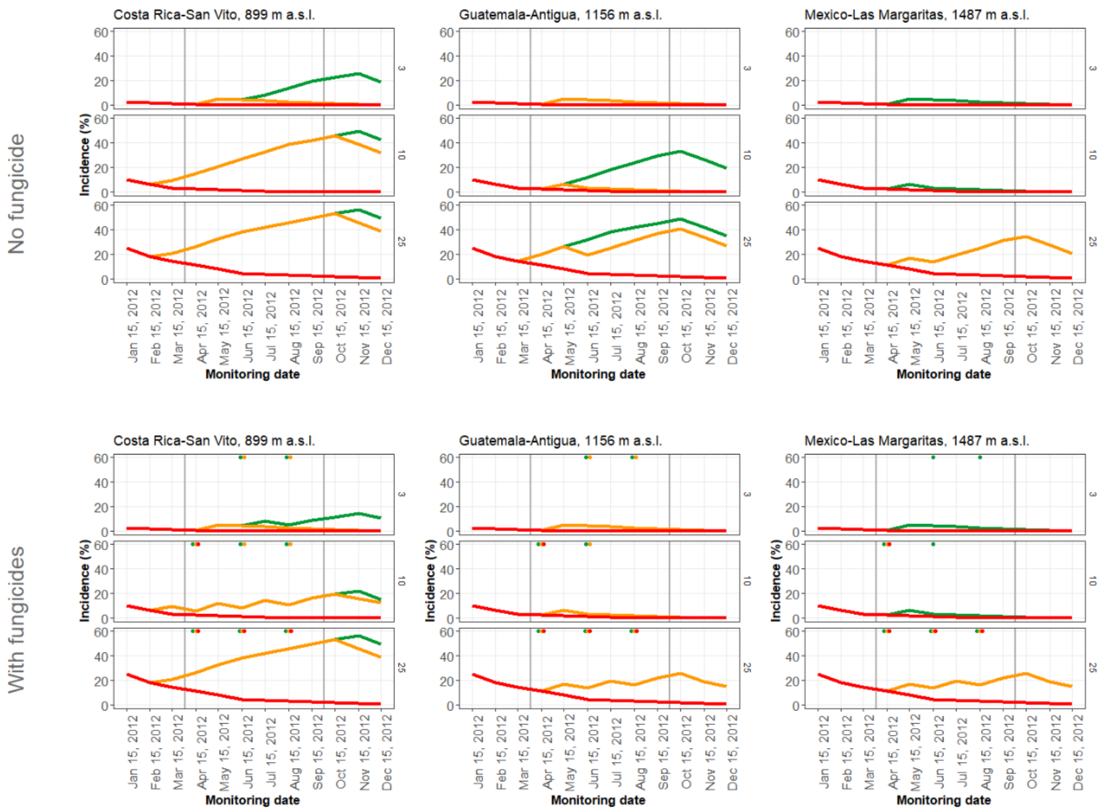

Figure 8. ExpeRoya simulations of the course of epidemics for three locations at increasing altitude in Latin America (Costa Rica, Guatemala and Mexico) using simulated weather data for the year 2012, which was favorable for CLR, with varying (i) temperatures but the same rainfall at the three locations (Appendix 5), (ii) shade cover (High shade (green lines), Medium shade (orange lines), Low shade or Full sun (red lines)), (ii) initial incidence (3%, 10% and 25%) at the beginning of the simulation (January 15, 2012) and (iii) application of fungicides (no fungicide (upper panel), with fungicides (lower panel)). All the other attributes of the model were fixed: medium fruit load (17-40q/ha), susceptible cultivar, no coffee fertilization and no pruning. In the lower panel “With fungicides”, the dots represent the fungicide applied for each degree of shade (High shade (green lines), Medium shade (orange lines), Low shade or Full sun (red lines)). The vertical grey lines represent the flowering date (April1, 2012) and the harvest date (October 1, 2012). Note that this figure is simply an illustration of how the model can be used over time and can discriminate between situations: as ExpeRoya was designed to be used with real data acquired at monthly intervals, and entry attributes that are updated each month, those simulations do not represent forecasts that could have been made with real monitoring data.

By accounting for the fact the same rainfall data were used for the three locations (so as to be able to compare the situations), the simulations produced with ExpeRoya satisfactorily describe the expected effect of altitude (which is a proxy for temperature) on the incidence of CLR: the higher the altitude, the cooler the temperature and hence the lower the incidence (Fig. 8). In San Vito, Costa Rica (the lowest elevation) more events with short and medium latent periods occurred than at the higher altitudes of Antigua, Guatemala and Las Margaritas, Mexico (Appendix 5). However, the altitude effect is counterbalanced when initial incidence (which is a proxy of the stock of inoculum) is greater than 3% or when there is shade. In our simulations, the incidence of CLR in coffee crops in full sun is much lower (max 20%) than under shade (where incidence can reach 50%) because shade increases the conditions that favor the spread of CLR: it buffers temperatures and reduces spore wash-off. If fungicide is applied, the application is only efficient if CLR incidence is below 10% and is not efficient at all if CLR incidence if greater than 30%. These results lead us to envisage the use of preventive methods as an alternative to the systematic use of fungicides. However, these simulations should be interpreted with caution, as ExpeRoya was designed to be used with real data acquired at monthly intervals, and entry attributes that are updated each month. It is also important to note that Figure 8 is simply an illustration of how the model can be used over time and can discriminate between situations.

4. Conclusion

Until now, the high complexity of the CLR-coffee pathosystem, comprising a large number of processes and system covariates, has been an obstacle to the development of mechanistic models. As a result, only a few mechanistic models have been developed (e.g. Bebber et al., 2016; Kushalappa et al., 1983) thereby limiting the range of possible scenarios with multiple interactions between factors. The model ExpeRoya improves forecasting of CLR. ExpeRoya is able of capturing the multifactorial feature of the CLR-coffee system by incorporating the main disease processes, host dynamics, and cropping practices - all of which interact with meteorological variables - in a comprehensive framework to forecast the monthly risk of an increase in CLR at the plot and national levels. ExpeRoya is powerful: it makes it possible to compute 229 possible interactions that exist within the CLR-coffee pathosystem based on only 12 input variables that are easily acquired in the field. ExpeRoya is a user-friendly model designed for all actors of the coffee sector, particularly for smallholder farmers and agricultural extension officers. Coffee technical services in Central America already use ExpeRoya hosted by the platform Pergamino (https://www.redpergamino.net/app-experoya), to help them prepare their monthly risk alert for producers and extension staff. ExpeRoya is adaptable: users can modify the model according to advances in knowledge and/or their own expertise of the system. ExpeRoya is part of a modeling strategy developed in a European Union project called Procagica initiated in 2016. Procagica aimed at implementing a regional network of national early warning systems to prevent new severe epidemics at national and regional levels in Central America. As part of this project, Cirad developed a toolbox that includes ExpeRoya, to help develop strategies for mitigating the effect of CLR on coffee producers' livelihoods, especially the most vulnerable producers.

In sum, ExpeRoya is both a framework and a proof of concept that improves both forecasting and the comprehensive modeling of CLR. We believe that beyond the context of forecasting CLR, ExpeRoya will be useful for many other CLR modeling approaches (e.g., statistical models, agent-based modeling, models based on machine learning) because it gathers a considerable amount of information on the behavior of the CLR-coffee pathosystem. The ExpeRoya framework presented here will certainly be useful for the design of multi-attribute models for other pathosystems.

Declaration of Competing Interest: The authors declare no competing interest.

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References

Aubertot, J.-N., Robin, M.-H., 2013. Injury Profile SIMulator, a qualitative aggregative modelling framework to predict crop injury profile as a function of cropping practices, and the abiotic and biotic environment. I. Conceptual bases. PloS One 8, e73202–e73202. https://doi.org/10.1371/journal.pone.0073202
Avelino, J., Cristancho, M., Georgiou, S., Imbach, P., Aguilar, L., Bornemann, G., Läderach, P., Anzueto, F., Hruska, A.J., Morales, C., 2015. The coffee rust crises in Colombia and Central America (2008–2013): impacts, plausible causes and proposed solutions. Food Secur. 7, 303–321. https://doi.org/10.1007/s12571-015-0446-9
Avelino, J., Rivas, G., 2013. La roya anaranjada del cafeto hal-01071036.
Avelino, J., Toledo, J.C., Medina, B., 1993. Développement de la rouille orangée (Hemileia vastatrix) dans une plantation du sud ouest du Guatemala et évaluation des dégâts qu'elle provoque. ASIC.
Avelino, J., Vilchez, S., Segura-Escobar, M.B., Brenes-Loaiza, M.A., Virginio Filho, E. de M., Casanoves, F., 2020. Shade tree Chloroleucon eurycyclum promotes coffee leaf rust by reducing uredospore wash-off by rain. Crop Prot. 129, 105038.
Avelino, J., Zelaya, H., Merlo, A., Pineda, A., Ordoñez, M., Savary, S., 2006. The intensity of a coffee rust epidemic is dependent on production situations. Ecol. Model. 197, 431–447. https://doi.org/10.1016/j.ecolmodel.2006.03.013
Bebber, D.P., Castillo, Á.D., Gurr, S.J., 2016. Modelling coffee leaf rust risk in Colombia with climate reanalysis data. Philos. Trans. R. Soc. B Biol. Sci. 371, 20150458.
Bohanec, M., 2020. DEXi: Program for Multi-Attribute Decision Making, User's Manual, IJS Report DP-13100. Jožef Stefan Institute, Ljubljana.
Boudrot, A., Pico, J., Merle, I., Granados, E., Vilchez, S., Tixier, P., Filho, E. de M.V., Casanoves, F., Tapia, A., Allinne, C., 2016. Shade effects on the dispersal of airborne Hemileia vastatrix uredospores. Phytopathology 106, 572–580.
Brown, J.S., Whan, J.H., Kenny, M.K., Merriman, P.R., 1995. The effect of coffee leaf rust on foliation and yield of coffee in Papua New Guinea. Crop Prot. 14, 589–592.
Carvalho, V.L., Chalfoun, S.M., Castro, H.A., Carvalho, V.D., 2001. Influence of different yield levels on coffee rust evolution and on phenolic compounds on leaves. Ciênc. E Agrotecnologia 25, 49–54.
Cerda, R., Avelino, J., Gary, C., Tixier, P., Lechevallier, E., Allinne, C., 2017. Primary and Secondary Yield Losses Caused by Pests and Diseases: Assessment and Modeling in Coffee. PloS One 12, e0169133–e0169133. https://doi.org/10.1371/journal.pone.0169133
Corrales, D.C., Casas, A.F., Ledezma, A., Corrales, J.C., 2016. Two-level classifier ensembles for coffee rust estimation in Colombian crops. Int. J. Agric. Environ. Inf. Syst. IJAEIS 7, 41–59.
Corrales, D.C., Figueroa, A., Ledezma, A., Corrales, J.C., 2015. An empirical multi-classifier for coffee rust detection in colombian crops, in: International Conference on Computational Science and Its Applications. Springer, pp. 60–74.
Costa, M.J., Zambolim, L., Rodrigues, F.A., 2006. Efeito de níveis de desbaste de frutos do cafeeiro na incidência da ferrugem, no teor de nutrientes, carboidratos e açúcares redutores. Fitopatol. Bras. 31, 564–571.
DaMatta, F.M., 2004. Ecophysiological constraints on the production of shaded and unshaded coffee: a review. Field Crops Res. 86, 99–114.
DaMatta, F.M., Ronchi, C.P., Maestri, M., Barros, R.S., 2007. Ecophysiology of coffee growth and production. Braz. J. Plant Physiol. 19, 485–510.

de Reffye, P., Hu, B., Kang, M., Letort, V., Jaeger, M., 2021. Two decades of research with the GreenLab model in Agronomy. Ann. Bot. 127, 281–295.
Deguine, J.-P., Robin, M.-H., Corrales, D.C., Vedy-Zecchini, M.-A., Doizy, A., Chiroleu, F., Quesnel, G., Païtard, I., Bohanec, M., Aubertot, J.-N., 2021. Qualitative modeling of fruit fly injuries on chayote in Réunion: Development and transfer to users. Crop Prot. 139, 105367.
Dordas, C., 2008. Role of nutrients in controlling plant diseases in sustainable agriculture. A review. Agron. Sustain. Dev. 28, 33–46.
Eskes, A.B., 1982. The use of leaf disk inoculations in assessing resistance to coffee leaf rust (Hemileia vastatrix). Neth. J. Plant Pathol. 88, 127–141.
Ferrandino, F.J., 2008. Effect of crop growth and canopy filtration on the dynamics of plant disease epidemics spread by aerially dispersed spores. Phytopathology 98, 492–503.
Galvao, J.A.H., Bettiol, W., 2014. Effects of UV-B radiation on Lecanicillium spp., biological control agents of the coffee leaf rust pathogen. Trop. Plant Pathol. 39, 392–400.
González, L.C., Nicao, M.E.L., Muiño, B.L., 2014. Compatibilidad de cuatro plaguicidas de diferentes grupos químicos con Lecanicillium lecanii (Zimm.) Zare & Gams. Rev. Protección Veg. 28.
Guzman, O., Gomez, L., 1987. Permanence of free water on coffee leaves. Exp. Agric. 23, 213–220.
Halford, G.S., Baker, R., McCredden, J.E., Bain, J.D., 2005. How many variables can humans process? Psychol. Sci. 16, 70–76.
Harou, I.L., Whitney, C., Kung'u, J., Luedeling, E., 2021. Crop modelling in data-poor environments – A knowledge-informed probabilistic approach to appreciate risks and uncertainties in flood-based farming systems. Agric. Syst. 187, 103014. https://doi.org/10.1016/j.agsy.2020.103014
Kushalappa, A., Akutsu, M., Ludwig, A., 1983. Application of survival ratio for monocyclic process of Hemileia vastatrix in predicting coffee rust infection rates. Phytopathology 73, 96–103.
Kushalappa, A.C., Chaves, G.M., 1980. An analysis of the development of coffee rust in the field. Fitopatol. Bras. 5, 95–103.
Kushalappa, A.C., Eskes, A.B., 1989a. Advances in coffee rust research. Annu. Rev. Phytopathol. 27, 503–531.
Kushalappa, A.C., Eskes, A.B., 1989b. Coffee rust: epidemiology, resistance, and management. CRC Press.
Kushalappa, A.C., Ludwig, A., 1982. Calculation of apparent infection rate in plant diseases: development. Phytopathology 72, 1373–1377.
Kushalappa, A.C., Martins, C.P., 1980. Incubation and generation periods for Hemileia vastatrix on coffee in Viçosa, Minas Gerais. Fitopatol. Bras. Bras. V 5 2 P 177-183.
Lacroix, O., 2020. Qualitative modelling of perennial weed management Elytrigia repens, Cirsium arvense and Sonchus arvensis. Life Sci. Q-Bio dumas-02972029.
Lasso, E., Corrales, D.C., Avelino, J., de Melo Virginio Filho, E., Corrales, J.C., 2020. Discovering weather periods and crop properties favorable for coffee rust incidence from feature selection approaches. Comput. Electron. Agric. 176, 105640.
López-Bravo, D.F., Virginio-Filho, E. de M., Avelino, J., 2012. Shade is conducive to coffee rust as compared to full sun exposure under standardized fruit load conditions. Crop Prot. 38, 21–29. https://doi.org/10.1016/j.cropro.2012.03.011

Merle, I., 2019. Effets du microclimat sur le développement de l'épidémie de rouille orangée du caféier Arabica (Hemileia vastatrix - Coffea arabica) dans une gamme de situations de production. Sciences agricoles. Université Montpellier. NNT: 2019MONTG086. tel-02861898.

Merle, I., Pico, J., Granados, E., Boudrot, A., Tixier, P., Virginio Filho, E. de M., Cilas, C., Avelino, J., 2019. Unraveling the Complexity of Coffee Leaf Rust Behavior and Development in Different Coffea arabica Agroecosystems. Phytopathology® 110, 418–427. https://doi.org/10.1094/PHYTO-03-19-0094-R

Merle, I., Tixier, P., de Melo Virginio Filho, E., Cilas, C., Avelino, J., 2020. Forecast models of coffee leaf rust symptoms and signs based on identified microclimatic combinations in coffee-based agroforestry systems in Costa Rica. Crop Prot. 130, 105046.

Morgan, M.G., 2014. Use (and abuse) of expert elicitation in support of decision making for public policy. Proc. Natl. Acad. Sci. 111, 7176–7184. https://doi.org/10.1073/pnas.1319946111

Motisi, N., 2021. Improved forecasting of coffee leaf rust by qualitative modeling: design and expert validation of the ExpeRoya model. https://doi.org/10.18167/DVN1/LSYFJR

Nutman, F.J., Roberts, F.M., Clarke, R.T., 1963. Studies on the biology of Hemileia vastatrix Berk. & Br. Trans. Br. Mycol. Soc. 46, 27–44.

Perfecto, I., Vandermeer, J., Philpott, S.M., 2014. Complex ecological interactions in the coffee agroecosystem. Annu. Rev. Ecol. Evol. Syst. 45, 137–158.

Pezzopane, J.R.M., Salva, T. de J.G., de Lima, V.B., Fazuoli, L.C., 2012. Agrometeorological parameters for prediction of the maturation period of Arabica coffee cultivars. Int. J. Biometeorol. 56, 843–851.

R Core Team, 2017. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.

Rivillas, C.A., Serna, C.A., Gaitán, A., 2011. La roya del cafeto en Colombia: Impacto manejo y costos del control. Cenicafé 36:1-51.

Robin, M.-H., Colbach, N., Lucas, P., Montfort, F., Cholez, C., Debaeke, P., Aubertot, J.-N., 2013. Injury profile SIMulator, a Qualitative aggregative modelling framework to predict injury profile as a function of cropping practices, and abiotic and biotic environment. II. Proof of concept: design of IPSIM-wheat-eyespot. PloS One 8, e75829–e75829. https://doi.org/10.1371/journal.pone.0075829

Rodríguez, D., Cure, J.R., Cotes, J.M., Gutierrez, A.P., Cantor, F., 2011. A coffee agroecosystem model: I. Growth and development of the coffee plant. Ecol. Model. 222, 3626–3639. https://doi.org/10.1016/j.ecolmodel.2011.08.003

Silva, M. do C., Várzea, V., Guerra-Guimarães, L., Azinheira, H.G., Fernandez, D., Petitot, A.-S., Bertrand, B., Lashermes, P., Nicole, M., 2006. Coffee resistance to the main diseases: leaf rust and coffee berry disease. Braz. J. Plant Physiol. 18, 119–147.

Staver, C., Guharay, F., Monterroso, D., Muschler, R.G., 2001. Designing pest-suppressive multistrata perennial crop systems: shade-grown coffee in Central America. Agrofor. Syst. 53, 151–170. https://doi.org/10.1023/A:1013372403359

Taugourdeau, S., Le Maire, G., Avelino, J., Jones, J.R., Ramirez, L.G., Quesada, M.J., Charbonnier, F., Gómez-Delgado, F., Harmand, J.-M., Rapidel, B., 2014. Leaf area index as an indicator of ecosystem services and management practices: An application for coffee agroforestry. Agric. Ecosyst. Environ. 192, 19–37.

Toniutti, L., Breitler, J.-C., Etienne, H., Campa, C., Doulbeau, S., Urban, L., Lambot, C., Pinilla, J.-C.H., Bertrand, B., 2017. Influence of environmental conditions and genetic background of Arabica coffee (C. arabica L) on leaf rust (Hemileia vastatrix) pathogenesis. Front. Plant Sci. 8, 2025.

Van Oijen, M., Dauzat, J., Harmand, J.-M., Lawson, G., Vaast, P., 2010. Coffee agroforestry systems in Central America: I. A review of quantitative information on physiological and ecological processes. Agrofor. Syst. 80, 341–359.

Vezy, R., Le Maire, G., Christina, M., Georgiou, S., Imbach, P., Hidalgo, H.G., Alfaro, E.J., Blitz-Frayret, C., Charbonnier, F., Lehner, P., 2020. DynACof: A process-based model to study growth, yield and ecosystem services of coffee agroforestry systems. Environ. Model. Softw. 124, 104609.

Walters, D.R., Bingham, I.J., 2007. Influence of nutrition on disease development caused by fungal pathogens: implications for plant disease control. Ann. Appl. Biol. 151, 307–324.

Zambolim, L., 2016. Current status and management of coffee leaf rust in Brazil. Trop. Plant Pathol. 41, 1–8.

Zambolim, L., Silva-Acuña, R., Do Vale, F.X.R., Chaves, G.M., 1992. Influencia da produção do cafeeiro sobre o desenvolvimento da ferrugem (Hemileia vastatrix). Fitopatol. Bras. 17, 32–35.

Zewdie, B., Tack, A.J., Ayalew, B., Adugna, G., Nemomissa, S., Hylander, K., 2021. Temporal dynamics and biocontrol potential of a hyperparasite on coffee leaf rust across a landscape in Arabica coffee's native range. Agric. Ecosyst. Environ. 311, 107297.

Appendices

Appendix 1

Effect of incidence of coffee leaf rust on monthly defoliation of coffee trees

We used the model for daily defoliation (Fig. A1.1) to deduce the model for monthly defoliation used in ExpeRoya (Fig. A1.2)

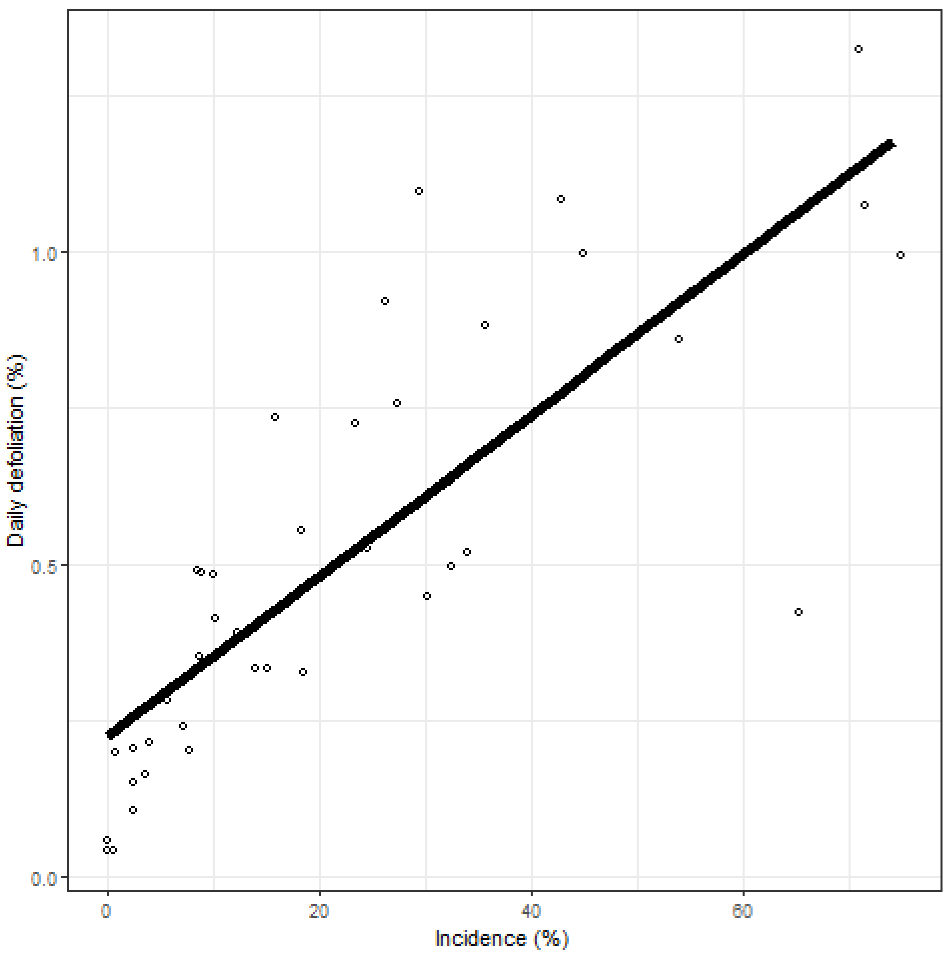


Fig. A1.1. Daily defoliation of coffee tree according to incidence of coffee leaf rust. Daily total defoliation is calculated between two successive dates of incidence assessments and averaged per day. The interval between two successive assessments in our dataset was 29.3 days on average, with a minimum of 17 days and a maximum of 51 days. Data come from three plots (two around Lake Yojoa in Honduras, and one at Turrialba, Costa Rica) that were monitored during two consecutive years (1994 and 1995 in Honduras, 2008 and 2009 in Costa Rica).

The linear model adjusted to the data:

daily_defoliation = 0.2249+ 0.0128* incidence

Where “daily_defoliation” is the percentage of daily total defoliation (healthy and diseased leaves) with respect to the total number of leaves present at the time when coffee leaf rust incidence (“incidence” in the equation) was assessed.

Monthly defoliation used in ExpeRoya

The monthly defoliation is deduced from the daily defoliation as follows:

monthly_defoliation = 30*(0.2249+ 0.0128* incidence)

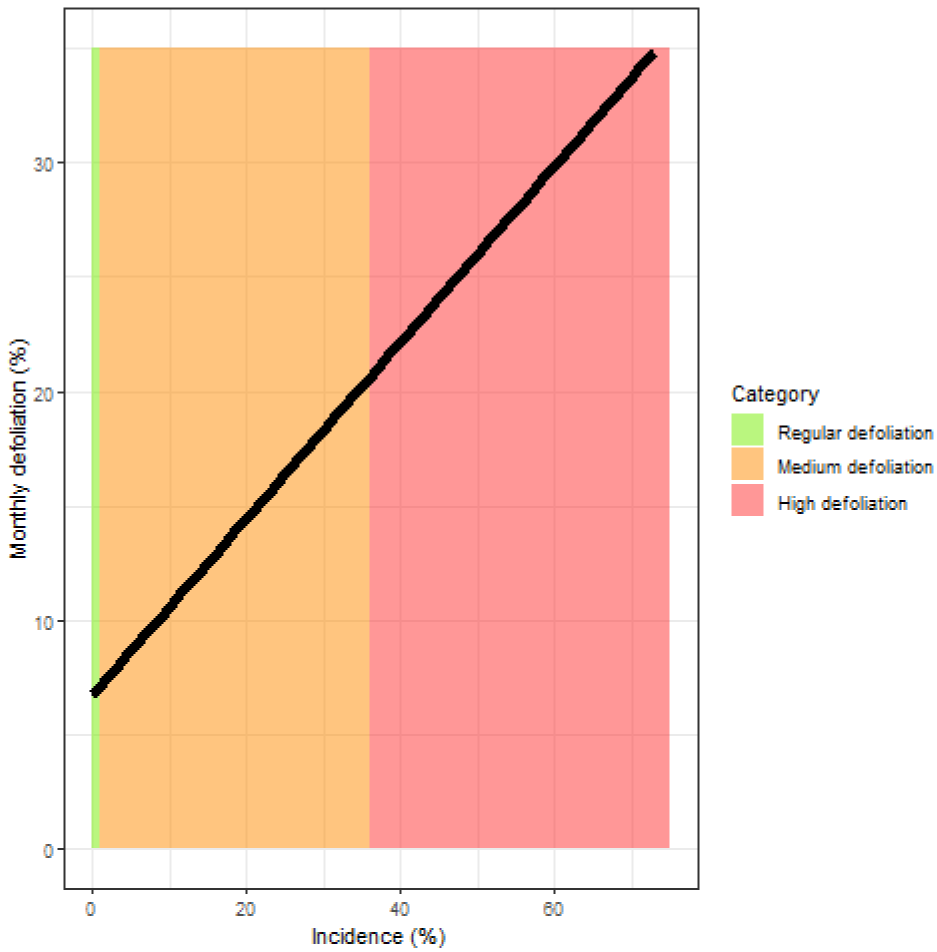


Fig. A1.2. Monthly defoliation of coffee tree according to incidence of coffee leaf rust. In ExpeRoya, defoliation is described by three ordinal categories, “High defoliation” (>20% of monthly defoliation when incidence is >36%), “Medium defoliation” ([6-20%] of monthly defoliation when incidence is [0-36%]) and “Regular defoliation” (<= 6% of monthly defoliation when incidence is equal to 0%).

Appendix 2

ExpeRoya model aggregation tables. The hierarchical structure of the model is available in the Dexi version in Cirad Dataverse (Motisi, 2021) and is summarized in Figure 3 in the main text. See Materials and Methods for justifications of the combinations of tables.

Table A2.1. Inoculum stock after hyperparasitism by *Lecanicilium lecanii* described by 18 interactions between (i) Shade (Process P9, Table 1), (ii) Incidence related to inoculum (Process P19, Table 1) and Fungicide (Process P6, Table 1).

	Shade	Incidence related to inoculum	Fungicides	Inoculum stock after hyperparasitism
1	High	Low quantity of inoculum	Yes	Low quantity of inoculum
2	High	Low quantity of inoculum	No	Low quantity of inoculum
3	High	Medium quantity of inoculum	Yes	Medium quantity of inoculum
4	High	Medium quantity of inoculum	No	Medium quantity of inoculum
5	High	High quantity of inoculum	Yes	High quantity of inoculum
6	High	High quantity of inoculum	No	Medium quantity of inoculum
7	Medium	Low quantity of inoculum	Yes	Low quantity of inoculum
8	Medium	Low quantity of inoculum	No	Low quantity of inoculum
9	Medium	Medium quantity of inoculum	Yes	Medium quantity of inoculum
10	Medium	Medium quantity of inoculum	No	Medium quantity of inoculum
11	Medium	High quantity of inoculum	Yes	High quantity of inoculum
12	Medium	High quantity of inoculum	No	Medium quantity of inoculum
13	Low or full sun	Low quantity of inoculum	Yes	Low quantity of inoculum
14	Low or full sun	Low quantity of inoculum	No	Low quantity of inoculum
15	Low or full sun	Medium quantity of inoculum	Yes	Medium quantity of inoculum
16	Low or full sun	Medium quantity of inoculum	No	Medium quantity of inoculum
17	Low or full sun	High quantity of inoculum	Yes	High quantity of inoculum
18	Low or full sun	High quantity of inoculum	No	High quantity of inoculum

Table A2.2. Spore loss described by 9 interactions between (i) the effect of rain wash-off on spore loss (Process P1, Table 1) and (ii) Shade (Process P8, Table 1).

	Spore loss by rain wash-off	Shade	Spore loss
1	Insufficient wash-off	High	**Low loss**
2	Insufficient wash-off	Medium	**Low loss**
3	Insufficient wash-off	Low shade or full sun	**Low loss**
4	Regular wash-off	High	**Low loss**
5	Regular wash-off	Medium	**Low loss**
6	Regular wash-off	Low shade or full sun	**Regular loss**
7	Efficient wash-off	High	**Regular loss**
8	Efficient wash-off	Medium	**High loss**
9	Efficient wash-off	Low shade or full sun	**High loss**

Table A2.3. Inoculum stock available for infection described by 9 interactions between (i) Inoculum stock after hyperparatism (Table A2.1) and (ii) Spore loss (Table A2.2).

	Inoculum stock after hyperparasitism	Spore loss	Inoculum stock available for infection
1	Low quantity of inoculum	Low loss	**Low quantity of spores**
2	Low quantity of inoculum	Regular loss	**Low quantity of spores**
3	Low quantity of inoculum	High loss	**Low quantity of spores**
4	Medium quantity of inoculum	Low loss	**Medium quantity of spores**
5	Medium quantity of inoculum	Regular loss	**Low quantity of spores**
6	Medium quantity of inoculum	High loss	**Low quantity of spores**
7	High quantity of inoculum	Low loss	**High quantity of spores**
8	High quantity of inoculum	Regular loss	**Medium quantity of spores**
9	High quantity of inoculum	High loss	**Low quantity of spores**

Table A2.4. Infection described by 9 interactions between (i) Infection of leaves by wetness (Process P2, Table 1) and (ii) Shade (Process P8. Table 1).

	Infection of leaves by wetness	Shade	Infection
1	High infection	High	**High infection**
2	High infection	Medium	**High infection**
3	High infection	Low shade or full sun	**High infection**
4	Medium infection	High	**High infection**
5	Medium infection	Medium	**High infection**
6	Medium infection	Low shade or full sun	**Medium infection**
7	Low infection	High	**Medium infection**
8	Low infection	Medium	**Medium infection**
9	Low infection	Low shade or full sun	**Low infection**

Table A2.5. The latent period described by 9 interactions between (i) Effect of temperature on the latent period (Process P4, Table 1) and (ii) Shade (Process P8, Table 1).

	Latent period by temperature	Shade	Latent period
1	Short latency	High	**Short latency**
2	Short latency	Medium	**Short latency**
3	Short latency	Low shade or full sun	**Short latency**
4	Regular latency	High	**Short latency**
5	Regular latency	Medium	**Regular latency**
6	Regular latency	Low shade or full sun	**Regular latency**
7	Long latency	High	**Regular latency**
8	Long latency	Medium	**Regular latency**
9	Long latency	Low shade or full sun	**Long latency**

Table A2.6. Pathogen population growth described by 27 interactions between (i) Inoculum stock available for infection (Table A2.3), (ii) Infection (Table A2.4) and (iii) the Latent period (Table A2.5).

	Inoculum stock available for infection	Infection	Latent period	Pathogen population growth
1	Low quantity of spores	High infection	Short latency	**Increase in pathogenic population**
2	Low quantity of spores	High infection	Regular latency	**Stable pathogen population**
3	Low quantity of spores	High infection	Long latency	**Stable pathogen population**
4	Low quantity of spores	Medium infection	Short latency	**Stable pathogen population**
5	Low quantity of spores	Medium infection	Regular latency	**Decrease in pathogenic population**
6	Low quantity of spores	Medium infection	Long latency	**Decrease in pathogenic population**
7	Low quantity of spores	Low infection	Short latency	**Stable pathogen population**
8	Low quantity of spores	Low infection	Regular latency	**Decrease in pathogenic population**
9	Low quantity of spores	Low infection	Long latency	**Decrease in pathogenic population**
10	Medium quantity of spores	High infection	Short latency	**Increase in pathogenic population**
11	Medium quantity of spores	High infection	Regular latency	**Increase in pathogenic population**
12	Medium quantity of spores	High infection	Long latency	**Stable pathogen population**
13	Medium quantity of spores	Medium infection	Short latency	**Increase in pathogenic population**
14	Medium quantity of spores	Medium infection	Regular latency	**Stable pathogen population**
15	Medium quantity of spores	Medium infection	Long latency	**Stable pathogen population**
16	Medium quantity of spores	Low infection	Short latency	**Stable pathogen population**
17	Medium quantity of spores	Low infection	Regular latency	**Decrease in pathogenic population**
18	Medium quantity of spores	Low infection	Long latency	**Decrease in pathogenic population**
19	High quantity of spores	High infection	Short latency	**Increase in pathogenic population**
20	High quantity of spores	High infection	Regular latency	**Increase in pathogenic population**
21	High quantity of spores	High infection	Long latency	**Stable pathogen population**
22	High quantity of spores	Medium infection	Short latency	**Increase in pathogenic population**
23	High quantity of spores	Medium infection	Regular latency	**Increase in pathogenic population**
24	High quantity of spores	Medium infection	Long latency	**Stable pathogen population**
25	High quantity of spores	Low infection	Short latency	**Increase in pathogenic population**
26	High quantity of spores	Low infection	Regular latency	**Stable pathogen population**
27	High quantity of spores	Low infection	Long latency	**Stable pathogen population**

Table A2.7. Fruit effect on leaf physiological susceptibility described by 9 interactions between (i) Coffee phenology (Processes P15 to P17, Table 1) and (ii) Fruit load (Process P12, Table 1).

	Coffee phenology	Fruit load	**Fruit effect on leaf physiological susceptibility**
1	From flowering to the beginning of harvest	High fruit load	**Medium susceptibility**
2	From flowering to the beginning of harvest	Medium fruit load	**Low susceptibility**
3	From flowering to the beginning of harvest	Low fruit load	**Low susceptibility**
4	During harvest	High fruit load	**High susceptibility**
5	During harvest	Medium fruit load	**High susceptibility**
6	During harvest	Low fruit load	**Medium susceptibility**
7	From the end of harvest to the beginning of flowering	High fruit load	**Low susceptibility**
8	From the end of harvest to the beginning of flowering	Medium fruit load	**Low susceptibility**
9	From the end of harvest to the beginning of flowering	Low fruit load	**Low susceptibility**

Table A2.8. Leaf physiological susceptibility described by 9 interactions between (i) Shade (Process P10, Table 1) and (ii) Fruit effect on the physiological susceptibility (Table A2.7).

	Shade	Fruit effect on leaf physiological susceptibility	**Leaf physiological susceptibility**
1	High	High susceptibility	**Medium susceptibility**
2	High	Medium susceptibility	**Low susceptibility**
3	High	Low susceptibility	**Low susceptibility**
4	Medium	High susceptibility	**Medium susceptibility**
5	Medium	Medium susceptibility	**Medium susceptibility**
6	Medium	Low susceptibility	**Low susceptibility**
7	Low shade or full sun	High susceptibility	**High susceptibility**
8	Low shade or full sun	Medium susceptibility	**High susceptibility**
9	Low shade or full sun	Low susceptibility	**Medium susceptibility**

Table A2.9. Overall host susceptibility (genetic and physiological, G+P) described by 9 interactions between (i) Leaf physiological susceptibility (Table A2.8) and (ii) Level of genetic resistance (Process P18, Table 1).

	Leaf physiological susceptibility	Level of genetic resistance	Overall host susceptibility (G+P)
1	High susceptibility	Susceptible	**High susceptibility**
2	High susceptibility	Moderately susceptible	**Medium susceptibility**
3	High susceptibility	Resistente	**Null susceptibility**
4	Medium susceptibility	Susceptible	**Medium susceptibility**
5	Medium susceptibility	Moderately susceptible	**Medium susceptibility**
6	Medium susceptibility	Resistente	**Null susceptibility**
7	Low susceptibility	Susceptible	**Medium susceptibility**
8	Low susceptibility	Moderately susceptible	**Low susceptibility**
9	Low susceptibility	Resistente	**Null susceptibility**

Table A2.10. Disease growth described by 12 interactions between (i) Pathogen population growth (Table A2.6) and (ii) Overall host susceptibility (G+P) (Table A2.9).

	Pathogen population growth	Overall host susceptibility (G+P)	Disease increase
1	Increase in pathogenic population	High susceptibility	**Favorable for an increase in the pathogen population**
2	Increase in pathogenic population	Medium susceptibility	**Favorable for an increase in the pathogen population**
3	Increase in pathogenic population	Low susceptibility	**Moderatly favorable for an increase in the pathogen population**
4	Increase in pathogenic population	Null susceptibility	**Unfavorable for an increase in the pathogen population**
5	Stable pathogen population	High susceptibility	**Moderatly favorable for an increase in the pathogen population**
6	Stable pathogen population	Medium susceptibility	**Moderatly favorable for an increase in the pathogen population**
7	Stable pathogen population	Low susceptibility	**Unfavorable for an increase in the pathogen population**
8	Stable pathogen population	Null susceptibility	**Unfavorable for an increase in the pathogen population**
9	Decrease in pathogenic population	High susceptibility	**Unfavorable for an increase in the pathogen population**
10	Decrease in pathogenic population	Medium susceptibility	**Unfavorable for an increase in the pathogen population**
11	Decrease in pathogenic population	Low susceptibility	**Unfavorable for an increase in the pathogen population**
12	Decrease in pathogenic population	Null susceptibility	**Unfavorable for an increase in the pathogen population**

Table A2.11. Fungicide efficacy described by 6 interactions between (i) the incidence related to inoculum (Effect of the inoculum stock on the efficacy of fungicide applications, Process P20, Table 1) and (ii) Fungicide application (Process P5, Table 1).

	Incidence related to inoculum	Fungicide application	**Fungicide efficacy**
1	Low quantity of inoculum	Yes	**High efficacy**
2	Low quantity of inoculum	No	**Low efficacy**
3	Medium quantity of inoculum	Yes	**Regular efficacy**
4	Medium quantity of inoculum	No	**Low efficacy**
5	High quantity of inoculum	Yes	**Low efficacy**
5	High quantity of inoculum	No	**Low efficacy**

Table A2.12. Disease increase considering fungicide application described by 9 interactions between (i) Disease growth (Table A2.10) and (ii) Fungicide efficacy (Table A2.11).

	Disease increase	Fungicide efficacy	**Disease increase considering fungicide application**
1	Favorable for an increase in the pathogen population	High efficacy	**Decrease in the pathogen population**
2	Favorable for an increase in the pathogen population	Regular efficacy	**Stable pathogen population**
3	Favorable for an increase in the pathogen population	Low efficacy	**Increase in the pathogen population**
4	Moderatly favorable for an increase in the pathogen population	High efficacy	**Decrease in the pathogen population**
5	Moderatly favorable for an increase in the pathogen population	Regular efficacy	**Decrease in the pathogen population**
5	Moderatly favorable for an increase in the pathogen population	Low efficacy	**Stable pathogen population**
7	Unfavorable for an increase in the pathogen population	High efficacy	**Decrease in the pathogen population**
3	Unfavorable for an increase in the pathogen population	Regular efficacy	**Decrease in the pathogen population**
9	Unfavorable for an increase in the pathogen population	Low efficacy	**Decrease in the pathogen population**

Table A2.13. Fruit effect on defoliation described by 9 interactions between (i) Coffee phenology (Processes P15 to P17, Table 1) and (ii) Fruit load (Process P13, Table 1).

	Coffee phenology	Fruit load	**Fruit effect on defoliation**
1	From flowering to the beginning of harvest	High fruit load	**Moderately favorable for defoliation**
2	From flowering to the beginning of harvest	Medium fruit load	**Unfavorable for defoliation**
3	From flowering to the beginning of harvest	Low fruit load	**Unfavorable for defoliation**
4	During harvest	High fruit load	**Favorable for defoliation**
5	During harvest	Medium fruit load	**Favorable for defoliation**
6	During harvest	Low fruit load	**Moderately favorable for defoliation**
7	From the end of harvest to the beginning of flowering	High fruit load	**Favorable for defoliation**
8	From the end of harvest to the beginning of flowering	Medium fruit load	**Favorable for defoliation**
9	From the end of harvest to the beginning of flowering	Low fruit load	**Moderately favorable for defoliation**

Table A2.14. Defoliation described by 9 interactions between (i) Incidence on defoliation (Process P21, Table 1) and (ii) Fruit effect on defoliation (Table A2.13).

	Incidence on defoliation	Fruit effect on defoliation	**Defoliation**
1	Regular effect of incidence on defoliation	Favorable for defoliation	**High defoliation**
2	Regular effect of incidence on defoliation	Moderately favorable for defoliation	**Medium defoliation**
3	Regular effect of incidence on defoliation	Unfavorable for defoliation	**Low or null defoliation**
4	Medium effect of incidence on defoliation	Favorable for defoliation	**High defoliation**
5	Medium effect of incidence on defoliation	Moderately favorable for defoliation	**Medium defoliation**
6	Medium effect of incidence on defoliation	Unfavorable for defoliation	**Medium defoliation**
7	High effect of incidence on defoliation	Favorable for defoliation	**High defoliation**
8	High effect of incidence on defoliation	Moderately favorable for defoliation	**High defoliation**
9	High effect of incidence on defoliation	Unfavorable for defoliation	**High defoliation**

Table A2.15. Fruit effect on leaf emergence described by 9 interactions between (i) Coffee phenology (Processes P15 to P17, Table 1) and (ii) Fruit load (Process P14, Table 1).

	Coffee phenology	Fruit load	Fruit effect on leaf emergence
1	From flowering to the beginning of harvest	High fruit load	Moderately favorable for vegetative growth
2	From flowering to the beginning of harvest	Medium fruit load	Favorable for vegetative growth
3	From flowering to the beginning of harvest	Low fruit load	Favorable for vegetative growth
4	During harvest	High fruit load	Unfavorable for vegetative growth
5	During harvest	Medium fruit load	Unfavorable for vegetative growth
6	During harvest	Low fruit load	Moderately favorable for vegetative growth
7	From the end of harvest to the beginning of flowering	High fruit load	Favorable for vegetative growth
8	From the end of harvest to the beginning of flowering	Medium fruit load	Favorable for vegetative growth
9	From the end of harvest to the beginning of flowering	Low fruit load	Favorable for vegetative growth

Table A2.16. Fruit x meteorology described by 9 interactions between (i) Fruit effect on leaf emergence (Table A2.15) and (ii) Rainfall (Process P3, Tables 1).

	Fruit effect on leaf emergence	Rainfall	Fruit x meteorology
1	Unfavorable for vegetative growth	Favorable for vegetative growth	Moderately favorable for vegetative growth
2	Unfavorable for vegetative growth	Moderately favorable for vegetative growth	Unfavorable for vegetative growth
3	Unfavorable for vegetative growth	Unfavorable for vegetative growth	Unfavorable for vegetative growth
4	Moderately favorable for vegetative growth	Favorable for vegetative growth	Moderately favorable for vegetative growth
5	Moderately favorable for vegetative growth	Moderately favorable for vegetative growth	Moderately favorable for vegetative growth
6	Moderately favorable for vegetative growth	Unfavorable for vegetative growth	Unfavorable for vegetative growth
7	Favorable for vegetative growth	Favorable for vegetative growth	Favorable for vegetative growth
8	Favorable for vegetative growth	Moderately favorable for vegetative growth	Moderately favorable for vegetative growth
9	Favorable for vegetative growth	Unfavorable for vegetative growth	Unfavorable for vegetative growth

Table A2.17. Fruit x meteorology x nutrition described by 6 interactions between (i) Fruit x Meteorology (Table A2.16) and (ii) Coffee nutrition (Process P7, Table 1).

	Fruit x meteorology	Coffee nutrition	Fruit x meteorology x nutrition
1	Favorable for vegetative growth	Sufficient	Favorable for vegetative growth
2	Favorable for vegetative growth	Insufficient	Moderately favorable for vegetative growth
3	Moderately favorable for vegetative growth	Sufficient	Moderately favorable for vegetative growth
4	Moderately favorable for vegetative growth	Insufficient	Unfavorable for vegetative growth
5	Unfavorable for vegetative growth	Sufficient	Unfavorable for vegetative growth
6	Unfavorable for vegetative growth	Insufficient	Unfavorable for vegetative growth

Table A2.18. Leaf emergence described by 9 interactions between (i) Shade (Process P10, Table 1) and (ii) Fruit x meteorology x nutrition (Table A2.17).

	Shade	Fruit x meteorology x nutrition	Leaf emergence
1	High	Favorable for vegetative growth	**Media emergence**
2	High	Moderately favorable for vegetative growth	**Low emergence**
3	High	Unfavorable for vegetative growth	**Low emergence**
4	Medium	Favorable for vegetative growth	**Media emergence**
5	Medium	Moderately favorable for vegetative growth	**Low emergence**
6	Medium	Unfavorable for vegetative growth	**Low emergence**
7	Low shade or full sun	Favorable for vegetative growth	**High emergence**
8	Low shade or full sun	Moderately favorable for vegetative growth	**Media emergence**
9	Low shade or full sun	Unfavorable for vegetative growth	**Low emergence**

Table A2.19. Incidence increase without pruning described by 27 interactions between (i) Disease growth x fungicides (Table A2.12), (ii) Defoliation (Table A2.14) and (iii) Leaf emergence (Table A2.18).

	Disease increase considering fungicide application	Defoliation	Leaf emergence	Incidence increase without pruning
1	Increase in the pathogen population	High defoliation	High emergence	**Incidence is stable or will increase slightly**
2	Increase in the pathogen population	High defoliation	Media emergence	**Incidence is stable or will increase slightly**
3	Increase in the pathogen population	High defoliation	Low emergence	**Incidence will increase**
4	Increase in the pathogen population	Medium defoliation	High emergence	**Incidence will increase**
5	Increase in the pathogen population	Medium defoliation	Media emergence	**Incidence will increase**
6	Increase in the pathogen population	Medium defoliation	Low emergence	**Incidence will increase drastically**
7	Increase in the pathogen population	Low or null defoliation	High emergence	**Incidence will increase**
8	Increase in the pathogen population	Low or null defoliation	Media emergence	**Incidence will increase**
9	Increase in the pathogen population	Low or null defoliation	Low emergence	**Incidence will increase drastically**
10	Stable pathogen population	High defoliation	High emergence	**Incidence will decrease**
11	Stable pathogen population	High defoliation	Media emergence	**Incidence will decrease**
12	Stable pathogen population	High defoliation	Low emergence	**Incidence will decrease**
13	Stable pathogen population	Medium defoliation	High emergence	**Incidence will decrease**
14	Stable pathogen population	Medium defoliation	Media emergence	**Incidence will decrease**
15	Stable pathogen population	Medium defoliation	Low emergence	**Incidence will decrease**
16	Stable pathogen population	Low or null defoliation	High emergence	**Incidence will decrease**
17	Stable pathogen population	Low or null defoliation	Media emergence	**Incidence will decrease**
18	Stable pathogen population	Low or null defoliation	Low emergence	**Incidence is stable or will increase slightly**
19	Decrease in the pathogen population	High defoliation	High emergence	**Incidence will decrease**
20	Decrease in the pathogen population	High defoliation	Media emergence	**Incidence will decrease**
21	Decrease in the pathogen population	High defoliation	Low emergence	**Incidence will decrease**
22	Decrease in the pathogen population	Medium defoliation	High emergence	**Incidence will decrease**
23	Decrease in the pathogen population	Medium defoliation	Media emergence	**Incidence will decrease**
24	Decrease in the pathogen population	Medium defoliation	Low emergence	**Incidence will decrease**
25	Decrease in the pathogen population	Low or null defoliation	High emergence	**Incidence will decrease**
26	Decrease in the pathogen population	Low or null defoliation	Media emergence	**Incidence will decrease**
27	Decrease in the pathogen population	Low or null defoliation	Low emergence	**Incidence will decrease**

Table A2.20. Risk of monthly increase in CLR incidence described by 16 interactions between (i) Pruning (Process P11, Table 1) and (ii) Incidence increase without pruning (Table A2.19).

	Pruning	Incidence increase without pruning	Risk of monthly increase in CLR incidence
1	Total pruning	Incidence will increase drastically	Incidence will decrease
2	Total pruning	Incidence will increase	Incidence will decrease
3	Total pruning	Incidence is stable or will increase slightly	Incidence will decrease
4	Total pruning	Incidence will decrease	Incidence will decrease
5	50% pruning	Incidence will increase drastically	Incidence is stable or will increase slightly
6	50% pruning	Incidence will increase	Incidence will decrease
7	50% pruning	Incidence is stable or will increase slightly	Incidence will decrease
8	50% pruning	Incidence will decrease	Incidence will decrease
9	25% pruning	Incidence will increase drastically	Incidence will increase
10	25% pruning	Incidence will increase	Incidence is stable or will increase slightly
11	25% pruning	Incidence is stable or will increase slightly	Incidence will decrease
12	25% pruning	Incidence will decrease	Incidence will decrease
13	No pruning	Incidence will increase drastically	Incidence will increase drastically
14	No pruning	Incidence will increase	Incidence will increase
15	No pruning	Incidence is stable or will increase slightly	Incidence is stable or will increase slightly
16	No pruning	Incidence will decrease	Incidence will decrease

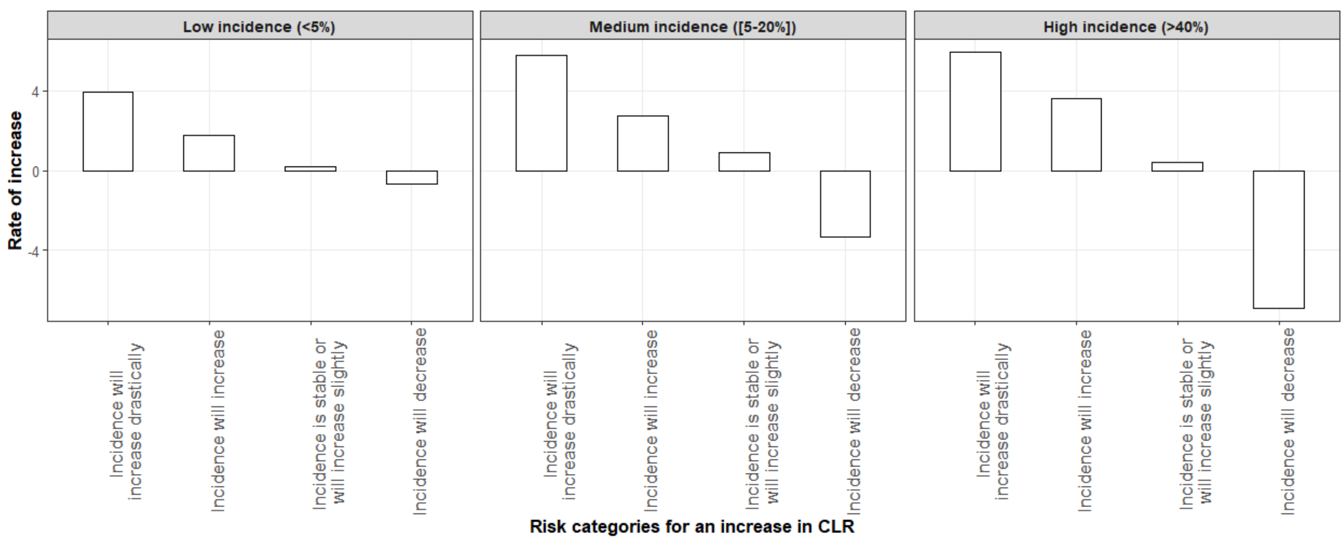
Appendix 3

Links to the questionnaires of the survey

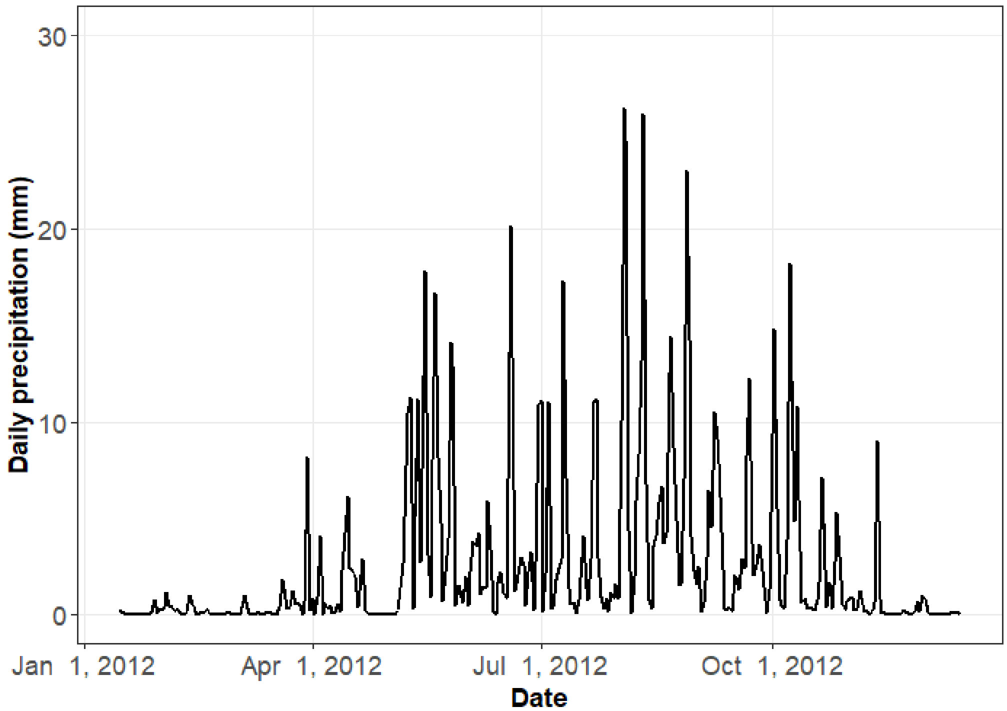
- English version https://forms.gle/xUxn53gEzhSV12GQ9
- Spanish version https://forms.gle/G98cu23kr47xghd88

Appendix 4

Figure A4. Increase in the incidence of CLR in a susceptible variety of coffee Arabica in the following month depending on (i) incidence at the monitoring date (Low (<5%), Medium ([5-20%]) and High incidence (>40%)) and (ii) the risk category for an increase in CLR in the following month (Incidence will increase drastically, Incidence will increase, Incidence is stable or will increase slightly, Incidence will decrease).



Appendix 5



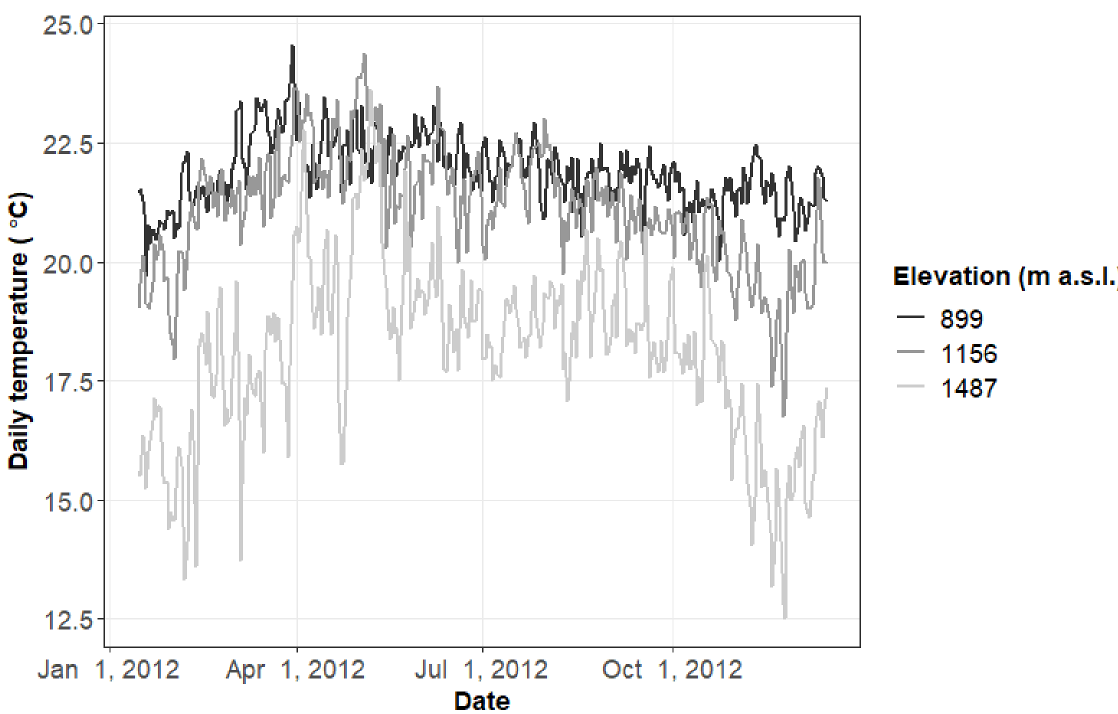


Figure A5.1. Daily rainfall and temperatures used for ExpeRoya simulations at three locations of increasing altitude in Latin America (Costa Rica (899 m a.s.l.), Guatemala (1,156 m a.s.l.) and Mexico (1,487 m a.s.l.)). To be able to compare the different situations, the same daily rainfall dataset was used for the three locations, whereas the temperatures datasets differed with the location.

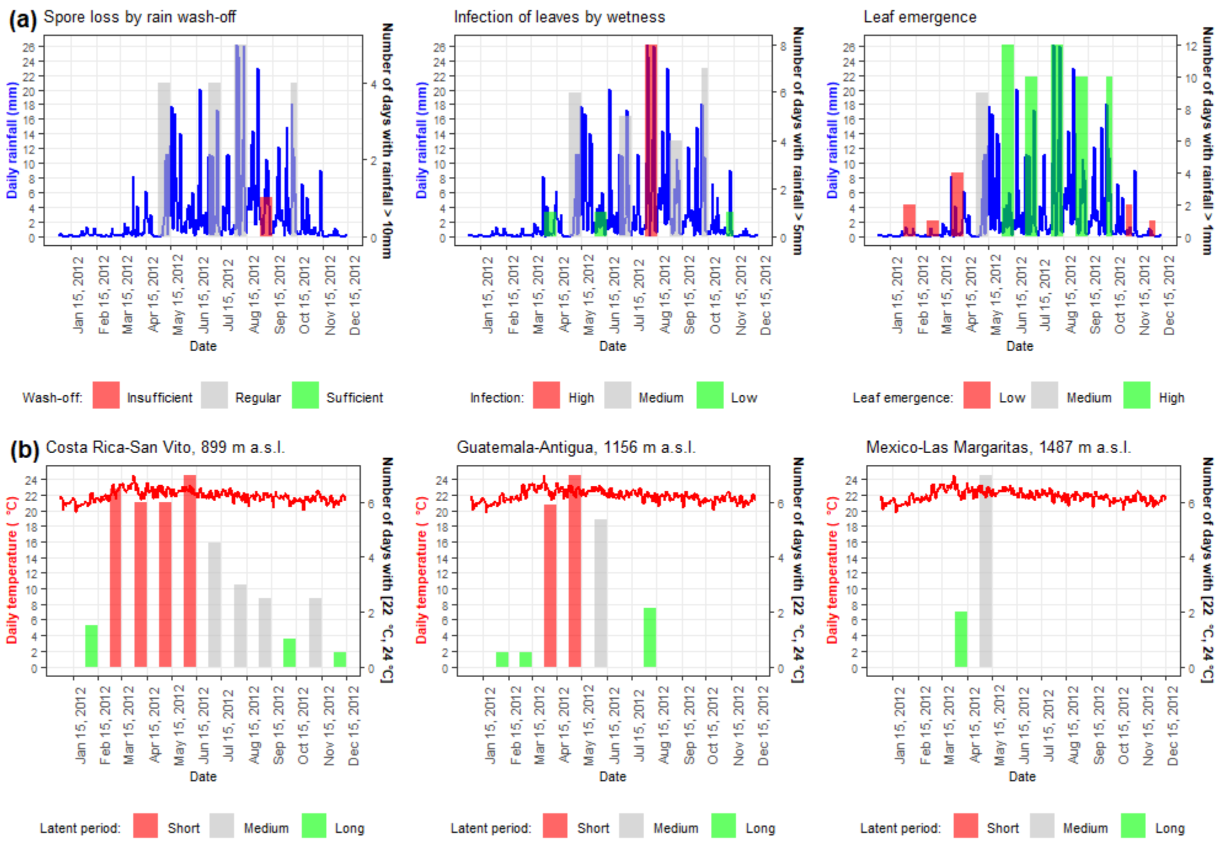


Figure A5.2. Effect (a) of rainfall on spore loss due to wash-off by rain, infection of leaves due to leaf wetness and leaf emergence and (b) of temperature on the latent period at three locations at increasing altitudes in Latin America (Costa Rica, Guatemala and Mexico). The weather was simulated for 2012, a year favorable for CLR. To be able to compare the different situations, in panel (a) the same daily rainfall dataset was used for the three locations, whereas in panel (b) the temperatures datasets differed with the location (cf. figure A5.1).

Abstract

CONTEXT

Coffee leaf rust (CLR) epidemics on *Coffea arabica* have led to severe socio-economic crises in Latin America starting in 2008. Until now, the scattered nature of scientific and empirical knowledge of the highly complex CLR-coffee pathosystem has been an obstacle to the development of CLR forecasting models.

OBJECTIVE

To help prevent new severe epidemics, we built ExpeRoya, a qualitative model, based on a review of the scientific literature and expert opinion, to forecast the risk of a monthly increase in the incidence of CLR at plot and landscape levels.

METHODS

We adopted the IPSIM (Injury Profile SIMulator) framework, a qualitative and aggregative modeling approach that describes the effects of the cropping system and the plot environment on injuries, thereby making it possible to incorporate scattered knowledge on the system and all its complexity in a simplified way. Involving experts makes this approach powerful and robust because it builds on empirical knowledge based on a very large number of field observations. We argue that broad expert knowledge provides more accurate information on the manifold interactions in the system than existing quantitative models can. The structure of ExpeRoya was discussed with coffee sector experts in 19 workshops and validated in an online survey with 17 CLR experts.

RESULTS AND CONCLUSIONS

ExpeRoya successfully integrates in a simple way 229 multiple interactions that exist within the CLR-coffee pathosystem based on only 12 input variables easily acquired in the field: one incidence monitoring variable; two meteorological variables (temperature and rainfall), four crop management variables (management of shade cover, fungicide application, nutrition and pruning of coffee trees) and five coffee tree characteristics (dates of flowering, beginning and end of harvest, fruit load and cultivar genetic resistance). Coffee institutes in Honduras and Nicaragua now use ExpeRoya, hosted by the platform Pergamino (https://www.redpergamino.net/app-experoya), to assist them in preparing their monthly CLR warning bulletins for growers. ExpeRoya is an improved forecasting model of CLR by fully incorporating the main biophysical factors affecting CLR at the plot and landscape levels.

SIGNIFICANCE

ExpeRoya is both a framework and a proof of concept that improves both forecasting and the comprehensive modeling of CLR. ExpeRoya is a powerful yet user-friendly model designed for all actors of the coffee sector, particularly smallholder farmers and extension agents. ExpeRoya is

adaptable: users can modify the model according to advances in knowledge and/or their own expertise of the system. ExpeRoya can help prevent future socio-economic crises.

Declaration of Competing Interest: The authors declare no competing interest.

Highlights

- Until now, scattered knowledge on the multifactorial coffee leaf rust (CLR)-coffee pathosystem has been an obstacle to CLR forecasting models
- Our ExpeRoya model accounts for interactions between disease, host, cropping practices and weather to forecast the monthly increase in CLR incidence
- ExpeRoya is powerful, it integrates in a simple way 229 multiple relationships to forecast the risk of CLR increase at plot and landscape levels
- Coffee institutes from Latin America already use ExpeRoya to assist them in preparing their monthly CLR warning bulletins for producers
- ExpeRoya is adaptable and user-friendly; it can help prevent future socio-economic crises of the coffee sector

Appendix 2

ExpeRoya model aggregation tables. The hierarchical structure of the model is available in the Dexi version in Cirad Dataverse (Motisi, 2021) and is summarized in Figure 3 in the main text. See Materials and Methods for justifications of the combinations of tables.

Table A2.1. Inoculum stock after hyperparasitism by *Lecanicilium lecanii* described by 18 interactions between (i) Shade (Process P9, Table 1), (ii) Incidence related to inoculum (Process P19, Table 1) and Fungicide (Process P6, Table 1).

	Shade	Incidence related to inoculum	Fungicides	**Inoculum stock after hyperparasitism**
1	High	Low quantity of inoculum	Yes	**Low quantity of inoculum**

2	High	Low quantity of inoculum	No	**Low quantity of inoculum**
3	High	Medium quantity of inoculum	Yes	**Medium quantity of inoculum**
4	High	Medium quantity of inoculum	No	**Medium quantity of inoculum**
5	High	High quantity of inoculum	Yes	**High quantity of inoculum**
6	High	High quantity of inoculum	No	**Medium quantity of inoculum**
7	Medium	Low quantity of inoculum	Yes	**Low quantity of inoculum**
8	Medium	Low quantity of inoculum	No	**Low quantity of inoculum**
9	Medium	Medium quantity of inoculum	Yes	**Medium quantity of inoculum**
10	Medium	Medium quantity of inoculum	No	**Medium quantity of inoculum**
11	Medium	High quantity of inoculum	Yes	**High quantity of inoculum**
12	Medium	High quantity of inoculum	No	**Medium quantity of inoculum**
13	Low of Full sun	Low quantity of inoculum	Yes	**Low quantity of inoculum**
14	Low of Full sun	Low quantity of inoculum	No	**Low quantity of inoculum**
15	Low of Full sun	Medium quantity of inoculum	Yes	**Medium quantity of inoculum**
16	Low of Full sun	Medium quantity of inoculum	No	**Medium quantity of inoculum**
17	Low of Full sun	High quantity of inoculum	Yes	**High quantity of inoculum**
18	Low of Full sun	High quantity of inoculum	No	**High quantity of inoculum**

Table A2.2. Spore loss described by 9 interactions between (i) the effect of rain wash-off on spore loss (Process P1, Table 1) and (ii) Shade (Process P8, Table 1).

	Spore loss by rain wash-off	Shade	**Spore loss**
1	Insufficient wash-off	High	**Low loss**
2	Insufficient wash-off	Medium	**Low loss**
3	Insufficient wash-off	Low shade or Full sun	**Low loss**
4	Regular wash-off	High	**Low loss**
5	Regular wash-off	Medium	**Low loss**
6	Regular wash-off	Low shade or Full sun	**Regular loss**
7	Efficient wash-off	High	**Regular loss**
8	Efficient wash-off	Medium	**High loss**
9	Efficient wash-off	Low shade or Full sun	**High loss**

Table A2.3. Inoculum stock available for infection described by 9 interactions between (i) Inoculum stock after hyperparatism (Table A2.1) and (ii) Spore loss (Table A2.2).

	Inoculum stock after hyperparasitism	Spore loss	**Inoculum stock available for infection**
1	Low quantity of inoculum	Low loss	**Low quantity of spores**
2	Low quantity of inoculum	Regular loss	**Low quantity of spores**
3	Low quantity of inoculum	High loss	**Low quantity of spores**
4	Medium quantity of inoculum	Low loss	**Medium quantity of spores**
5	Medium quantity of inoculum	Regular loss	**Low quantity of spores**
6	Medium quantity of inoculum	High loss	**Low quantity of spores**
7	High quantity of inoculum	Low loss	**High quantity of spores**
8	High quantity of inoculum	Regular loss	**Medium quantity of spores**
9	High quantity of inoculum	High loss	**Low quantity of spores**

Table A2.4. Infection described by 9 interactions between (i) Infection of leaves by wetness (Process P2, Table 1) and (ii) Shade (Process P8. Table 1).

	Infection of leaves by wetness	Shade	**Infection**
1	High infection	High	**High infection**
2	High infection	Medium	**High infection**
3	High infection	Low shade of Full sun	**High infection**
4	Medium infection	High	**High infection**
5	Medium infection	Medium	**High infection**
6	Medium infection	Low shade of Full sun	**Medium infection**
7	Low infection	High	**Medium infection**
8	Low infection	Medium	**Medium infection**
9	Low infection	Low shade of Full sun	**Low infection**

Table A2.5. The latent period described by 9 interactions between (i) Effect of temperature on the latent period (Process P4, Table 1) and (ii) Shade (Process P8, Table 1).

	Latent period by temperature	Shade	**Latent period**
1	Short latent period	High	**Short latent period**
2	Short latent period	Medium	**Short latent period**
3	Short latent period	Low shade or Full sun	**Short latent period**
4	Regular latent period	High	**Short latent period**
5	Regular latent period	Medium	**Regular latent period**
6	Regular latent period	Low shade or Full sun	**Regular latent period**
7	Long latent period	High	**Regular latent period**
8	Long latent period	Medium	**Regular latent period**
9	Long latent period	Low shade or Full sun	**Long latent period**

Table A2.6. Pathogen population growth described by 27 interactions between (i) Inoculum stock available for infection (Table A2.3), (ii) Infection (Table A2.4) and (iii) the Latent period (Table A2.5).

	Inoculum stock available for infection	Infection	Latent period	**Pathogen population growth**
1	Low quantity of spores	High infection	Short latent period	**Increase in the pathogen population**
2	Low quantity of spores	High infection	Regular latent period	**Stable pathogen population**
3	Low quantity of spores	High infection	Long latent period	**Stable pathogen population**
4	Low quantity of spores	Medium infection	Short latent period	**Stable pathogen population**
5	Low quantity of spores	Medium infection	Regular latent period	**Decrease in the pathogen population**
6	Low quantity of spores	Medium infection	Long latent period	**Decrease in the pathogen population**
7	Low quantity of spores	Low infection	Short latent period	**Stable pathogen population**
8	Low quantity of spores	Low infection	Regular latent period	**Decrease in the pathogen population**
9	Low quantity of spores	Low infection	Long latent period	**Decrease in the pathogen population**
10	Medium quantity of spores	High infection	Short latent period	**Increase in the pathogen population**
11	Medium quantity of spores	High infection	Regular latent period	**Increase in the pathogen population**
12	Medium quantity of spores	High infection	Long latent period	**Stable pathogen population**
13	Medium quantity of spores	Medium infection	Short latent period	**Increase in the pathogen population**
14	Medium quantity of spores	Medium infection	Regular latent period	**Stable pathogen population**
15	Medium quantity of spores	Medium infection	Long latent period	**Stable pathogen population**
16	Medium quantity of spores	Low infection	Short latent period	**Stable pathogen population**
17	Medium quantity of spores	Low infection	Regular latent period	**Decrease in the pathogen population**
18	Medium quantity of spores	Low infection	Long latent period	**Decrease in the pathogen population**
19	High quantity of spores	High infection	Short latent period	**Increase in the pathogen population**
20	High quantity of spores	High infection	Regular latent period	**Increase in the pathogen population**
21	High quantity of spores	High infection	Long latent period	**Stable pathogen population**
22	High quantity of spores	Medium infection	Short latent period	**Increase in the pathogen population**
2	High quantity of spores	Medium	Regular latent	**Increase in the pathogen**

23		infection	period	**population**
24	High quantity of spores	Medium infection	Long latent period	**Stable pathogen population**
25	High quantity of spores	Low infection	Short latent period	**Increase in the pathogen population**
26	High quantity of spores	Low infection	Regular latent period	**Stable pathogen population**
27	High quantity of spores	Low infection	Long latent period	**Stable pathogen population**

Table A2.7. Fruit effect on leaf physiological susceptibility described by 9 interactions between (i) Coffee phenology (Processes P15 to P17, Table 1) and (ii) Fruit load (Process P12, Table 1).

	Coffee phenology	Fruit load	**Fruit effect on leaf physiological susceptibility**
1	From flowering to the beginning of harvest	High fruit load	**Medium susceptibility**
2	From flowering to the beginning of harvest	Medium fruit load	**Low susceptibility**
3	From flowering to the beginning of harvest	Low fruit load	**Low susceptibility**
4	During harvest	High fruit load	**High susceptibility**
5	During harvest	Medium fruit load	**High susceptibility**
6	During harvest	Low fruit load	**Medium susceptibility**
7	From the end of harvest to the beginning of flowering	High fruit load	**Low susceptibility**
8	From the end of harvest to the beginning of flowering	Medium fruit load	**Low susceptibility**
9	From the end of harvest to the beginning of flowering	Low fruit load	**Low susceptibility**

Table A2.8. Leaf physiological susceptibility described by 9 interactions between (i) Shade (Process P10, Table 1) and (ii) Fruit effect on the physiological susceptibility (Table A2.7).

	Shade	Fruit effect on leaf physiological susceptibility	**Leaf physiological susceptibility**
1	High	High susceptibility	**Medium susceptibility**
2	High	Medium susceptibility	**Low susceptibility**
3	High	Low susceptibility	**Low susceptibility**
4	Medium	High susceptibility	**Medium susceptibility**
5	Medium	Medium susceptibility	**Medium susceptibility**
6	Medium	Low susceptibility	**Low susceptibility**
7	Low shade or Full sun	High susceptibility	**High susceptibility**
8	Low shade or Full sun	Medium susceptibility	**High susceptibility**
9	Low shade or Full sun	Low susceptibility	**Medium susceptibility**

Table A2.9. Overall host susceptibility (genetic and physiological, G+P) described by 9 interactions between (i) Leaf physiological susceptibility (Table A2.8) and (ii) Genetic resistance (Process P18, Table 1).

	Leaf physiological susceptibility	Genetic resistance	**Overall host susceptibility (G+P)**
1	High susceptibility	Susceptible	**High susceptibility**
2	High susceptibility	Moderately susceptible	**Medium susceptibility**
3	High susceptibility	Resistent	**Null susceptibility**
4	Medium susceptibility	Susceptible	**Medium susceptibility**
5	Medium susceptibility	Moderately susceptible	**Medium susceptibility**
6	Medium susceptibility	Resistent	**Null susceptibility**
7	Low susceptibility	Susceptible	**Medium susceptibility**
8	Low susceptibility	Moderately susceptible	**Low susceptibility**
9	Low susceptibility	Resistent	**Null susceptibility**

Table A2.10. Disease growth described by 12 interactions between (i) Pathogen population growth (Table A2.6) and (ii) Overall host susceptibility (G+P) (Table A2.9).

	Pathogen population growth	Overall host susceptibility (G+P)	**Disease growth**
1	Increase in the pathogen population	High susceptibility	**Favorable for an increase in the pathogen population**
2	Increase in the pathogen population	Medium susceptibility	**Favorable for an increase in the pathogen population**
3	Increase in the pathogen population	Low susceptibility	**Moderately for an increase in the pathogen population**
4	Increase in the pathogen population	Null susceptibility	**Unfavorable for an increase in the pathogen population**
5	Stable pathogen population	High susceptibility	**Moderately for an increase in the pathogen population**
6	Stable pathogen population	Medium susceptibility	**Moderately for an increase in the pathogen population**
7	Stable pathogen population	Low susceptibility	**Unfavorable for an increase in the pathogen population**
8	Stable pathogen population	Null susceptibility	**Unfavorable for an increase in the pathogen population**
9	Decrease in the pathogen population	High susceptibility	**Unfavorable for an increase in the pathogen population**
10	Decrease in the pathogen population	Medium susceptibility	**Unfavorable for an increase in the pathogen population**
11	Decrease in the pathogen population	Low susceptibility	**Unfavorable for an increase in the pathogen population**
12	Decrease in the pathogen population	Null susceptibility	**Unfavorable for an increase in the pathogen population**

Table A2.11. Fungicide efficacy described by 6 interactions between (i) the incidence related to inoculum (Effect of the inoculum stock on the efficacy of fungicide applications, Process P20, Table 1) and (ii) Fungicide application (Process P5, Table 1).

	Incidence related to inoculum	Fungicide application	**Fungicide efficacy**
1	Low quantity of inoculum	Yes	**High efficacy**
2	Low quantity of inoculum	No	**Low efficacy**
3	Medium quantity of inoculum	Yes	**Regular efficacy**
4	Medium quantity of inoculum	No	**Low efficacy**
5	High quantity of inoculum	Yes	**Low efficacy**
6	High quantity of inoculum	No	**Low efficacy**

Table A2.12. Disease increase considering fungicide application described by 9 interactions between (i) Disease growth (Table A2.10) and (ii) Fungicide efficacy (Table A2.11).

	Disease growth	Fungicide efficacy	**Disease increase considering fungicide application**
1	Favorable for an increase in the pathogen population	High efficacy	**Decrease in the pathogen population**
2	Favorable for an increase in the pathogen population	Regular efficacy	**Stable pathogen population**
3	Favorable for an increase in the pathogen population	Low efficacy	**Increase in the pathogen population**
4	Moderately for an increase in the pathogen population	High efficacy	**Decrease in the pathogen population**
5	Moderately for an increase in the pathogen population	Regular efficacy	**Decrease in the pathogen population**
6	Moderately for an increase in the pathogen population	Low efficacy	**Stable pathogen population**
7	Unfavorable for an increase in the pathogen population	High efficacy	**Decrease in the pathogen population**
8	Unfavorable for an increase in the pathogen population	Regular efficacy	**Decrease in the pathogen population**
9	Unfavorable for an increase in the pathogen population	Low efficacy	**Decrease in the pathogen population**

Table A2.13. Fruit effect on defoliation described by 9 interactions between (i) Coffee phenology (Processes P15 to P17, Table 1) and (ii) Fruit load (Process P13, Table 1).

	Coffee phenology	Fruit load	**Fruit effect on defoliation**
1	From flowering to the beginning of harvest	High fruit load	**Moderately favorable for defoliation**
2	From flowering to the beginning of harvest	Medium fruit load	**Unfavorable for defoliation**
3	From flowering to the beginning of harvest	Low fruit load	**Unfavorable for defoliation**

4	During harvest	High fruit load	**Favorable for defoliation**
5	During harvest	Medium fruit load	**Favorable for defoliation**
6	During harvest	Low fruit load	**Moderately favorable for defoliation**
7	From the end of harvest to the beginning of flowering	High fruit load	**Favorable for defoliation**
8	From the end of harvest to the beginning of flowering	Medium fruit load	**Favorable for defoliation**
9	From the end of harvest to the beginning of flowering	Low fruit load	**Moderately favorable for defoliation**

Table A2.14. Defoliation described by 9 interactions between (i) Incidence on defoliation (Process P21, Table 1) and (ii) Fruit effect on defoliation (Table A2.13).

	Incidence on defoliation	Fruit effect on defoliation	**Defoliation**
1	Regular effect of incidence on defoliation	Favorable for defoliation	**High defoliation**
2	Regular effect of incidence on defoliation	Moderately favorable for defoliation	**Medium defoliation**
3	Regular effect of incidence on defoliation	Unfavorable for defoliation	**Low or null defoliation**
4	Medium effect of incidence on defoliation	Favorable for defoliation	**High defoliation**
5	Medium effect of incidence on defoliation	Moderately favorable for defoliation	**Medium defoliation**
6	Medium effect of incidence on defoliation	Unfavorable for defoliation	**Medium defoliation**
7	High effect of incidence on defoliation	Favorable for defoliation	**High defoliation**
8	High effect of incidence on defoliation	Moderately favorable for defoliation	**High defoliation**
9	High effect of incidence on defoliation	Unfavorable for defoliation	**High defoliation**

Table A2.15. Fruit effect on leaf emergence described by 9 interactions between (i) Coffee phenology (Processes P15 to P17, Table 1) and (ii) Fruit load (Process P14, Table 1).

	Coffee phenology	Fruit load	**Fruit effect on leaf emergence**
1	From flowering to the beginning of harvest	High fruit load	**Moderately favorable for vegetative growth**
2	From flowering to the beginning of harvest	Medium fruit load	**Favorable for vegetative growth**
3	From flowering to the beginning of harvest	Low fruit load	**Favorable for vegetative growth**
4	During harvest	High fruit load	**Unavorable for vegetative growth**
5	During harvest	Medium fruit load	**Unavorable for vegetative growth**
6	During harvest	Low fruit load	**Moderately favorable for vegetative growth**
7	From the end of harvest to the beginning of flowering	High fruit load	**Favorable for vegetative growth**
8	From the end of harvest to the beginning of flowering	Medium fruit load	**Favorable for vegetative growth**

9	From the end of harvest to the beginning of flowering	Low fruit load	**Favorable for vegetative growth**

Table A2.16. Fruit x meteorology described by 9 interactions between (i) Fruit effect on leaf emergence (Table A2.15) and (ii) Rainfall (Process P3, Tables 1).

	Fruit effect on leaf emergence	Rainfall	**Fruit x meteorology**
1	Unfavorable for vegetative growth	Favorable for vegetative growth	**Moderately favorable for vegetative growth**
2	Unfavorable for vegetative growth	Moderately favorable for vegetative growth	**Unfavorable for vegetative growth**
3	Unfavorable for vegetative growth	Unfavorable for vegetative growth	**Unfavorable for vegetative growth**
4	Moderately favorable for vegetative growth	Favorable for vegetative growth	**Moderately favorable for vegetative growth**
5	Moderately favorable for vegetative growth	Moderately favorable for vegetative growth	**Moderately favorable for vegetative growth**
6	Moderately favorable for vegetative growth	Unfavorable for vegetative growth	**Unfavorable for vegetative growth**
7	Favorable for vegetative growth	Favorable for vegetative growth	**Favorable for vegetative growth**
8	Favorable for vegetative growth	Moderately favorable for vegetative growth	**Moderately favorable for vegetative growth**
9	Favorable for vegetative growth	Unfavorable for vegetative growth	**Unfavorable for vegetative growth**

Table A2.17. Fruit x meteorology x nutrition described by 6 interactions between (i) Fruit x Meteorology (Table A2.16) and (ii) Coffee nutrition (Process P7, Table 1).

	Fruit x meteorology	Coffee nutrition	**Fruit x meteorology x nutrition**
1	Favorable for vegetative growth	Sufficient	**Favorable for vegetative growth**
2	Favorable for vegetative growth	Insufficient	**Moderately favorable for vegetative growth**
3	Moderately favorable for vegetative growth	Sufficient	**Moderately favorable for vegetative growth**
4	Moderately favorable for vegetative growth	Insufficient	**Unfavorable for vegetative growth**
5	Unfavorable for vegetative growth	Sufficient	**Unfavorable for vegetative growth**
6	Unfavorable for vegetative growth	Insufficient	**Unfavorable for vegetative growth**

Table A2.18. Leaf emergence described by 9 interactions between (i) Shade (Process P10, Table 1) and (ii) Fruit x meteorology x nutrition (Table A2.17).

	Shade	Fruit x meteorology x nutrition	**Leaf emergence**
1	High	Favorable for vegetative growth	**Medium emergence**
2	High	Moderately favorable for vegetative growth	**Low emergence**
3	High	Unfavorable for vegetative growth	**Low emergence**

4	Medium	Favorable for vegetative growth	**Medium emergence**
5	Medium	Moderately favorable for vegetative growth	**Low emergence**
6	Medium	Unfavorable for vegetative growth	**Low emergence**
7	Low shade or Full sun	Favorable for vegetative growth	**High emergence**
8	Low shade or Full sun	Moderately favorable for vegetative growth	**Medium emergence**
9	Low shade or Full sun	Unfavorable for vegetative growth	**Low emergence**

Table A2.19. Incidence increase without pruning described by 27 interactions between (i) Disease growth x fungicides (Table A2.12), (ii) Defoliation (Table A2.14) and (iii) Leaf emergence (Table A2.18).

	Disease increase considering fungicide application	Defoliation	Leaf emergence	**Incidence increase without pruning**
1	Increase in the pathogen population	High defoliation	High emergence	**Incidence is stable or will increase slightly**
2	Increase in the pathogen population	High defoliation	Medium emergence	**Incidence is stable or will increase slightly**
3	Increase in the pathogen population	High defoliation	Low emergence	**Incidence will increase**
4	Increase in the pathogen population	Medium defoliation	High emergence	**Incidence will increase**
5	Increase in the pathogen population	Medium defoliation	Medium emergence	**Incidence will increase**
6	Increase in the pathogen population	Medium defoliation	Low emergence	**Incidence will increase drastically**
7	Increase in the pathogen population	Low or null defoliation	High emergence	**Incidence will increase**
8	Increase in the pathogen population	Low or null defoliation	Medium emergence	**Incidence will increase**
9	Increase in the pathogen population	Low or null defoliation	Low emergence	**Incidence will increase drastically**
10	Stable pathogen population	High defoliation	High emergence	**Incidence will decrease**
11	Stable pathogen population	High defoliation	Medium emergence	**Incidence will decrease**
12	Stable pathogen population	High defoliation	Low emergence	**Incidence will decrease**
13	Stable pathogen population	Medium defoliation	High emergence	**Incidence will decrease**
14	Stable pathogen population	Medium defoliation	Medium emergence	**Incidence will decrease**
15	Stable pathogen population	Medium defoliation	Low emergence	**Incidence will decrease**
16	Stable pathogen population	Low or null defoliation	High emergence	**Incidence will decrease**
17	Stable pathogen population	Low or null defoliation	Medium emergence	**Incidence will decrease**
1	Stable pathogen population	Low or null	Low emergence	**Incidence is stable or will increase**

8		defoliation		**slightly**
19	Decrease in the pathogen population	High defoliation	High emergence	**Incidence will decrease**
20	Decrease in the pathogen population	High defoliation	Medium emergence	**Incidence will decrease**
21	Decrease in the pathogen population	High defoliation	Low emergence	**Incidence will decrease**
22	Decrease in the pathogen population	Medium defoliation	High emergence	**Incidence will decrease**
23	Decrease in the pathogen population	Medium defoliation	Medium emergence	**Incidence will decrease**
24	Decrease in the pathogen population	Medium defoliation	Low emergence	**Incidence will decrease**
25	Decrease in the pathogen population	Low or null defoliation	High emergence	**Incidence will decrease**
26	Decrease in the pathogen population	Low or null defoliation	Medium emergence	**Incidence will decrease**
27	Decrease in the pathogen population	Low or null defoliation	Low emergence	**Incidence will decrease**

	Pruning	Incidence increase without pruning	**Risk of monthly increase in CLR incidence**
1	Total pruning	Incidence will increase drastically	**Incidence will decrease**
2	Total pruning	Incidence will increase	**Incidence will decrease**
3	Total pruning	Incidence is stable or will increase slightly	**Incidence will decrease**
4	Total pruning	Incidence will decrease	**Incidence will decrease**
5	50% pruning	Incidence will increase drastically	**Incidence is stable or will increase slightly**
6	50% pruning	Incidence will increase	**Incidence will decrease**
7	50% pruning	Incidence is stable or will increase slightly	**Incidence will decrease**
8	50% pruning	Incidence will decrease	**Incidence will decrease**
9	25% pruning	Incidence will increase drastically	**Incidence will increase**
10	25% pruning	Incidence will increase	**Incidence is stable or will increase slightly**
11	25% pruning	Incidence is stable or will increase slightly	**Incidence will decrease**
12	25% pruning	Incidence will decrease	**Incidence will decrease**
13	No pruning	Incidence will increase drastically	**Incidence will increase drastically**
14	No pruning	Incidence will increase	**Incidence will increase**
15	No pruning	Incidence is stable or will increase slightly	**Incidence is stable or will increase slightly**
16	No pruning	Incidence will decrease	**Incidence will decrease**

Table A2.20. Risk of monthly increase in CLR incidence described by 16 interactions between (i) Pruning (Process P11, Table 1) and (ii) Incidence increase without pruning (Table A2.19).