Faculté des bioingénieurs

Field-scale modelling of the potato late blight infection risk in Wallonia

Validation and sensitivity analysis of the current model, test and calibration of the French model "Milsol", and effect of host resistance on the disease cycle

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Contents

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Introduction

Among the crops dedicated to human consumption, potatoes (*Solanum tuberosum*) are the third most important crop in terms of area in Wallonia (after winter wheat and almost at the same level as sugar beet) [58] . Most of the production is dedicated to the processing sector, in particular the French fry industry, which is on the rise in Belgium.

Potato late blight, caused by the phytopathogenic "fungus-like" *Phytophthora infestans*, is undoubtedly the most concerning disease in potato farming in our region.

This devastating disease can wreck a field in just a few days. The importance of all kinds of prophylactic measures, but also fungicidal treatments (copper salts in organic farming) remain essential to control this disease. In order to better target these treatments or even to avoid some of them (because of production and environmental costs concerns), epidemiological models for forecasting the risk of late blight have been developed since the middle of the 20th century in developed countries.

These models, which were initially based solely on meteorological data, became more complex over time, modelling the pathogen cycle more rigorously, adjusting on strains evolutions, and taking into account more and more external parameters such as fields observations to track inoculum sources, consideration of host varietal resistance, or fungicide spraying (type, dose, persistence, leaching).

But the statement today is undeniable: despite all the techniques and knowledge available, Belgium is the European country that largely sprays the highest number of fungicide treatments per season (almost one per week!) [31]. In the light of Wallonia's "zero phyto" objective, which stems from European Directive 2009/128/EC [1] establishing a framework for Community action to achieve a use of pesticides compatible with sustainable development, serious work had to be undertaken to develop concrete solutions to this situation.

This is the objective of the "PotatoSMART" project [19], in which this thesis is part of. This project, carried out jointly by the Walloon Agricultural Research Centre (CRA-W), the Fiwap (*Filière wallonne de la pomme de terre*), and UCLouvain, aims to develop a decision support tool for integrated protection and biological control of potato late blight at the field scale.

This thesis will first review the epidemiology of the pathogen, the development of the disease, and their management in potato farming. It will also synthesize the main existing models and decision support tools available and used around the world (mainly in Europe) to control potato late blight.

Then, a sensitivity analysis of the Guntz and Divoux epidemiological model (the model on which the late blight warnings are based currently in Wallonia) will be performed. Its goal is, on the one hand, to determine the accuracy of a treatment prediction on basis of this model, when the reference meteorological station is at a certain distance from the field. And on the other hand, the sensitivity analysis will also be carried out regarding to the uncertainty of future "AGROMET" data (Walloon project to provide weather data at a very small spatial and temporal scale).

After that, the performances of the current Walloon decision support system and the epidemiological model used in France, "Milsol", to control potato late blight will be evaluated by retrospectively comparing the recommendations of the models with field-observations of disease monitoring, using a contingency scores method.

Lastly, and still through a method of computing contingency scores, the last goal of this thesis is to try to calibrate some parameters of the Milsol model. On the one hand in order to validate the original values of these parameters in the Walloon context. And on the other hand to try to identify the effect of the level of potato varietal resistance on the pathogen cycle.

Part I

Bibliographical review

Chapter 1

Potato farming in our regions

1.1 Agricultural context

The potato sector has an important part in Belgian agriculture. Since the 90's, production increased by approximately 50% due to an increase in yields and cultivated areas. The large majority of potatoes (*Solanum tuberosum*) are dedicated to the processing industry. Between the 90's and today, volumes of potatoes processed in Belgium (mainly frozen french fries) have exploded (nearly quadrupled) [28].

The main variety in the sector is Bintje, appreciated for its yield, good conservation and morphological qualities (adapted to the industrial french fries processing sector) and despite its high susceptibility to late blight [3]. The other main cultivated varieties are Fontane, Innovator and Challenger, which are also french fries varieties but have a better resistance to late blight. The share of other varieties (than Bintje) in the total cultivated area has been increasing for about two decades.

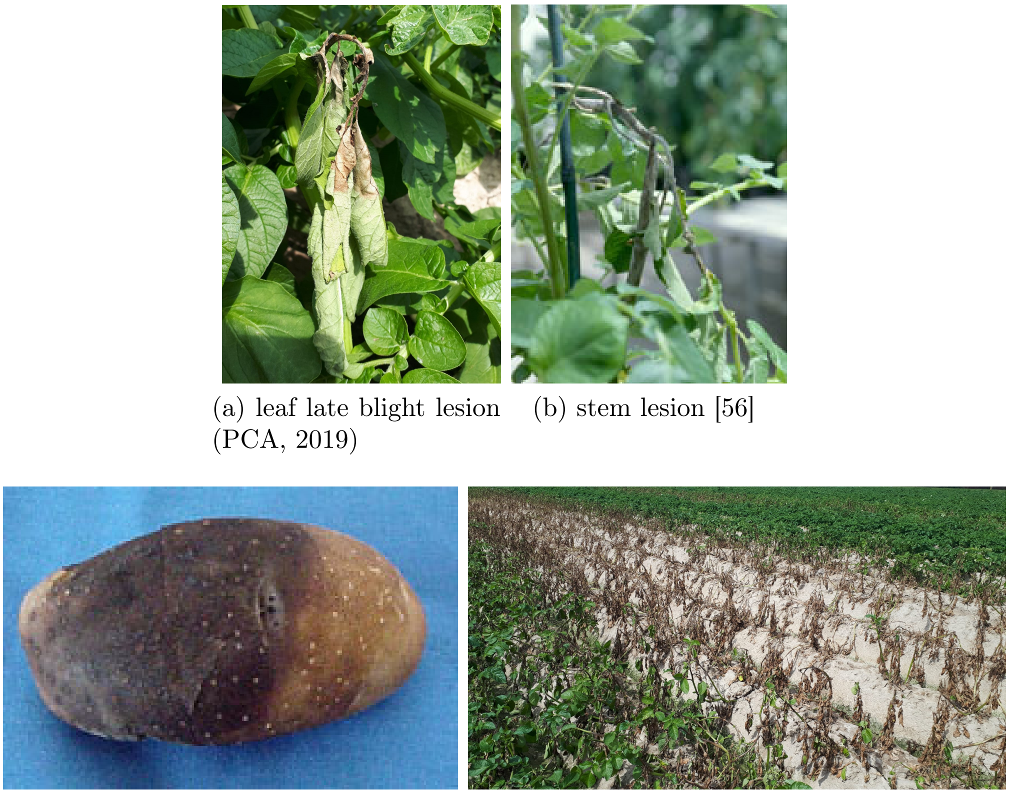
In Wallonia, average yields are around 45-50 t/ha. About 37000 ha (in Wallonia) are dedicated to potato crop, most of this area being located in the Hainaut and Brabant-Wallon province (61.5% and 15.0% respectively). This area is quite fluctuating (in the order of a thousand hectares), depending on the price fluctuations, which are themselves linked to the climate. There are about 4000 Walloon farmers, the average size of their farm being about 10 ha [26]. Potatoes are sold between farmers and industries largely through "fixed price tonnes" contracts. Both parties set a pre-season price per quantity of potatoes delivered, regardless of the area cultivated [50].

The most problematic disease in potatoes is undoubtedly late blight, caused by the phytopathogen *Phytophthora infestans* (see section 1.2 below). Furthermore, Alternaria blight (also known as early blight) is caused by the fungus *Alternaria solani* and attacks the foliage after flowering. It is a more recent and much less well-known disease that may be of increasing concern.

1.2 Potato late blight and its management

Late blight is by far the most concerning disease in potatoes. It was for example responsible of the well-known Irish potato famine (1844-1845). The same disease (and same pathogen) can be found in tomatoes (*Solanum lycopersicum*). It is caused by the plant pathogen *Phytophtora infestans*, which is an Oomycete (Oomycota). This phylogenetic class was often associated by Fungi because they share many biological, ecological, morphological and structural characteristics (like unicellular eukaryotism and mycelium development) while it actually form a distinct phylogenetic lineage of eukaryotic microorganisms [4][5]. For example, the nuclei are diploid while it is haploid for most fungi [56].

P. infestans develops preferentially under wet conditions and causes blackish/brownish lesions on potato leaves and stems (see figure 1.1 below). Potato tubers can also become infected when sporangia from a leaf lesion are washed (by rain or irrigation) into the soil. Within a few days, a few infected plants can lead to complete destruction ("burning") of the field. This ability to destroy the crop very quickly underlines the importance of disease prevention both in terms of prophylactic measures and appropriate planning of preventive fungicide treatments.



(a) leaf late blight lesion (PCA, 2019) (b) stem lesion [56]

(c) infected tuber [56] (d) infected field (PCA, 2019)

Figure 1.1: Late blight symptoms

Figure 1.2 below shows the complete epidemic cycle of *Phytophthora infestans*. The pathogen is able to reproduce in a sexual or asexual way. The sexual reproduction (far left of the figure) needs two "partners" of different mating types (A_1 and A_2) and takes more time than asexual reproduction (more than 15 days). It leads to the formation of oospores, which can remain active in the soil for several years and germinate when optimal conditions are met [7]. Oospores are therefore a potential source of primary inoculum. Sexual reproduction has also consequences on the genetic diversity of *P. infestans* strains on large spatial and temporal scales [16]. Until the end of the 20th century, only the A_1 mating type was found in Europe. Since the 80's, new genotypes (A_2 mating type) have been introduced into Europe, probably by migration from Mexico [29]. Because of the geographical variation in the distribution of the two mating types, the lower rate (frequency and speed), and the recent finding of sexual reproduction cases in fields, the sexual reproduction process per se is neglected in epidemiological models. Nevertheless, the ability of *P. infestans* to generate genetic diversity through sexual reproduction, combined with the pathogen's intrinsic plasticity, threatens to enhance capability of the pathogen to adapt to different factors, e. g. weather, cultivar resistance, chemical control or other cultivation measures [6] and therefore requires scientists to closely monitor the evolution of strains in order to keep model calibration up to date. Recent research suggests that new strains generated by sexual reproduction are more aggressive.

On the other hand, asexual reproduction is by far the most frequent (and quickest) reproduction method on field. It consists in the formation of sporangiophores on the surface of the infected plant tissues. Once leaves or stems are infected (either by direct or indirect germination), a mycelium develops in the vegetal tissue leading to the formation of surface sporangiophores which form sporangia at night (this incubation period requires high humidity and temperature between 8.5 and 26°C, with an optimum of 19-22°C) and release them during the morning (when humidity falls) [7]. These sporangia can either germinate directly (at temperatures above 12-15°C) developping a germ tube and then a hyphal outgrowth through the plant tissue. These sporangia can also differentiate into numerous motile zoospores (at temparature below 12°C) which will germinate in the presence of free water. It is called indirect germination. The sporangia released by sporangiophores can either act as secondary inoculum and launch new infection cycle on the same crop and/or can be transported by wind over (tens of) kilometers (air dispersal), acting as primary inoculum and onsetting disease on other crops [30][7]. Sporangia as primary inoculum come from a source external to the field itself: cull (discarded potatoes) or storage piles, regrowth of infected tubers in other fields, home gardens and organic fields are considerd as significant inoculum sources and relays. The respective importance of these different sources of primary inoculum is difficult to assess. Initially infected seed tubers can also be a potential (minor) source of inoculum.

The epidemiological multiplication cycle of *P. infestans* can be considered in a simplified way as described in figure 1.3. Sporangia in free water germinate either via a germ tube at higher temperatures (optimum around 20–25°C), or by releasing zoospores at lower temperatures (optimum between 10 and 15°C). The biflagellated zoospores are motile for a short time (often less than 60 min) before encysting. Encysted zoospores germinate directly via a germ tube to penetrate leaf or stem tissue [29]. Then, *Phytophthora infestans* mycelium develops in the plant tissues. This incubation step is dependent on the temperature which must be between 7 and 25°C, with an optimum around 18°C. At the end of the incubation period, sporulation may occur and is encouraged by high humidity close to foliage associated with surface moisture. Sporulation in the field is inhibited by light during the day, a feature that ensures that sporangia are formed only at night when humidity and temperature conditions are favourable for the sporulation. Sporulation is associated with the appearance of late blight symptoms on leaves and/or stems (blackish/brownish lesions, see figure 1.1).

It had been mentioned earlier that new strains of *P. infestans* have appeared (by sexual reproduction) in the last decades. Turkensteen and Mulder (1999) have reported that pathogen during the last 25 years has developed a shorter life cycle (by 30%), ability to cause more leaf spots, shorter infestation period (6 instead of 8h), tolerance to a greater temperature range (5 to 27°C instead of 10 to 25°C), form stem lesions more frequently, develops oospores and sporulation on tubers and is more inclined to develop resistance to fungicide metalaxyl [7].

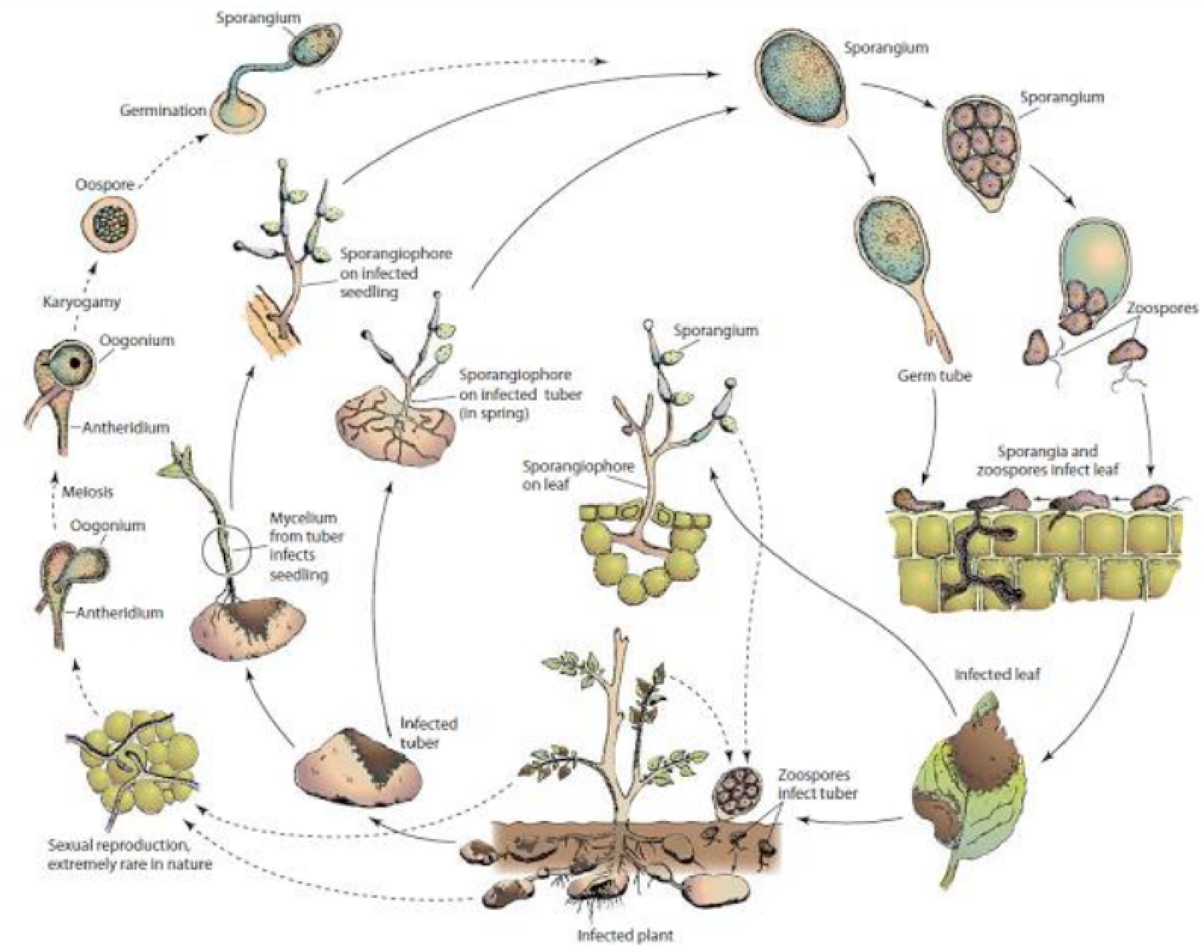


Figure 1.2: *P. infestans* life cycle (Agrios, 2005)

The good knowledge of *P. infestans* epidemiology as well as the high dependence of the infection risk on meteorological conditions (mainly humidity, temperature and precipitation) has allowed for decades the effective use of risk prediction models as decision support tools for the management (mainly treatment planning) of potato fields by farmers (see chapter 2 below). The efficiency of these models is essential. On the one hand, the number of recommended treatments must be sufficient to maintain disease control. But on the other hand, there are many incentives to limit the number of fungicide applications as much as possible (in order to limit production costs but also environmental impacts). Farmers who do not follow a decision support system (DSS) apply a "classical spraying schedule", i.e. systematic treatments (every 5-7 days).

Considering the dramatic consequences of late blight infection on yield, farmers apply different prophylactic measures to prevent the introduction of the disease into their fields [12]. First, they regularly apply preventive fungicides, often following the warnings given by a decision support system (DSS). In organic farming, farmers use "Bordeaux mixture" (copper sulphate and lime) treatments. Farmers (organic and conventionnal) may also be careful to use healthy (uninfected) potato seedlings; there are official certifications that attest to the health of the seedlings. In addition, farmers rotate the potato in rotations, which has the effect of limiting the impact of infected tubers regrowth and oospores persistence in the soil. The typical rotation in fertile areas consists of a 4-years rotation alternating potatoes, wheat, sugar beet and again wheat [55]. In addition, regrowths of old infected tubers in potato crops can also be tracked and destroyed. Furthermore,

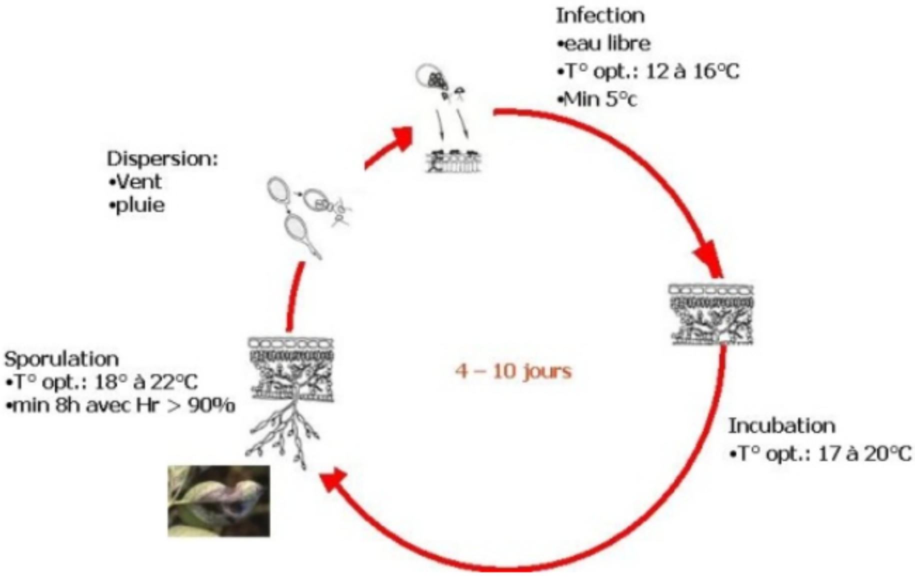


Figure 1.3: *P. infestans* multiplication cycle (Michelante, 2003). The **infection** step corresponds to the survival of the sporangia, their germination (direct or indirect) and the subsequent penetration of plant tissues. The **incubation** stage corresponds to the development of the pathogen's mycelium in the plant tissues. **Sporulation** occurs at the end of the incubation period and corresponds to the release of sporangia out of the plant tissue.

farmers must manage (cover, lime or destroy) their potato cull piles as quickly as possible. At last, farmers also can use more resistant cultivars to late blight.

Despite the emergence of relatively effective resistant varieties (like Sarpo-Mira, Bionica or Carolus), susceptible varieties (particularly Bintje) remain mainly used. In western Europe, resistant cultivars are not grown on a large scale because commercially important characteristics such as quality, yield and earliness are usually not combined in the same cultivar with late blight resistance. In the grower's perspective, the savings in fungicide input that can be achieved with resistant cultivars are generally outweighed by the higher perceived risk of blight [16]. For this reason, as well as the speed and destructive ability of the disease, fungicidal treatments (in particular preventive applications) are unavoidable in conventional farming. It should be pointed out that Belgium is among the European countries that spray the most treatments per season; 15-20 for ware potatos (see table 1.1), followed by The Netherlands and France (about 15 treatmens per season) and then Northern Ireland and UK (about ten). Eastern, Northern and Central (Germany, Switzerland) European countries apply less than 10 treatments per season. It is not clear how combinations of blight weather conditions, the importance of different inoculum sources (i.e. dumps, volunteers and oospores), the use of resistant cultivars, varying pathogen populations, the use of DSS's and the density of potato fields influence differences in fungicide use between European countries [31].

Table 1.1: Number of fungicides applications used in potato farming in 2008 [31]

COUNTRY	NUMBER OF FUNGICIDE APPLICATIONS USED IN WARE POTATOES			NUMBER OF FUNGICIDE APPLICATIONS USED IN ALL TYPES OF POTATOES		
	min	max	mean	min	max	mean
Finland	3	9	5	4	9	6
Sweden	4	15	7.5			
Norway	2	8	5.5	2	8	5.5
Denmark	4	9	7	4	14	8.5
Estonia	3	9	5	3	9	5
Latvia	3	5	4	1	5	3
Lithuania	4	10	5	1	4	2.5
Belarus	2	7	4		7	4
Poland						
Germany	4	15	7	4	15	7
Czech Republic	5	12	7	2	8	6
Slovakia	4	8	5			
Russian Federation				1	10	3
Switzerland			8			
Northern Ireland	5	14	10	5	14	10
Scotland						
England	10	12	11	10	12	11
Belgium	17	22	19	10	22	15
Netherlands	8	18	14	6	18	13
France	14	18	15	8	20	15

The different fungicides used to control potato late blight and certified in Belgium can be classified according to the table 1.2 below [12][27]. They differ according to their mechanism of action, and therefore their effect.

- Contact fungicides (type 1 and 2): ensure the protection of the leaves from future spore deposits. It only has a preventive effect. Most of them have an effective mode of action on a large number of biochemical sites. This class of fungicide is relatively quickly washed away by rainfall (about a week). Type 1 contact fungicides do not provide protection for tubers, while type 2 contact fungicides do.

- Penetrating (or translaminar) fungicides (type 3): enter into leaf tissues, providing longer protection (6-10 days) than contact fungicides and less impacted by rainfall. Most of them have a targeted mode of action on a specific biochemical site. They have an anti-sporulating and a (slight) curative (retroactive) effect, but (like contact fungicides) do not protect newly formed leaves.

- Systemic fungicides (type 4): penetrate into the leaf and partially diffuse to the newly formed leaves. Their mode of action is also targeted on a specific biochemical site. They have a real curative power.

The penetrating fungicides - and even more the systemic ones - contribute to the development of resistance of the pathogen to the active components. Strains resistant to metalaxyl are already found worldwide [7][16]. Therefore, their use is limited as much as possible, or combined with a contact fungicide application. In general, in order to avoid the development of fungicide resistance and to optimize the effect of sprays on disease control, treatments often consist of a mixture of two active ingredients, typically a translaminar with a contact, or a systemic with a contact. Furthermore, contact fungicides are the most cost effective. Therefore, penetrating and systemic fungicides are used especially when the crop enters the rapid phase of growth and when unsettled weather, conducive to blight, increases the difficulty in maintaining an application schedule.

Table 1.2: Summary table of the different fungicides certified for the control of potato late blight

Type	**Active compound**	**Leaching resistance [mm rainfall]**	**Action site**
Contact (simple)	Mancozeb	20-25	multi-sites
	Maneb	20-25	mutli-sites
	Chlorothalonil	25-30	multi-sites
	Ametoctradin	30-45	complex 3 (cellular respiration) inhibition
Contact with tuber protection	Copper hydroxides/ oxychlorides/sulphates	20	multi-sites
	Fluazinam	30-45	multi-sites
	Azoxystrobine	25-30	complex 3 inhibition
	Amisulbrom	>45	complex 3 inhibition
	Cyazofamid	>45	complex 3 inhibition
	Zoxamid	30-45	cell division inhibition
Penetrating and translaminar	Fluopicolid	30-45	spectrins redistribution
	Propamocarb	30-45	cell wall elongation
	Benthiavalicarbisopropyl	30-45	cell wall formation
	Dimethomorph	30-45	cell wall formation
	Pyraclostrobin	30-45	complex 3 inhibition
	Valiphenalat	>45	cellulose synthesis
	Mandipropamid	>45	cellulose synthesis
	Difenoconazol	30-45	sterol biosynthesis inhibition
	Cymoxanil	30-45	unknown
	Famoxadon	30-45	multi-sites
Systemic	Benalaxyl	>45	RNA synthesis inhibition
	Metalaxyl	>45	RNA synthesis inhibition
	Oxathiapiprolin	>45	homeostasis and lipids transfer/storage

Chapter 2

Decision support tools for potato late blight

The first section of this chapter (section 2.1) describes the main (best known, most used and referenced) epidemiological models used to predict the (presence of) risk of potato late blight. The second section (2.1) presents the main decision support tools, i.e. the systems that integrate forecast models in order to provide a treatment advice (or not). Almost all these models and decision support systems are based on mechanistic modelling of the pathogen. That means that they reproduce the evolution of *P. infestans* cycle according to different inputs (mainly meteorological ones) and parameters.

2.1 Forecast models

This section lists the main existing models used to predict the risk of potato late blight infection, how they work, the weather inputs considered, their original geographical use area, the time when the model was developed, and any comments that may have been included. They are presented in chronological order of their development. All models mentioned hereunder assume that the primary inoculum is present constantly quantitatively and temporally, which is a rather coarse assumption. Once the weather conditions are met, they therefore consider a definite development of the disease. These models are exclusively determined by (agro)meteorological inputs.

Model: Dutch rules (Van Everdingen) [7][37]

Inputs: Dewy period (night temperature and relative humidity), rainfall, cloudiness

Description: Late blight is considered to be at risk if the following conditions are met: night dew (night temperature below dew point) for at least 4 hours, minimum T° of 10°C, average cloudiness of at least 0.8 the following day, presence (minimum 0.1 mm) of rainfall during the next 24H.

Geographic area: Netherlands

Development year: 1926

Comments: Late blight sometimes appears when the conditions are not met.

Model: Beaumont rules [7][9]

Inputs: Relative humidity and temperature

Description: If we observe 2 days or more, during which the minimum temperature is not lower than 10°C and the relative humidity is not below 75%, late blight is considered to be at risk and its onset is suspected within 15-22 days.

Geographic area: England

Development year: 1947

Comments: Beaumont rules are an adaptation of the Dutch rules to the conditions of the United Kingdom. However, this method did not predict the disease in areas where rainfall did not occur or was irregular during the harvest period.

Model: Irish rules [60][61]

Inputs: Relative humidity, temperature, rainfall

Description: The number of consecutive hours during which the T° is above 10°C and the RH above 90% is computed. If this period was rainy (precipitation occurs in the interval from 7 to 15 hours after the start of the period) and exceeds 12 hours, effective blight hours (EBH) begin to be counted. If this period was not rainy and exceeds 16 hours, EBH begin to be counted. The accumulation of these EBH continues as long as the failure of the starting conditions lasts 5 hours or less. As long as the number of EBH remains at 0, the model considers that there is no infection risk. If there is between 0 and 12 EBH, there is an medium infection risk. And if there are more than 12 EBH, the risk is high.

Geographic area: Ireland

Development year: 1953

Comments:

Model: Moving days (Hyre) [61]

Inputs: Temperature (max and min) and rainfall

Description: Predicts the onset of late blight 7-14 days after the accumulation of 10 consecutive favourable days. A day is considered as "favourable" if the average T° of the last 5 days is below 25.5° and if, for the last 10 days, at least 3 cm of total precipitation has been recorded. Days with a min T° below 7.2°C are considered unfavourable.

Geographic area: Northeast USA

Development year: 1954

Comments:

Model: Smith periods [49][61]

Inputs: Relative humidity and temperature

Description: According to the Smith criteria, two consecutive days with minimum temperature of $10°C$ with at least 11 hours of relative humidity 90% or higher [each day] are favorable for the development of *P. infestans* on potato. A treatment is then advised.

Geographical area: England and Wales

Development year: 1956

Comments: The model points out periods with a very high disease risk. This model was proposed as an alternative to reduce the number of invalid late blight forecasts by the Beaumont rules in England and Wales. In high risk areas for late blight, the model advised the same number of sprays as the routine spray program, but in low risk areas it advised 3 to 5 fewer sprays.

Model: Severity values (Wallin) [61]

Inputs: Relative humidity and temperature

Description: Gives a number of "severity values" depending on the length of the period during which the RH>90% and the average temperature during this period (table 2.1). Accumulation of severity values start at the plant emergence. Once 18-20 severity values have been accumulated, the model predicts the first onset of late blight 7-14 days later. Indeed, the severity values model the stage of infection by the pathogen, so the onset of symptoms is expected 1 to 2 weeks later, depending on the duration of incubation. The intervals between subsequent sprays are scheduled according to the following accumulation of severity values.

Table 2.1: Relationship of temperature and relative humidity (RH) periods as used in the Wallin late blight forecasting model [61].

Average Temperature Range	Severity values Hours of 90% RH or greater				
	0	1	2	3	4
7.2 - 11.6 C	15	16-18	19-21	22-24	25+
11.7 - 15.0 C	12	13-15	16-18	19-21	22+
15.1 - 26.6 C	9	10-12	13-15	16-18	19+

Geographic area: Implemented in the northeast of the USA but validated around the world.

Development year: 1962

Comments:

Model: Guntz-Divoux [7][48][62]

Inputs: Relative humidity, temperature, rainfall

Description: First, the number of consecutive hours during which the foliage is wet ('wet period', depending on RH and T°) is calculated. The foliage is considered as wet during an hour if:

- RH is $\geq$ 90% during this hour.
- Rainfall has been observed (minimum 0.1 mm) during this hour.
- RH $\geq$ 85% during this hour and at least one of the previous three hours had RH $\geq$ 90%.

If more than 10 consecutive "wet foliage" hours are observed, a risk of late blight infection is computed (between 0 and 4) depending on the length of the wet period and the average temperature during this period (table 2.2(a)). In a second step, an incubation cycle is initiated from each infection time. The length of the incubation period is computed as a function of temperature, by accumulation of incubation units (table 2.2(b)). Once the accumulated incubation unit has reached 7, it is considered that there is sporulation. The optimal moment to spray is when accumulated incubation units has reached 5.5 - 6.0 (1 to 2 days before sporulation).

Table 2.2: Guntz-Divoux tables [48]

(a) Guntz-Divoux table for gravity infection

Wet period average temperature	Light	Medium	Strong	Very strong
7	16,5	19,5	22,5	25,5
8	16	19	22	25
9	15,5	18,5	21,5	24,5
10	15	18	21	24
11	14	17,5	20,5	23,5
12	13,5	17	19,5	22,5
13	13	16	19	21,5
14	11,5	15	18	21
15	10,75	14	17	20
16	10,75	13	16	19
17	10,75	12	15	18
18	10,75	11	14	17
19	10,75	11	13	16
20	10,75	11	12	15
21	10,75	11	11,5	13

(b) Guntz-Divoux table for infection development

Temperature ranges	Hour value for development of infection
-99 to 7,9°C	0,000
8 to 12,0°C	0,031
12,1 to 16,5°C	0,042
16,6 to 20°C	0,083
20,1 to 30°C	0,042
30,1 to 99°C	0,000

Geographic area: France, Belgium

Development year: 1963

Comments: This model was initially calibrated in Belgium for the "Bintje" variety. In order to better correspond to the evolution of the pathogen, these tables have recently been adapted by CARAH (see figure 2.2 at section 2.2).

Model: Negative prognosis (Ulrich & Schrodter) [61]

Inputs: Relative humidity, temperature, rainfall.

Description: Compute (daily and weekly) risk values depending on the number of hours during which RH $\geqq$ 90% or rainfall is $\geqq 0.1mm$ and depending on temperature at each of these hours (see table 2.3). Until the "150" risk value threshold has not been reached, the disease is not expected to be observed.

To calculate risk values, count the number of hours (h) fro which the average temperature falls within the temperature range in the second column and the conditions of relative humidity or rainfall indicated in the third column. Since there are 14 rows in the table, there should be 14 values of h, some of which may be zero. Then, multiply each of these 14 h-values by the corresponding r-value of the first column and sum up the 14 products (r x h). The sum of the products is the risk value.

Table 2.3: Risk values for the negative prognosis model [61].

Multiplication factor (r)	Number of hours hourly temperature averages are in this range (h), or other conditions to be met	RH or Precipitation Requirements, or other conditions to be met
0.899	10.0 - 11.9	Only count hours that co-occur with 4 or more consecutive hours at RH>=90% or rain>=0.1 mm/hr
0.4118	14.0 - 15.9	
0.5336	16.0 - 17.9	
0.8816	18.0 - 19.9	
1.0498	20.0 - 21.9	
0.5858	22.0 - 23.9	
0.3924	10.0 - 11.9	Only count hours that co-occur with 10 or more consecutive hours at RH>=90% or rain>=0.1 mm/hr
0.0702	14.0 - 15.9	
0.1278	16.0 - 17.9	
0.9108	18.0 - 19.9	
1.4706	20.0 - 21.9	
0.855	22.0 - 23.9	
0.1639	15.0 - 19.9	Do not consider RH or rain, add 7.5479 to the product of r x h
0.0468	Number of hours with average RH < 70%	Subtract 7.8624 from the product of r x h

Geographical area: Validated in Germany, implemented in Europe
Development year: 1966
Comments:

Model: Milsol [8][15][53]
Inputs: Temperature and relative humidity.
Description: Milsol is a relatively complex mechanistic model based on *P. infestans* life cycle and depending only on temperature and relative humidity. It is composed of three linked cells (see figure2.1 below): the first for spore survival and contamination, the second for incubation and potential sporulation, and the third for actual sporulation and inflicted damage. Spore survival at different stages and mycelium development are very precisely defined according to intermediate variables and meteorological data. The time step of the model corresponds to the launch of a potential "cohort" of *P. infestans* every 24 (or 12) hours. However, within a cohort, the variables are computed at the hourly time step.

The treatment decision is essentially based on exceeding a threshold value (dependent on host resistance) for the SPORUL variable, which corresponds to the number of spores actually produced, and for the number of simulated late blight generations (see table 2.10 at section 2.2).
Geographic area: France
Year of development: 1985
Comments:

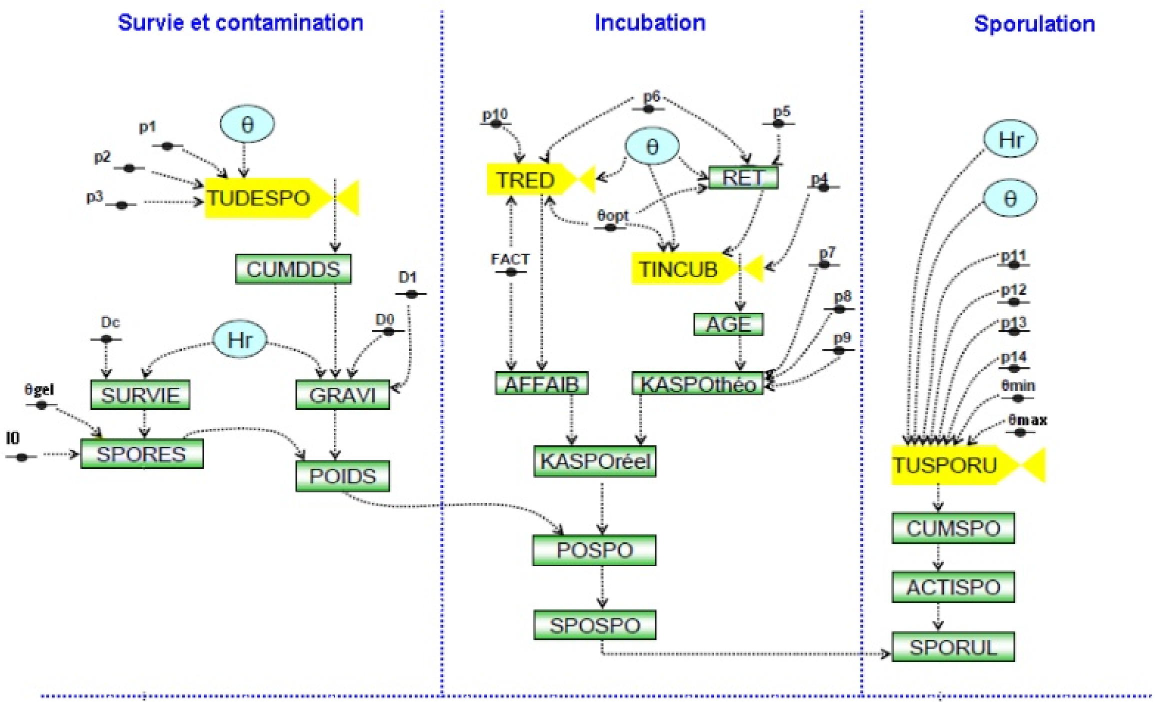


Figure 2.1: Forester diagram of the Milsol model [15]. The model is divided into three components, each of which simulates the evolution of a step of *P. infestans* cycle:

1. **Infection:** TUDESPO is the rate of spore development (increases with temperature and reaches a ceiling at 18°C). CUMDDS is the integral of TUDESPO and therefore the degree of spore development. SURVIE corresponds to the survival rate of the primary inoculum (SPORES). GRAVI is the contamination rate (proportion of spores that have germinated). SURVIE and GRAVI depend both on the spores degree of development (CUMDDS) and the RH conditions. POIDS (number of contaminating spores) is the product of the surviving primary inoculum and the contamination rate (GRAVI).

2. **Incubation:** TINCUB represents the mycelium development rate (optimum at 18°C), slowed by the RET variable when it is too hot (T°>18°C). AGE corresponds to the integral of TINCUB and therefore to the degree of development of the mycelium. KASPO is the sporulation capacity as a function of the degree of mycelium development (AGE), optimal when AGE=150. TRED and AFFAIB compute the reduction of the sporulation potential due to heat (T°>18°C). The POSPO variable makes the link (product) between the number of contaminating spores from the infection stage (POIDS) and the sporulation calculated according to the evolution of the incubation.

3. **Sporulation:** TUSPORU is the rate of development of sporulation. The integral of TUSPORU is CUMSPO, the degree of development of sporulation. ACTISPO is the simulated proportion of spores that have actually been released, according to CUMSPO.

Model: Winstelcast [49][61]
Inputs: Relative humidity and temperature
Description: This model is composed of two phases. Phase 1 predicts infection, which is forecasted after the following requirements are met: daily average temperature between 10 and 23 °C, 10 hours or more of temperatures greater than 10 °C, and relative humidity greater than 90% (such periods are considered to be the same as leaf wetness). Phase 2 sets criteria for pathogen growth. Phase 2 occurs when the maximum daily temperature for two consecutive days is between 23 C and 30 C. Phase 2 must occur at least 24 hours but not later than 10 days after phase 1. Initiate treatment when phase 1 occurs and is followed by phase 2. Subsequent treatments should be based on calendar and material.
Geographical area: Germany
Development year: 1993
Comments: This model was developed for early potato varieties.

2.2 Decision support system (DSS)

Decision support tools are systems (often computerized and automatized) using one or more prediction models (based on meteorological data), incorporating different variables (virulence of pathogen strains, host resistance, field observations, field protection status, etc) and intended to provide decision support for the farmer, usually a (non-)spray planning, and possibly other measures that can be taken to limit the possible development of the disease (prophylactic measures, observations, etc). This section lists the main (best known, most used and referenced) decision support systems in a chronological order, their basic forecast model, how they work, and their time and area of development.

DSS: Met. Eireann (Irish Meteorological Service Warning System) [61]
Basic forecast model: Irish rules
Description: Synoptic weathers maps and computer weather models are used to predict up to a week in advance the time of arrival of the Irish rules conditions. The suitability of the weather conditions are also taken into account for optimal fungicide spray (absorption and wash-off). The warnings are released by the government at a 2-weeks interval, considering fungicide sprays protect crops for this period (except if a major outbreak is imminent).
Geographic area: Ireland
Year of development: 1953
Comments:

DSS: BLITECAST [49][61]

Basic forecast model: Moving days (Hyre) + severity values (Wallin)

Description: The first part of the program forecasts the initial occurrence of late blight 7-14 days after the first accumulation of 10 rain-favorable days (Hyre's criteria of moving days), OR the accumulation of 18 severity values (Wallin's model). The first spray is then recommended. The second part of the program recommends subsequent fungicide sprays based on the number of rain-favorable days (Hyre's criteria) and severity values (Wallin) accumulated during the previous seven days (see table 2.4 below). Blitecast uses 76.5 percent relative humidity to discontinue accumulation of conducive infection conditions. Accumulation of rain-favorable days and severity values begins when distinct green rows can be seen in the potato field, and ends at vine kill.

Table 2.4: Adjustable matrix used to relate severity values and rain-favorable days and generate spray recommendation for Blitecast [61]

Total number of rain-favorable days during the last 7 days	Severity values during the last seven days					
	<3	3	4	5	6	>6
	Message number					
<5	-1	-1	0	1	1	2
>4	-1	0	1	2	2	2

Meaning of message numbers is:
-1 = No spray is recommended.
0 = A late blight warning (treat or review conditions in 2 to 3 days. If the short range forecast is for blight favorable weather, follow a 7-day spray schedule)
1 = A 7-day spray schedule is recommended.
2 = A 5 day spray schedule is recommended.
Note: Some researchers have advised reverting to a regular spray schedule at 1% disease severity.

Geographic area: Eastern USA originally, but implemented in other parts of the world

Year of development: 1975

Comments:

DSS: The Late Blight Infection Model of Fry (also called "Simcast") [49][61]

Basic forecast model: A specific forecast model has been constructed for this DSS. First, it computes for each day (noon to noon) a number of "blight units" depending on the number of consecutive hours of $RH \geqq 90\%$, the average T° (considering 6 temperature intervals), and the cultivar resistance (considering 3 resistance levels: susceptible, moderately susceptible, and moderately resistant) (see table 2.5).

Table 2.5: Blight units for the late blight infection model of Fry [61].

Average temperature	Cultivar resistance	Consecutive hours of relative humidity >=90% that should result in blight units of:							
(C)		0	1	2	3	4	5	6	7
>27	**S** /b	24							
	MS /c	24							
	MR /d	24							
23-27	**S**	6	7-9	10-12	13-15	16-18	19-24		
	MS	9	10-18	19-24					
	MR	15	16-24						
13-22	**S**	6					7-9	10-12	13-24
	MS	6	7	8	9	10	11-12	13-24	
	MR	6	7	8	9	10-12	13-24		
8-12	**S**	6	7	8-9	10	11-12	13-15	16-24	
	MS	6	7-9	10-12	13-15	16-18	19-24		
	MR	9	10-12	13-15	16-24				
3-7	**S**	9	10-12	13-15	16-18	19-24			
	MS	12	13-24						
	MR	18	19-24						
<3	**S**	24							
	MS	24							
	MR	24							
/a High relative humidity >=90%. Blight unit estimation period is 24 hr (noon to noon).									
/b S = susceptible cultivars.									
/c MS = moderately susceptible cultivars.									
/d MR = moderately resistant cultivars									

Description: In addition to the "blight units", "fungicide units" are also computed, depending on the number of days since the last application and the daily amount of rainfall (see table 2.6 below which is calibrated for fungicide "chlorothalonil").

Table 2.6: Fungicide units (for chlorothalonil) for the potato late blight infection model of Fry [61].

Time (days) since fungicide application	Daily rainfall amounts (mm) that result in fungicide units of						
	1	**2**	**3**	**4**	**5**	**6**	**7**
1	<1			1	2-3	4-6	>6
2	<1		1	2-4	5-8	>8	
3	<1		1-2	3-5	>5		
4-5	<1		1-3	3-8	>8		
6-9	<1		1-4	>4			
10-14	<1	1	2-8	>8			
>14	<1	1-8	>8				

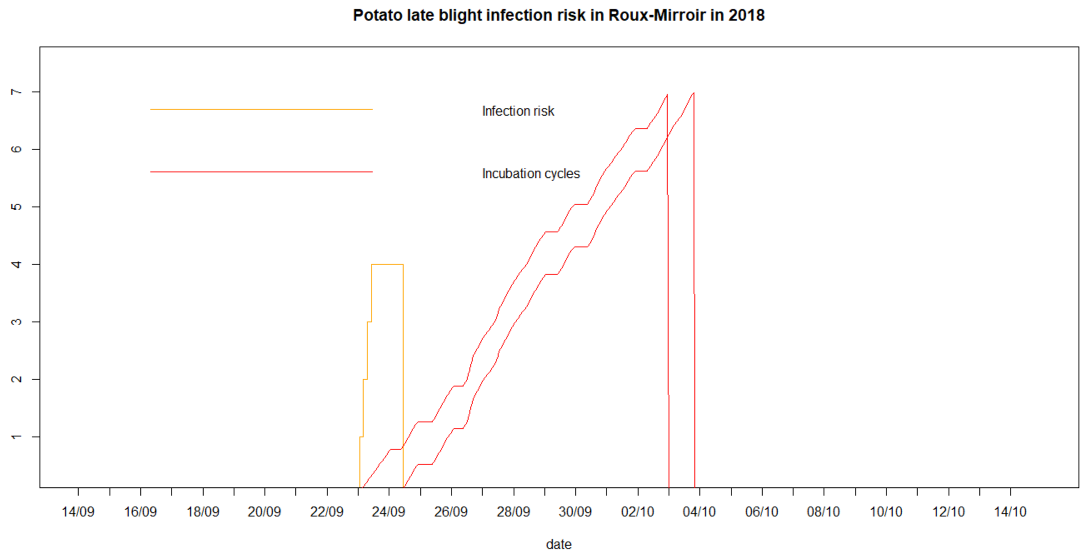
On basis of cumulative blight units since last spray, cumulative fungicide units since last spray, and number of days since last spray, a decision about fungicide application (or not) is taken (see table 2.7).

Table 2.7: Decision rule for the potato late blight infection model of Fry [61].

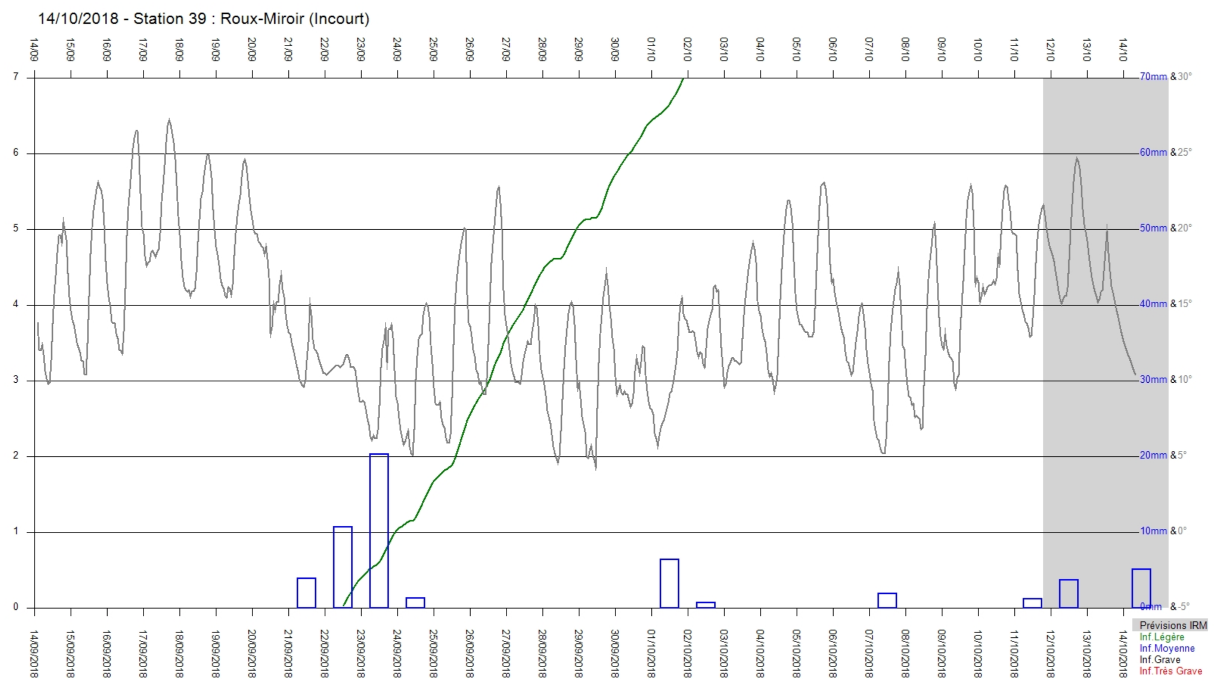
Logic statements	Cultivar resistance		
	Susceptible	Moderately susceptible	Moderately resistant
Fungicide should be applied if fungicide has not been applied within 5 days			
AND cumulative blight units since last spray exceed:	30	35	40
OR cumulative fungicide units since last spray exceed:	15	20	25

Geographic area: Europe
Year of development: 1983
Comments: The cultivar used for the model calibration are "Hudson" for the susceptible cultivar, and "Rosa" for the moderately resistant cultivar. "This model has been modified to time metalaxyl applications and to include weather forecasts".

DSS: CARAH avertissements mildiou [14][47][48][62]
Basic forecast model: Guntz-Divoux. The model used by the CARAH (Centre for Agronomy and Agro-Industry of Hainaut Province) is based on the same operating principle as the Guntz-Divoux model but the parameters have been calibrated according to systematic field experiments (B. Couvreur, personnal communication). The parameters of the recalibrated model are not publicly available but a quick comparison is shown in the figure 2.2. This comparison suggests that slight changes have been made for both Guntz-Divoux tables (table 2.2)



(a) Original Guntz-Divoux model output. Infection cycles are marked in red. The severity of infection is indicated by the orange bars (risk of level 1 for the first infection, and level 4 for the second one).



(b) Recalibrated (CARAH) Guntz-Divoux model output. The infection cycle is marked in green. The green color indicates that this cycle is initiated from an infection risk of level 1.

Figure 2.2: Comparison between the original Guntz-Divoux model and recalibrated Guntz-Divoux model (CARAH) outputs for Roux-Mirroir, 14/9/18 - 14/10/18. It can be noted that two infection cycles are simulated in the original model, whereas there is only one cycle for the recalibrated model. The first infection occurs half a day later in the original model than in the recalibrated one. Finally, the incubation period is more or less the same in both models, although in the original model there are periods during which the temperature is too low so the incubation does not progress and remains stable. While in the CARAH model, incubation progresses well but at a low rate. These observations therefore suggest that slight changes have been made for both Guntz-Divoux tables (see table 2.2).

Description: The recalibrated Guntz-Divoux model is run for about 40 weather stations spread throughout Wallonia and by incorporating 3-day weather forecasts provided by the Royal Belgian Meteorological Institute. Then, an operator writes a warning notice based on the results of the model (infection risk, incubation periods, but especially expected sporulation dates) and taking into account different external parameters: field observations, potato varieties resistance levels, fungicide activity (wash-off).

No treatment is recommended until the first symptoms are observed somewhere in Wallonia (on cull piles, personnal gardens, or in fields). This is a way of detecting the presence of primary inoculum. The first notice of treatment is usually given at the end of the 3rd simulated incubation cycle for susceptible varieties, except if conditions are very favourable to the disease (mild winters, infected early days, heavy rainfall and humidity, etc.) in which case it may be launched at the end of the second serious cycle. For higher host resistance levels, another one, two or three simulated cycles (depending on the resistance level) will be waited before recommending the first spray. Host resistance levels are checked and possibly adjusted annually for each variety through systematic field experiments called "MILVAR trials".

Because of the continuous formation of new leaves up to the tuberization stage, treatment will be repeated at the end of the next potential infection. Fungicide applications are advised when the cumulative incubation units is as close as possible to the 5.5 - 6.0 values (applications that are too early may be washed out by the rains before the next infection) and when the start of a new cycle closely follows the sporulation time of a previous cycle, or when the sporulation dates follow one another, leading to a risk of epidemic. This means that in general, if a cycle is not overlapped by other cycles, this period will not be considered at risk.

Cumulative rainfall of 20 mm, especially in high rain intensity, is considered to have washed the active ingredient of contact fungicides off the leaves: a new treatment is recommended as soon as a potential new infection is observed.

Geographic area: Belgium (Wallonia)

Year of development: 1986

Comments: The CARAH is currently working on a more automated DSS in which the farmer could provide information on the type of fungicide he is using, the potato variety, its treatment dates, etc. in order to directly obtain a warning more adapted to his situation.

DSS: Prophy [46][61]

Basic forecast model: A day is consider as "favorable" for late blight infection if at least 6 hours with high RH and at least 2 hours of leaf wetness or rain occur in a period from 8pm on the previous day until 12am one the evaluation day. The temperature must be in the range of 8 to 25°C. If viable lesions are observed close to the site, calculation of favorable days is overruled and a spray is advised.

Description: The first fungicide spray is advised when the crop height reach 15cm for sensitive cultivar and 10 days later for resistant cultivar. It is recommended earlier if late blight is present in the region. Subsequent treatments are scheduled following the weather conditions and the fungicide protection status of the crop (yes or no); sprays are recommended when the crop is not protected by fungicide and when the day is consider as favorable. The model considers that a sensitive potato cultivar is protected for 8 days after spraying (protectant fungicide). This period is extended for more resistant cultivar. This period is also adjusted by the dosage and type of fungicide, development stage of the crop, wash-off factors, and risk factor (blight sources in the area).

Geographic area: Netherlands

Year of development: 1988

Comments: Unfortunately, it is difficult to obtain more detailed information on this DSS because it belongs to a private Dutch company (AgroVision, previously known as Opticrop).

DSS: Phytophthora model Weihenstephan = PHYTEB (part of PROGEB) [34][38][39][61]

Basic forecast model: SIMPHYT

Description: The DSS consists of three modules. SIMPHYT 1 forecasts the first occurrence of late blight, depending on date of crop emergence and agro-meteorological conditions, and for two risk categorisations (following the moisture impact of the site). SIMPHYT 2 is a complex expert system which simulates *P. infestans* epidemics on a plot-specific scale taking into consideration weather, crop data (starch production or consume potato, two cultivar resistances), fungicide resistance status of regional pathogen populations, and fungicide properties for its recommendations. SIMPHYT 2 calculates the spraying interval and the type of fungicide. SIMPHYT 3 is a simplification of the SIMPHYT 2 model, solely weather-dependent, that compute infection pressure to calculate length of spraying intervals on a regional level.

Geographic area: Germany

Year of development: 1993

Comments:

DSS: PhytoPRE [61]

Basic forecast model: Negative prognosis + logistic model computing an infection probability

Description: An infection probability (IP) is calculated following equation 2.1 below.

$$IP = \frac{e^{rt+\ln[\frac{y}{1-y}]}}{1+e^{rt+\ln[\frac{y}{1-y}]}} \tag{2.1}$$

where $t = (d_F - d_{OR} + L)$ and where constants r and y take the value 0.2 $[day^{-1}]$ and 0.03 [] respectively. d_{OR} represents the julian day of the FLB and d_F represents the day on which the forecast is done.

The Ulrich and Schrodter risk values (RV) are compared between the region of the FLB (the region in which the first national late blight record was reported) and the region in which the forecast is done. If the RV of the studied region is lower than the RV of the FLB region, d_{OR} is calculated as described in equation 2.2, delaying the start of the forecasted epidemic.

$$d_{OR} = d_O + [\frac{RVFLB}{RVREG} - 1] * K \tag{2.2}$$

where d_O is the Julian day of the FLB, RVFLB is the RV of the FLB region on d_O, RVREG is the RV on d_O for the forecasted region. K equals to 14 days (constant).

The timing of the first and subsequent fungicide treatments depends on host susceptibility, IP values, amount of rainfall, fungicides used and amount of time since the last application. Basic decision rules are indicated in table 2.8 below.

Table 2.8: Timing of fungicide spray following PhytoPRE DSS[61]

Potato Susceptibility	First Treatment	Subsequent Treatments
High	IP[a] > 1%	TIME> 6-9 days[b] since last application and RAIN[c] > 29 mm since last application or TIME > 14 days
Medium	IP > 1%	TIME > 7-11 days[b] since last application and RAIN[c] > 29 mm since last application
Low	IP > 25% and RAIN[d] last 10 days > 29 mm and GS > 69	TIME > 14 days since last application and RAIN[d] > 29 mm since last application

Where IP = infection probability; TIME = time since last application; GS = Growth Stage
[a] Except for fields near (>1 km) early potatoes
[b] Exact number of days depends on fungicides used
[c] Amount of rain since last application
[d] Amount of rain within last 10 days

Geographic area: Switzerland
Year of development: 1993
Comments: This DSS was developed based on observed disease progress curves in Switzerland. This DSS is the only one presented here that is based on a stochastic (logistical) approach.

DSS: Plant-Plus [52]
Basic forecast model: Plant-plus-specific
Description: PLANT-Plus uses a biological model that is based on the lifecycle of the fungus and combines (submodel 3) infection events (submodel 2: formation, ejection, dispersal, germination and penetration of spores) with the unprotected part of the crop (submodel 1: newly formed leaves and fungicide degradation and wash-off). The model will recommend when to apply a new spray and what type of chemical to use. Plant-Plus include a 5-days weather forecast.
Geographic area: Netherlands
Year of development: 1994
Comments: Unfortunately, it is difficult to obtain more detailed information on the submodels because it belongs to a private Dutch company (DACOM PLANT). The development of 'new blight' with sexual reproduction and more aggressive strains of *P. infestans* is integrated into the system [52].

DSS: NegFry [49][61]
Basic forecast models: Negative prognosis + infection model of Fry
Description: The negative prognosis model (Ulrich & Schrodter) defines the date of the first spray. Depending on the last year disease pressure, a threshold of 150 or 250 is used for the weekly risk value. The daily risk value have to be above 8 for the previous night. Then, the next treatments (preventative sprays of Mancozep or Chlorothalonil) are advised following the infection model of Fry.
Geographic area: originally northern countries (Denmark, Norway, Sweden, Finland), now eastern countries (Poland, Czech Republic)
Year of development: 1995
Comments:

DSS: NoBlight [49]

Basic forecast model: Severity values (Wallin)

Description: The NoBlight model calculates the number of severity values as described by Wallin. Once 18 severity values have accumulated after emergence, a protective fungicide application is recommended. Then, depending on the number of severity values accumulated and rainfall during the previous 7 days, the interval between subsequent sprays is adjusted (see table 2.9 below). NoBlight also differs from Blitecast in the accumulation of severity values; NoBlight does not stop accumulating conducive conditions where the relative humidity drops below 90 percent. Blitecast uses 76.5 percent relative humidity to discontinue accumulation of conducive infection conditions.

Table 2.9: Calculation of spray intervals based on severity values for the NoBlight DSS [49]

7-Day Severity Value Accumulation	7-Day Severity Value Accumulation	Spray Interval
(< 1.18 inches of rain)	(≥1.18 inches of rain)	
≥6	≥5	5 day
≥5 <6	≥4 <5	7 day
>4 <5	>3 <4	10 day
≤4	≤3	10–14 day

Geographic area: Maine (Northern Eastern USA)

Year of development: 2006

Comments:

DSS: Mileos [8][15][36][40][53]

Basic forecast model: Milsol

Description: Treatment decisions are based on the amount of simulated spores produced (SPORUL variable, as reported by the Milsol model), the number of simulated late blight generations, the crop's growth stage and its protection status (see figure 2.3), and the host resistance level (see table 2.10).

Geographic area: France

Year of development: 2009

Comments:

Other DSS's: China-blight (China), PhytoPRE+2000 and Bio-PhytoPRE (Switzerland), PROPLANT (Germany), BlightWatch (UK), VNIIFBlight (Russia).

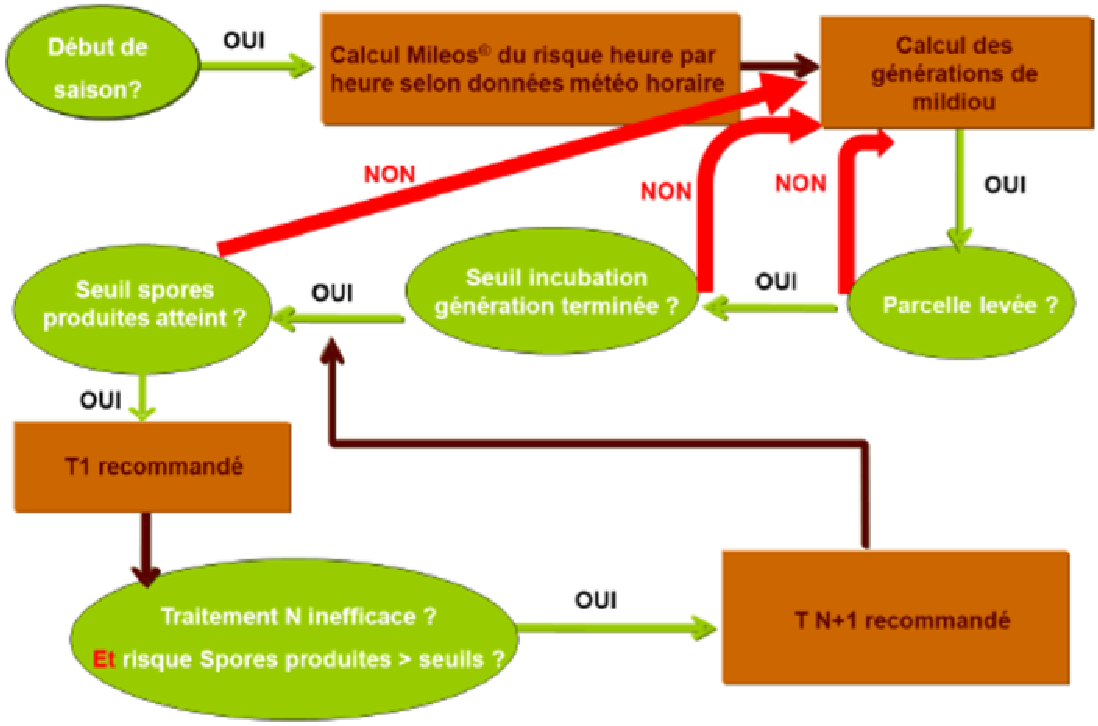


Figure 2.3: Treatment decision tree of Mileos [8]. A late blight "generation" is the achievement of a complete cycle in the Milsol model, i. e. an infection has been simulated, incubation is over and simulated sporulation has occurred. The number of "spores produced" corresponds to the output variable "SPORUL" of the Milsol model. The ineffectiveness of a treatment is computed based on the previous spraying reported by the farmer in the system (date, fungicide used and persistence) and by rain leaching of the fungicide. The thresholds of "completed generations" and "produced spores" that determine the treatment advice depend on the resistance level of the variety (see table 2.10).

Table 2.10: Mileos treatment decision table according to host resistance level [8]. The simulation of a late blight "generation" corresponds to the simulation of a complete cycle in the Milsol model (infection-incubation-sporulation). The "produced spore" thresholds reported here are expressed in common logarithm (log_{10}) of the variable "SPORUL" from the Milsol model.

	1er traitement	2eme traitement et plus
1ere condition	Stade « levée à 30% » renseigné	Parcelle non protégée
Variétés Sensibles	Génération 3 atteinte et incubation terminée + Spores produites ≥ 2	Spores produites ≥ 2
Variétés Intermédiaires	Génération 4 atteinte et incubation terminée + Spores produites ≥ 3	Spores produites ≥ 3
Variétés Résistantes	Génération 5 atteinte et incubation terminée + Spores produites ≥ 4	Spores produites ≥ 4

2.3 Comparison of the efficiency of different DSS's

In Europe, almost every country uses a different DSS. This is probably due to several factors like:

1. The lack of openness in terms of data and knowledge transfer in general (despite the European network for potato late blight, "Euroblight").

2. The high variation among countries in terms of quantity of resources invested to control late blight.

3. The path dependency. The mastery and expertise related to the operation of a DSS takes years to establish itself in a country (and thus resists model change).

4. The adaptation of models to the climatic (and disease pressure) conditions of the country in which they are developed.

Many international and inter-model experiments have been carried out in the framework of the "Euroblight" workshops to try to identify the best models. Here is a summary of them. The constant adaptation and evolution of some (parameters in) models makes it sometimes difficult to compare and evaluate them. However, some broad guidelines can be outlined.

- In 1994-1997, the models Blitecast, NegFry, Sparks, Ulrich & Schrodter, and Smith Period were evaluated in England and Wales [10]. No single system proved effective at all sites in all years. Only the Smith Period was consistently successful in triggering spray applications prior to blight appearing in the crop.

- In 1996 and 1997, the Guntz-Divoux model has been validated in Wallonia [54]. The sprays have been reduced (compared to a routine treatment) by 1 to 4 applications, depending on the weather conditions (disease favourable or not). The plots treated following the warning service have the same level of infection as the fields protected following the classical schedule. Furthermore, a control platform (composed by untreated plots) in Libramont "showed that each treatment recommended by the warning Service is unavoidable". Nevertheless, following the results of the control platforms, we can observe that it could be possible to save one more treatment per year. However, these results proved the relevance for high susceptible cultivar (Bintje) of the warning system based on the Guntz-Divoux model in Wallonia.

- In 1997, Plant-Plus and the negative prognosis (Ulrich & Schrodter) model was compared with different routine spray programmes in the East Midlands UK [35]. Fungicide recommendations made by the Plant Plus model were more likely to coincide prior to an infection period than Ulrich & Schrodter, thus allowing a greater chance of preventive spraying. The severe infection conditions exposed weaknesses in assumptions made by the Ulrich & Schrodter negative prognosis model. The Ulrich & Schrodter model assumes that product [fungicide] activity is complete for the period of its duration while in reality, protection declines with new growth and product degradation with time. Plant-Plus takes into account this parameters. Furthermore, Plant Plus is more successful at timing sprays before or shortly after infection periods, because the model incorporates a 5-days weather forecast. Moreover, Plant Plus model allows for present infection sources and evaluate infection risk correspondingly to the level of disease in the area.

- In 1996-1997, field trials compared routine fungicide applications with NegFry and Met. Eireann (Irish) system [41]. There was no significant differences in disease control or yield between routine fungicide application and the NegFry system. The Met Eireann performed well in 1996 but not in 1997. The NegFry model failed to suggest the first spray early enough in 1997. Both NegFry and Met Eirann system performed well in a low disease pressure year (1996) but failed to control the disease in a high one (1997).

- In 1996-1998, routine applications was compared with NegFry [42]. There was no significant difference in disease control or yield while the reduction in fungicide use was between 20 and 56%.

- In 1997-1998, trials to use the models Milsol and Guntz-Divoux were set up in Northern France for three different susceptibility varieties in order to reduce even more the number of treatments beyond the present "supervised protection-warning" by relaxing (increasing) the risk thresholds [23]. It revealed that on Bintje, during year under high disease pressure, there was not almost any flexibility to reduce the number of treatments. While on less susceptible varieties, it was possible to avoid some treatments by increasing the thresholds to be reached for spraying.

- In 1999 and 2000, field experiments in the Netherlands compared Plant-Plus, Prophy, NegFry and Simphyt with a practice spraying schedule [21][57]. In 1999, in all three trials, NegFry did not control potato late blight sufficiently under Dutch potato growing conditions and Simphyt started spraying too late in one trial. Prophy and Plant-Plus managed to control the disease to an acceptable level in all trials. In 2000, Simphyt started spraying too late while the three other models managed to control the disease to an acceptable level.

- In 2001, field experiments in Ireland compared NegFry and Met. Eireann DSS's with a routine program [43]. The Met Eireann DSS resulted in a larger decrease in fungicide use (compared to the routine program) than NegFry. But the Met Eireann DSS resulted in inferior disease control, yield and quality while the NegFry DSS was similar to the 10-days routine programme in terms of late blight control, quality and marketable yield. Why then does the Met Eireann DSS remain currently used in Ireland? According to Dowley and Burke (2004) [22], the cost of fungicide application in potatoes is low and therefore growers will need another incentive [like consumer demand to reduce fungicide inputs] to introduce a [new] DSS system into their production programmes.

- In 2001, field trials (mostly susceptible varieties) in different European countries (including Belgium) validated Simphyt, Plant-Plus, NegFry, ProPhy, Guntz-Divoux and/or PhytoPre+2000 [33]. No one single DSS always obtained a better control effect than other DSSs tested. In general, Prophy recommended first spray earlier than other DSS's. NegFry recommends fewer sprays but provide less effective disease control (in France) or even disease onset (in Holland). NegFry's poor results are suspected to be linked with type of humidity sensors (in Holland), which would be different from those used for model validation (in Denmark). In France and Belgium, Simphyt recommended more sprays than ProPhy and Plant-Plus and Guntz-Divoux and Milsol obtained a good control effect and at the same time with reduced fungicides input. The correlation between DSS use and level of tuber blight infections was unclear. First spray was often recommended much earlier than first observations at the trial sites. The importance of different inoculum sources for first outbreak is not well understood and DSS sub-models and methods need to be improved in this area.

- In 2004, field experiments in Ireland compared the NegFry, Simphyt, Prophy and Plant-Plus DSS with a routine program for two (moderately) susceptible cultivars [22]. None of the DSS's resulted in inferior foliage blight control when compared with routine application. Compared with routine control, the NegFry and SimPhyt programmes resulted in a 58-44% reduction in application frequency. The ProPhy and Plant-Plus programmes resulted in more modest savings; between 10 and 25%.
- In 2009 in Brazil, on "Asterix" cultivar, Prophy model predicted higher number of fungicide sprayings than Blitecast system, without improving disease control [59].
- In 2018, a Spanish study [25] compared different simple models (Smith periods, negative prognosis, fry model, severity values, and winstelcast) with the presence of airborne spores. The study suggests that negative prognosis and Winstelcast are the models for which the risk of infection is most correlated with the presence of aerial sporangia peaks, especially for years with medium inoculum levels. It should be noted that they considered in the model a significantly lower relative humidity threshold value (75%) than the original one (90%).

Some old models like Dutch and Beaumont rules, Severity values, Moving days, Blitecast and Simcast, seem to be no longer relevant (and used) in Europe because they are no longer even discussed or mentioned frequently in Euroblight workshops.

As expected, it appears that NegFry (and negative prognosis model only) are model adapted to regions with low late blight pressure, because it has been developed and validated in Northern countries. For example in Finland, only an average of 3-5 fungicides applications are needed to control late blight [32]. Regarding to the bad disease control NegFry has given in high pressure regions (Netherlands, France, UK, where severe infection conditions are regularly met), this model does not seem to be promising for the Walloon context either.

It seems that the Met Eireann system (based on the irish rules) has worked relatively well and for a long time in Ireland, but has not established itself in other countries. Since the Met. Eireann system has given even more fungicide reductions than Negfry and inferior disease control [43], it can be classified in the same category of models (as Negfry), i.e. a relatively "tolerant" model adapted to lower disease pressure. The same conclusion is applied to the SIMPHYT model since it sometimes started recommending treatment too late [21][57] and it recommends the same sprays amount than Negfry [22].

The Dutch models Prophy and Plant-plus seem to have demonstrated their ability to control late blight safely over many years and areas, even under severe disease pressure conditions. These DSS's have even been exported to other European countries. It would be very interesting to test these two Dutch DSS's under Walloon conditions, but unfortunately their availability is limited because they belong to private companies.

Mileos is the rather complex result of the fusion between previous models and seems to give good results in France.

The Guntz-Divoux model has recently been calibrated in Wallonia to better match the pathogen's reality and also gives satisfactory results in Belgium (B. Couvreur, personnal communication).

Part II

In-field late blight risk prediction

Chapter 3

Sensitivity analysis of the Guntz-Divoux model

3.1 Introduction

In Wallonia currently, late blight warnings in terms of spatial ditribution, are given for each of the 38 weather stations of the "Pameseb" network. The objective of the Pameseb network is to collect hourly agro-meteorological data, i.e. meteorological data that takes into account the climatic conditions measured within a field. A map of the Pameseb network is shown figure 5.7 in Annex 1. The data we are interested in as part of the prediction of late blight risk are temperature, relative humidity, and rainfall. The air temperature is measured at 1,50m from the surface with an accuracy of 0.2°C. The same probe measures the relative humidity of the air with an accuracy of 1.6%. Rainfall is measured by tipping bucket rain gauge with a resolution of 0.1mm [2]. In order to minimize local variations, stations are installed, as much as possible, at a sufficient distance from obstacles. The ideal conditions for a station to be representative of the regional climate or topoclimate are: homogeneous vegetation within a radius of at least 100 metres around the measuring station, and a location on open ground far from buildings and from curtains of trees more than 10 times their height.

Actually, the distribution of the late blight treatment notices issued by the CARAH (Centre for Agronomy and Agro-industry of Hainaut Province) consists of a table showing the recommended spraying date for each station (see section 2.2 for more informations about CARAH warnings). They supply the (recalibrated Guntz-Divoux) model with the data from each pameseb station and, on the basis of the outputs of each simulation, recommend a treatment date for each station. A farmer must therefore base his treatment decision on the data collected by the weather station closest to his field in question. However, meteorological data (especially relative humidity and rainfall) can quickly deviate with the distance between the station and the field. Consequently, the treatment advice given on the basis of weather data from the nearest station (generally 10 - 20 km away from the field) may not be representative of local weather conditions on the field itself. So, the first goal of this chapter is to perform a sensitivity analysis on the model regarding to the uncertainty linked to the distance between the field and the "nearest" Pameseb reference station, i.e. to assess the difference between the times of the recommended treatments (so the model outputs) based on data from a "nearby" weather station of the Pameseb network, and the times of the recommended treatments based on a station present on the field.

In addition, the Walloon Agricultural Research Centre (CRA-W) is currently carrying out a project ("AGROMET") to build an operational web platform for the real-time dissemination of high-resolution agro-meteorological data in space ($1km^2$) and time (hourly) [18]. Future AGROMET data will be available via an API (application programming interface), in "json" format. Within the framework of the PotatoSMART project, the Walloon model of late blight will be supplied with the data provided by this new tool. However, the data provided by the AGROMET project resulting from spatial interpolations, they are therefore subject to uncertainty. The second objective of this section is to perform a sensitivity analysis on the model regarding to the AGROMET uncertainty, i.e. to assess the difference between the times of the recommended treatments (so the model outputs) based on "AGROMET-like data" (with uncertainty) and the times of the recommended sprayings based on real data (from a Pameseb station).

Finally, by linking the results of the two objectives, we will be able to evaluate the interest of supplying the Walloon late blight model by the AGROMET system compared to the current forecasting based on a "nearby" station. Since the model used in practice by the CARAH is confidential, we will use the Guntz-Divoux model on which the CARAH model is based. We assume that the CARAH model has only slightly calibrated the values of the Guntz-Divoux model, and therefore behaves more or less in the same way as the latter. Weather data are provided by the CRA-W/pameseb network.

3.2 Material and method

3.2.1 Sensitivity analysis for "nearby" station-based forecasting

In order to achieve the first objective, we will consider several pairs of Pameseb meteorological stations and several years. We can imagine that at one of the two stations there is a farm cultivating a potato field. And that this farm can base its treatment decisions on the model supplied by data either from station 1 (located $10 - 20km$ away) or station 2 (located in the field itself). The distance between the two stations correspond approximately to the average range of a pameseb weather station in the loamy region (main Walloon potato crop region), i.e. 12km [54]. In order to include more station pairs and more realistic distances, we will take station couples from 10 to 20 km away. Figure 5.7 in Annex 1 shows the extent of territory covered if we consider a 15 km station scope.

For each stations couple, the process shown in the figure 3.1 will be applied. The Guntz-Divoux model is performed on the two stations and the maximum hourly infection risk (IR)[1] is taken for each day. Indeed, although the model provides an infection risk for each hour, it is the maximum infection risk over the day that will define the launch of a new incubation cycle, and so the decision (or not) to treat. For each station couple, three metrics are computed to evaluate the differences between the model output from the 2 simulations (2 stations) over a growing season (we will consider from March to September):

1. The number (and %) of days forecasted with exactly the same max infection risk value for the 2 stations.

2. The number (and %) of days predicted with the same occurrence (presence or absence) of max infection risk, regardless of its value, for the 2 stations.

[1]When we talk about the "infection risk" in this chapter, we are talking about the infection risk as output from the Guntz-Divoux model, not the actual infection risk.

3. The critical success index (CSI): Among the days on which an infection risk was present at at least one of the two stations, the number of days (and %) on which the infection risk was also present (regardless of its value) at the other station is calculated. This corresponds to the second metric from which the "true negative" (days when the risk of infection is zero at both stations) have been removed. The equation 3.1 shows the calculation of the CSI based on the contingency scores

$$CSI = \frac{a}{a+b+c} \tag{3.1}$$

where a = number of days forecasted with a positive infection risk at both stations.
b = number of days forecasted with a positive infection risk at the station 1 (reference station) but not at the station 2 ("real data").
c = number of days forecasted with a positive infection risk at the station 2 but not at the station 1.

Metrics 2 and 3 are the most important for the interpretation of model output because the IR value is of minor importance for treatment recommendations, especially in susceptible varieties (in most cases, the presence of cycles, even of low risk, will lead to treatment advice). In particular, we will focus on the CSI, which is a good measure of the accuracy of a forecasting model.

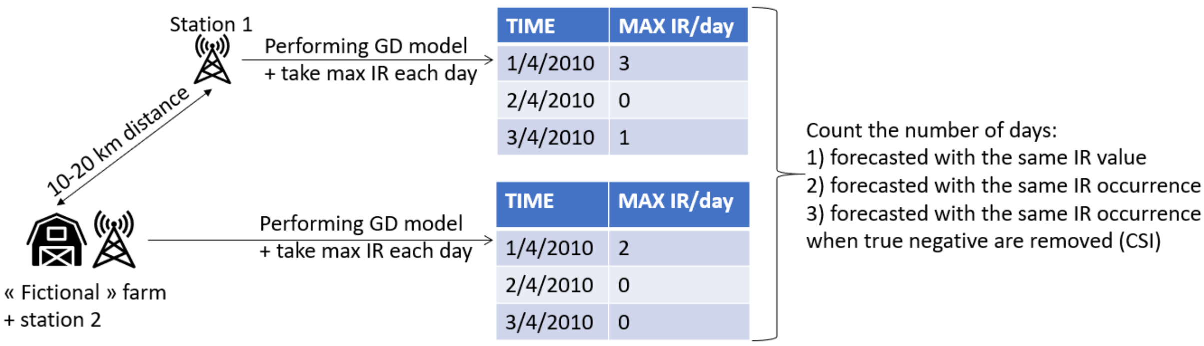
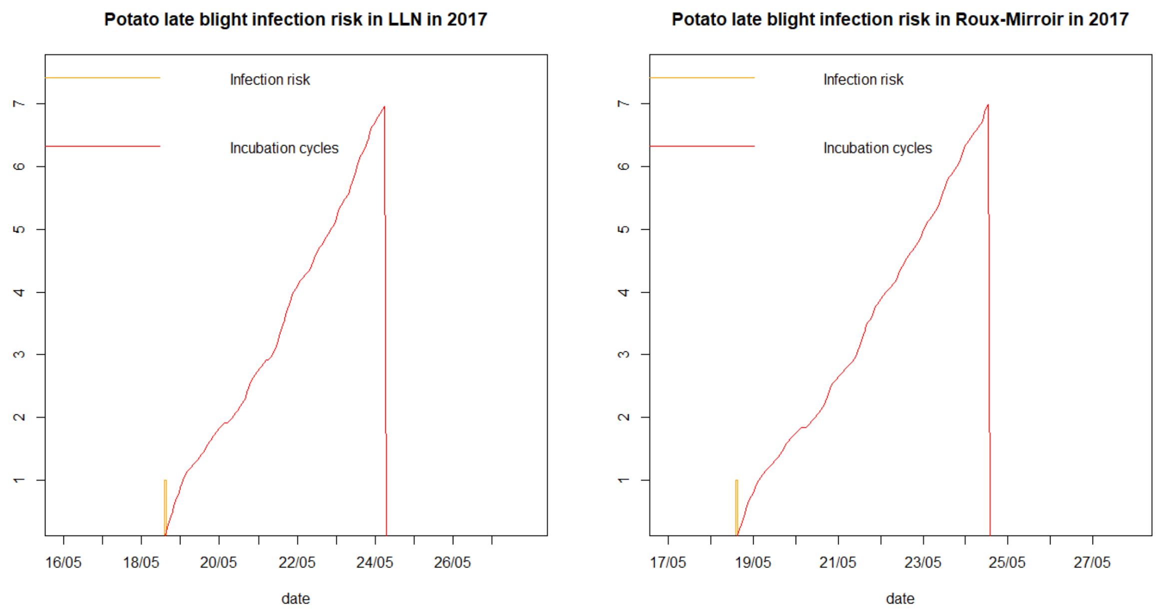


Figure 3.1: Method applied to each station couple to study the sensitivity of late blight daily infection risk when the Guntz-Divoux model is supplied by meteorological data from a "near" Pameseb station.

This method (as well as the one presented at next subsection 3.2.2) is based on four major assumptions:

1. The maximum level of infection risk on a day determines unilaterally the recommended treatment date. In other words, if infection risk is present on a day at the 2 near stations, the incubation period is the same for these 2 stations. This assumption is considered reasonable because, in general for near stations, it is observed in the warnings that the recommended treatment date is often the same. In addition, even if the estimated incubation period is not accurate at the hourly scale, it is not a problem since the treatment will be recommended at the daytime scale. As an illustration, the figure 3.2 shows that this assumption is realistic.



(a) Louvain-La-Neuve, may 2017 (b) Roux-Mirroir, may 2017

Figure 3.2: Comparison of the duration of the incubation period computed by the Guntz-Divoux model for two near stations in May 2017. It can be seen that, for both stations, incubation began on 18/5 (since a risk of infection was present) and ended on 24/5.

2. The meteorological data from the Pameseb stations are considered to be the real data, i.e. the uncertainty associated with the measuring devices is ignored.

3. The model is perfectly accurate.

4. The results of the sensitivity analysis evaluated here with the original Guntz-Divoux model will also be valid for the recalibrated Guntz-Divoux model (CARAH), since only slight changes were made to the tables, the general working of the model remaining the same.

The selected pairs of stations are located in the loamy region where the large majority of Walloon potatoes are grown. The method is applied for 3 years of 3 different levels of late blight pressure: low (2018), medium (2015) and high (2016).

The result obtained by this method will be a percentage of days for the three metrics, for each station pair and for each year studied. An ANOVA statistical analysis will be conducted on these results.

The R code implemented to compute this sensitivity analysis of the Guntz-Divoux model between two nearby stations is submitted in Annex 2.

3.2.2 Sensitivity analysis for AGROMET uncertainty

To achieve the second goal of this chapter, and since the AGROMET system is not yet fully developed, we will generate simulated outputs (weather data) of the AGROMET project. To do this, a bias will be systematically added to the real meteorological data (from Pameseb stations). This bias represents the uncertainty related to the data, the deviation between the actual data and those obtained by the future AGROMET system. For temperature and relative humidity data, the bias is randomly selected according to a normal distribution that approximately describes the uncertainty associated with these data. These normal distributions are therefore centered in 0 and have a standard deviation of 0.33 and 1.67 respectively for temperature and relative humidity. So the uncertainty has a high chance (99%) of being between -1 and +1°C for temperature and between -5 and +5% for humidity. These statistics are an approximation of the uncertainty associated with the future AGROMET data provided by Damien Rosillon from the CRA-W who is the coordinator of the AGROMET project. Regarding the rainfall, the same method cannot be applied because it would generate unrealistic rainfall patterns (non-stop rainfall throughout the season) and therefore systematically excessive risks of infection (maximum infection risk throughout the season). In the AGROMET data, rainfall will be evaluated by radars. To represent the uncertainty on rainfall, it is therefore appropriate to introduce a probability that the radars correctly detect the presence or absence of rain. The rainfall detection probability statistics we will use come from a study published in 2011 and conducted (among others) by the Royal Meteorological Institute of Belgium, the University of Liège, and UCLouvain [44]. The purpose of this study was to assess the site-specific risk of septoria leaf blotch in winter wheat using weather-radar rainfall estimates. Among the results, they reported some statistics comparing weather-radar rainfall estimates with rain gauge measurements. Here are the statistics we will adopt:

- The Probability Of Detection (POD) is the probability that the radar detect the occurrence of rain at a place when it has actually occurred (rain is measured by rain gauge at that place). $POD = 0.87 \pm 0.08$. So, $1 - POD$ is the probability that the radar does not detect occurrence of rain while it actually occurred.

- The False Alarm Ratio (FAR) is the probability that the radar detect the occurrence of rain at a place while it did not actually occurred. $FAR = 0.13 \pm 0.04$.

These two statistics ($1 - POD$ and FAR) will therefore also be estimated according to a normal distribution of mean 0.13 and standard deviation 0.027 and 0.013 respectively. With these two statistics, uncertainty on rainfall can be generated on the real data to simulate the radar estimations.

Then, we will compare in the same way as for the analysis done with the "nearby station forecast", the difference between the maximum daily value of infection risk between the actual data and the deviated data, by computing the three metrics presented at the subsection 3.2.1 above. The method is also applied for 3 years of different disease pressure levels (2015, 2016 and 2018). The method used for this sensitivity analysis is outlined in the figure 3.3 below and is applied 100 times for each station-year couple.

The R code implementing this sensitivity analysis of the Guntz-Divoux model when it is supplied by AGROMET-like data is submitted in Annex 3.

It should be noted that the method presented here generates slightly unrealistic weather times series. Indeed, the interactions between the different weather data are not taken into account. Each data (temperature, humidity, and rainfall) is associated with a random uncertainty, independent of the other data. However, in reality these data are linked (for example, if the temperature is high and it has rained a lot, the relative humidity will be very high).

It should also be noted that the method used here considers the same uncertainty pattern (same standard deviation of weather data) for all places. Actually, it is likely that some locations will have a lower uncertainty than others (because of the proximity of a real weather station, a more stable microclimate, etc).

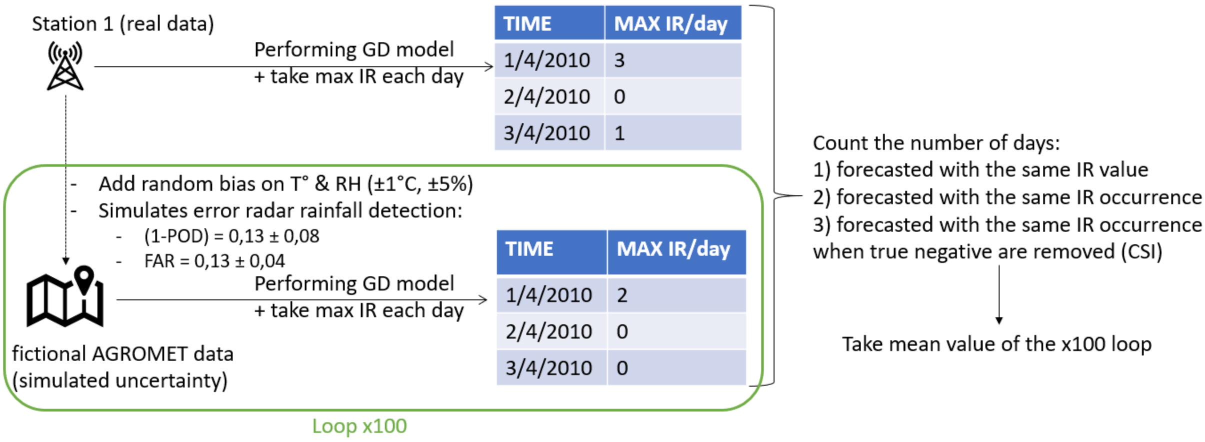


Figure 3.3: Method applied 100 times to each station to study the sensitivity of late blight daily infection risk according to simulated uncertainty linked to "AGROMET-like" data

3.3 Results

3.3.1 Sensitivity analysis for "nearby" station forecast

The table 3.1 below presents the results obtained for the sensitivity analysis based on the forecasting of the infection risk when the Guntz-Divoux model is supplied with data from a nearby Pameseb station.

It can already be seen that the average values of "% days with same IR value" and "% days with same IR occurrence" are very high, these values being probably inflated, as it was expected, by the "true negative". Over a growing season, there are indeed many more days with a null IR rather than positive ones. For this reason, the focus will be on the results obtained for the critical success index.

For your information, the analysis presented below for the CSI was also performed for the measurement of the "number of days with the same occurrence of IR". The results showed no statistical difference in this metric between the supply of the model from a nearby station or from AGROMET-like data. This conclusion seemed surprising and led us not to consider the days without infection risk, which drew our attention to the critical success index.

Table 3.1: Sensitivity analysis of the Guntz-Divoux model supplied with "nearby" station weather data. For each year and station pair, 3 metrics are computed to measure the difference between the 2 simulations (2 stations): % of days with exactly same infection risk (IR) value, % of days with same occurrence of IR, and Critical Success Index (CSI).

Stations couple	**distance [km]**	**Year**	**% days same IR value**	**% days same IR occurrence**	**CSI [%]**
Roux-Mirroir	11.5	2015	91.6	95.8	75.7
LLN		2016	93.5	95.8	79.1
		2018	88.8	93.9	59.4
LLN	14.5	2015	89.7	95.3	75.6
Baisy-Thy		2016	91.1	95.8	80.4
		2018	91.6	97.2	81.8
Baisy-Thy	10.04	2015	85.0	92.0	63.8
Sombreffe		2016	89.2	94.4	73.3
		2018	90.2	95.3	67.7
Sombreffe	14.39	2015	85	86.9	37.8
Floriffoux		2016	87.4	92	58.5
		2018	89.7	92.5	40.7
Feluy	13.35	2015	87.4	94.9	80.0
Casteau		2016	90.2	96.3	83.0
		2018	90.6	94.4	67.6
Sombreffe	21.09	2015	87.8	92.5	62.8
Leuze		2016	91.6	95.3	75.0
		2018	90.2	92.5	55.6
Leuze	18.49	2015	89.3	91.6	50.0
Couthuin		2016	95.8	97.7	85.7
		2018	87.9	92.5	52.9
	MEAN		89.4	94.2	67.0

Figure 3.4 shows the average CSI results by station pair with 90% confidence intervals. First, it can be seen that the average CSI value varies considerably between station pairs. It goes from 45.7% for the worst couple (Sombreffe-Floriffoux) to 79.3% for the best one (LLN - Baisy-Thy). The lower average CSI values cannot be assigned to a greater distance between the stations because Sombreffe and Floriffoux are only 14.4km away while some pairs of more distant stations obtain a much better result, for example Sombreffe-Leuze (21.1km). The most likely hypothesis was that this difference is due to local parameters inherent to one of these stations (proximity to a watercourse, shadows, microclimate, etc) or to the geographical transect linking the two stations (topography). The hypothesis of proximity to a watercourse is the most likely. Indeed, Floriffoux Pameseb station is located 350 metres from the shores of the Sambre river, which could slightly influence local weather variables, particularly relative humidity while most other stations (including Sombreffe) are not located so close to a watercourse.

Secondly, we notice that the interannual variability (within-stations pairs) is very variable between the couples of stations. For example, it is very low for the couples "Baisy-Thy - Sombreffe" and "LLN - Baisy-Thy" (confidence interval less than 10%) while it is huge for the couples Sombreffe-Floriffoux" and "Leuze-Couthuin" (confidence interval of over 60% for the last one).

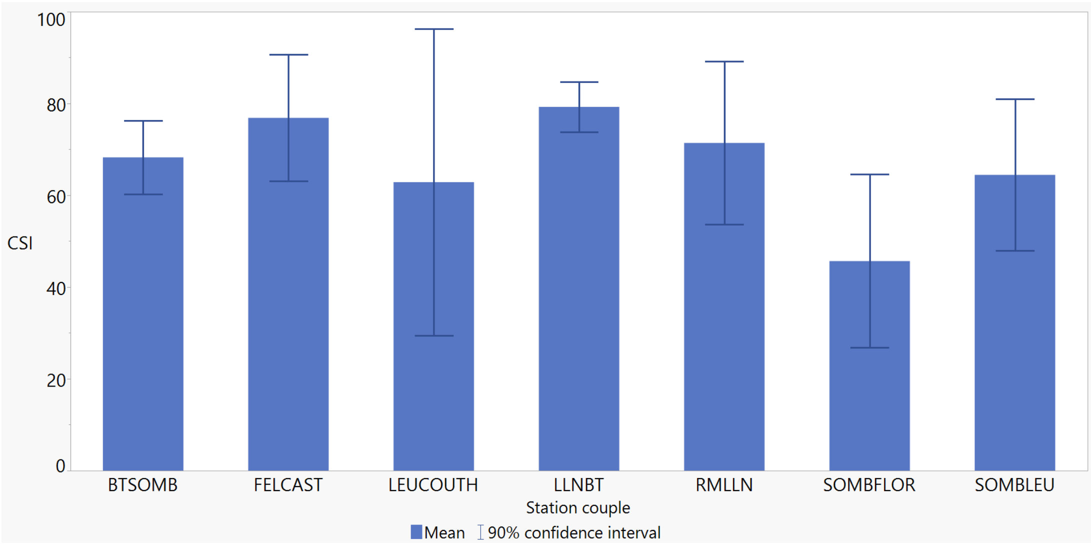


Figure 3.4: Critical success index (CSI) by station couple for the sensitivity analysis of the Guntz-Divoux model when the model is supplied with data from a near (10-20km) Pameseb meteorological station. The following abbreviations are used to name the stations: BT=Baisy-Thy. SOMB=Sombreffe. FEL= Feluy. CAST=Casteau. LEU=Leuze. COUTH=Couthuin. LLN=Louvain-La-Neuve. RM=Roux-Mirroir. FLOR=Floriffoux.

Now let's focus on interannual variability, all station pairs combined. The table 3.2 shows the result of a Tukey-Kramer test ($\alpha = 0.1$) on the differences on average CSI values between years. In order for the Tukey-Kramer test to be valid, it was first proven (by a Levene test) that the inter-couple of stations variance (intra-year) of the CSI is not different over the 3 years. It can be seen that the higher disease pressure level, the higher the mean CSI value (2016>2015>2018). The average CSI values are significantly different between 2016 and 2018.

Table 3.2: Tukey-Kramer test comparing averages CSI values (obtained for the sensitivity analysis of the Guntz-Divoux model supplied by data from a "near" station) according to the years.

Connecting Letters Report

Level			Mean
2016	A		76,428571
2015	A	B	63,671429
2018		B	60,814286

Levels not connected by same letter are significantly different.

3.3.2 Sensitivity analysis for AGROMET uncertainty

The table 3.3 below presents the results obtained for the sensitivity analysis based on the prediction of the infection risk when the model is supplied with data with uncertainty, simulating data outputs from the AGROMET system.

Figure 3.5 shows the average CSI results by station, with 90% confidence intervals. The inter-station and interannual variability appears to be lower than in the case of the sensitivity analysis of a "nearby" station (figure 3.4). The average CSI values are also higher.

Table 3.3: Sensitivity analysis of the Guntz-Divoux model supplied with simulated AGROMET data. For each year and each station, 3 metrics are computed to measure the difference between the 2 simulations (real and "AGROMET-like" data): % of days with exactly same infection risk (IR) value, % of days with same occurrence of IR, and Critical Success Index (CSI).

Station	**Year**	**% days same IR value**	**% days same occurrence of IR**	**CSI [%]**
Roux-Mirroir	2015	91.7	95.0	77.3
	2016	90.9	94.6	80.2
	2018	93.2	96.0	74.3
LLN	2015	89.7	93.7	74.6
	2016	90.4	94.7	81.9
	2018	90.8	95.1	75.7
Baisy-Thy	2015	88.4	93.0	68.2
	2016	88.4	92.5	76.2
	2018	91.5	95.0	77.7
Sombreffe	2015	88.6	93.6	81.9
	2016	90.9	94.4	82.4
	2018	93.5	96	71.5
Floriffoux	2015	93.1	94.8	63.0
	2016	88.6	93.1	72.6
	2018	93.3	95.0	55.7
Feluy	2015	87.2	92.4	78.1
	2016	89.1	93.7	82.5
	2018	89.7	94.6	81.1
Casteau	2015	88.1	94.4	86.7
	2016	89.9	94.4	84.9
	2018	91.7	94.4	63.7
MEAN		90.4	94.3	75.7

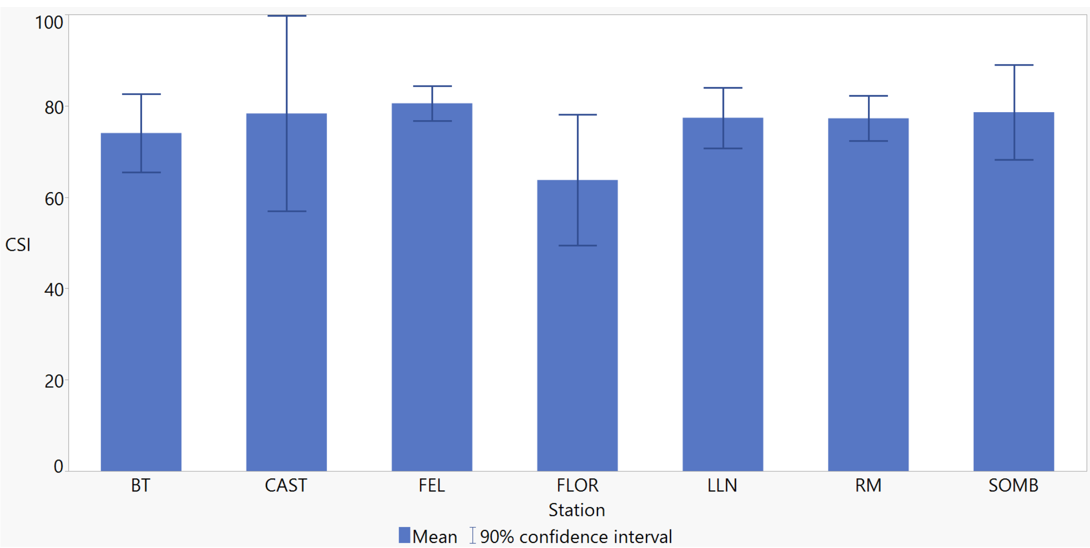


Figure 3.5: Critical success index by station couple for the sensitivity analysis of the Guntz-Divoux model when the model is supplied with AGROMET-like data.

For the average CSI per year (all stations combined), the same trend is obtained as for the "near" station sensitivity analysis; the lower the disease pressure in the year, the more sensitive the model is to uncertainties and therefore the average CSI decreases (see table 3.4).

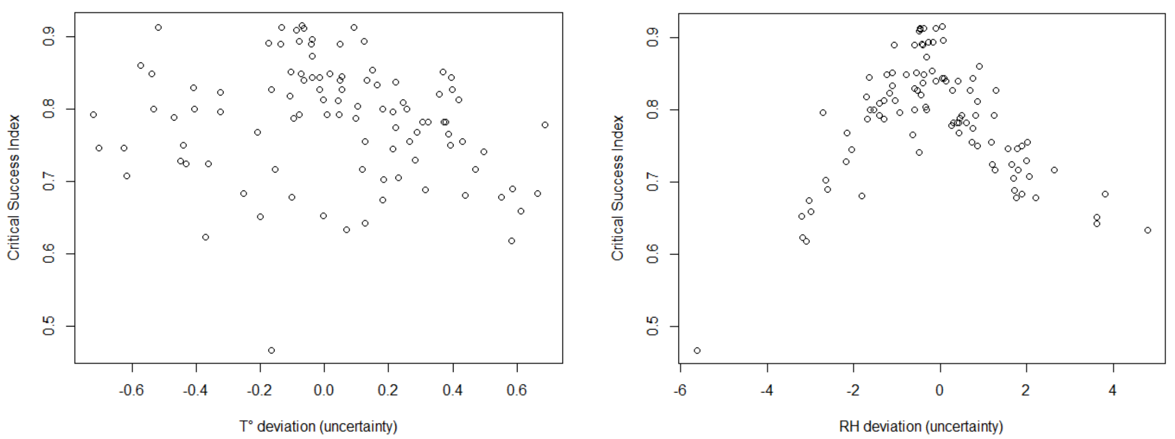
Table 3.4: Tukey-Kramer test comparing averages CSI values (obtained for the sensitivity analysis of the Guntz-Divoux model supplied by AGROMET-like data) according to the years.

Connecting Letters Report

Level			Mean
2016	A		80,057143
2015	A	B	75,685714
2018		B	71,385714

Levels not connected by same letter are significantly different.

At last, it is also interesting to note that, in the ranges of uncertainty considered in this analysis ($\pm 1°C$ for temperature and $\pm 5\%$ for relative humidity), the Guntz-Divoux model seems more sensitive to variations in relative humidity than temperature. The sensitivity analysis for AGROMET uncertainties shows this trend because, for each station and each year, a loop is run 100 times where an uncertainty (different for each iteration, derived from a normal distribution, see method figure 3.3) is added on the real meteorological inputs. This allows us to look at the evolution of the CSI as a function of the intensity of the uncertainty at figure 3.6. It is clear from the graph 3.6(a) that no particular pattern can be identified to correlate the CSI and temperature deviation. While in the figure 3.6(b), it is clear that the greater the deviation on the relative humidity (moves further away from 0), the more the CSI decreases.



(a) CSI depending on temperature deviation

(b) CSI depending on RH deviation

Figure 3.6: Critical success index obtained for the sensitivity analysis of the Guntz-Divoux model to AGROMET uncertainties for the Feluy Pameseb station in 2015, depending on intensity of uncertainty on temperature and relative humidity.

3.3.3 Sensitivity analysis: forecasting from a "near" station or uncertain AGROMET data

Let us now study the effect of the source of uncertainty ("near" station or AGROMET data) on the average value of the CSI, all years and stations combined.

First, a Levene test ($\alpha = 0.1$) is applied to compare the variances of the two groups (two sources of uncertainty) at figure 3.7. As expected, it appears that the variance (intersations and interyear) of the CSI is significanly higher when the Guntz-Divoux model is supplied by data from a nearby station than by AGROMET-like data.

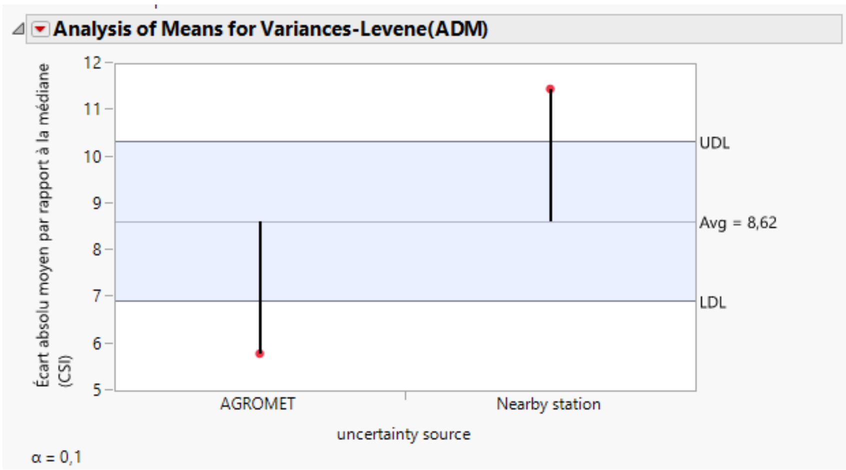


Figure 3.7: Levene test comparing the variance of CSI when the Guntz-Divoux model is supplied by data from a "near" Pameseb station or by AGROMET-like data.

Since the variance of the CSI is not the same according to the source of uncertainty, a Welch test[2] ($\alpha = 0.1$) is applied to compare the averages CSI values for the two sources of uncertainty. The test (see table 3.5) reveals (low Prob>F value) that the average CSI (i.e. the accuracy of infection risk prediction) of the Guntz-Divoux model is significantly better when the model is supplied with AGROMET-like data (mean $CSI = 75.7\%$) than when it is supplied with data from a nearby (10-20km) Pameseb station (mean $CSI = 67.0\%$).

Table 3.5: Welch's test comparing averages CSI values according to the source of uncertainty of the data that supplies the Guntz-Divoux model ("near" station or AGROMET uncertainty).

Welch's Test

Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
6,2683	1	31,429	0,0177*

t Test
2,5037

[2]The Welch test is an adaptation of the Student t-test used in particular to statistically test the hypothesis of equality of two means with two samples of unequal variances.

3.4 Discussion

The final result of this analysis - and the most important one - is that the supply of the Guntz-Divoux model with AGROMET meteorological data will allow a better forecasting of the infection risk, more adapted to the farmer's geographical location than if the model is supplied with meteorological data from a Pameseb station near from the farm (located at a distance of 10 to 20km), as is the case at present. Indeed, the critical success index is almost 10% higher for the source of uncertainty "AGROMET" than "near station". The timing of the treatments should therefore be slightly better targeted.

The variability (especially interstations) in the accuracy of the infection risk forecasting by the Guntz-Divoux model is also lower when the uncertainty comes from the AGROMET data than when it comes from a nearby station. This may be partly due to the fact that we have considered here the same degree of uncertainty in all places for the AGROMET data. While for station pairs, the intensity of the deviation of meteorological data (and therefore of the model outputs) between the two stations depends on the station pair (the geographical transect) considered.

An unexpected trend also emerged; the Guntz-Divoux model is more sensitive to uncertainties (whether this uncertainty comes from AGROMET data or from a nearby station) for a year with a low late blight risk than for a year with a high disease pressure. This is a surprising but interesting result. Indeed, even if the absolute number of days at positive infection risk is lower in a year with low pressure, the CSI value should not be impacted because it is a ratio. One explanation could be that a year at low disease pressure (such as 2018), climatic conditions are often close to the necessary infection conditions, sometimes exceeding them but only slightly. In these cases, uncertainty about the meteorological data will be decisive for the presence or absence of infection risk. On the contrary, in a year of high pressure (such as 2016), climatic conditions often exceed the necessary infection conditions. The risk of infection is therefore often positive (with a high value), and deviations in meteorological data will at most shift the value of the infection risk by one (or 2) unit, but will not be sufficient to move from a high infection risk to a zero risk.

The results obtained for the "nearby" station sensitivity analysis (and in particular for the station couple "Sombreffe - Floriffoux") shows that in the range of distance studied here ($10 - 20km$), a slightly greater distance (a few km) between the reference weather station and the field is not necessarily correlated with a less reliable estimate of the infection risk. It is suspected that local parameters (in particular the influence of a near watercourse, but maybe also topography, proximity to a forest, etc) influence the weather data deviation between the two stations (an so on the response of the Guntz-Divoux model) more than the distance between them.

It was pointed out that uncertainty about relative humidity is a determining factor in the response of the Guntz-Divoux model, much more so than temperature. For this reason, every effort should be made to minimize the error made on the interpolation of relative humidity in the AGROMET system.

At last, it is also important to note that the AGROMET system could be a useful tool to supply other components of a future decision support system than the epidemiological model itself, such as the computation of the fungicide leaching by rainfall.

Chapter 4

Assessment of the current Walloon model and the French model "Milsol"

4.1 Introduction

For more than 30 years now, the Guntz-Divoux model has been the basis for treatment advice to control potato late blight in Wallonia. The model has been validated several times [54] and is certainly a reliable basis for predicting the risk of infection. However, the PotatoSMART project is a good opportunity to reconsider the use of this model, at a time when neighbouring countries have developed more automated and/or quantitative decision support systems (SIMPHYT in Germany, Plant-Plus and Prophy in The Netherlands, Mileos in France).

According to Rakotonindraina [53], the Guntz-Divoux model is quite accurate during high-risk periods. But it overestimates the number of treatments in periods of low risk. This observation led to the development of the French model "Milsol" which is quantitative.

In this chapter, we will assess the current validity of the Guntz-Divoux model in Wallonia. We will also evaluate the performance (timing of (non-)treatment recommendations based on actual (non-)observed infections) of this model and the warnings from the CARAH, compared to the Milsol model and virtual warnings based on it, as it is done in Mileos. This will be done on ex-post epidemiological data and for three different host resistance levels against potato late blight.

The choice of the Milsol model is explained by two main reasons:

1. It is worth testing a model developed in a country close to Belgium because it means that it has been calibrated for the same agricultural context (climate, industrial requirements, agricultural practices, etc.)

2. On the one hand, the Dutch models Plant-Plus and Prophy were developed by private companies. The precise working of these models is therefore not publicly available, and their use is restricted by intellectual property rights. There is also very little detailed information on the German SIMPHYT models. On the other hand, Milsol is under public license (GNU General Public License) [11]. All the detailed equations of the Milsol model are included in Rakotonindraina's thesis [53]. In addition, a Git containing the coding of the model in C++ was put online [11] by the "RECORD" platform (platform for computer modelling and simulation of

agro-ecosystems, developed by the French national institute on agronomic research, INRA). This makes it possible to rewrite the model in R.

4.2 Material and method

The Guntz-Divoux model has been transcribed into R (available at Annex 4) and the recommended treatment dates by the CARAH for the years 2010 - 2015 are taken from the brochures of the Centre Pilote de la Pomme de terre (CPP) [13], which contain annual reviews of the CARAH warning service. For the years 2017 and 2018, the recommended treatment dates are taken directly from the original warning notices. When there are inconsistencies between the outputs of the Guntz-Divoux model and the treatments recommended by the CARAH, the treatments actually recommended in the warnings are always considered because it is assumed that the interpretation step is part of the decision support system.

The Milsol model has also been transcribed into R (see Annex 5) and the recommended treatment times are evaluated according to the Mileos thresholds for the output variable "SPORUL" and for the "number of simulated generations" reached (see table 2.10 and figure 2.3 presented in section 2.2). To calculate the number of treatments per season, we consider that a treatment is persistent for 7 days and that it must be renewed after this period if the Milsol output thresholds are exceeded.

The validation method used in this chapter is similar to that used in chapter 5 of Duvivier's thesis [24]. Duvivier was working on wheat leaf rust, a wheat disease caused by the fungus *Puccinia triticina*. His study consisted of comparing two disease forecasting models (an original model based on meteorological data, and the same model but upgraded with spore presence data). It is considered that the method used by Duvivier is also suitable for late blight, given the many similarities in the behaviour of *P. infestans* (cycle, symptoms, etc.) with a classical cycle of a plant pathogenic fungus. The method consists in calculating four metrics based on contingency scores [63] in order to measure the effectiveness and the accuracy of model predictions compared to actual epidemiological data observed in fields :

a = observed and predicted infections
b = predicted infections, but not observed
c = observed infections, but not predicted

Probability Of Detection (POD) gives the ratio of forecasted infections among all the observed infection events. Perfect POD=1.

$$POD = \frac{a}{a+c} \tag{4.1}$$

False Alarm Ratio (FAR) gives the fraction of the predicted "infection" events that did not occurred in reality. Perfect FAR=0.

$$FAR = \frac{b}{a+b} \tag{4.2}$$

Critical Success Index (CSI) measures how well the forecasted infection events did correspond to the observed infection events. It can be seen as a measure of the accuracy (like POD) but taking into account the false alarms (predicted infection but not observed). Perfect CSI=1.

$$CSI = \frac{a}{a+b+c} \tag{4.3}$$

BIAS (ratio between the frequency of predicted events and the frequency of observed events) indicates whether the forecast system has a tendency to underforecast (BIAS<1) or overforecast (BIAS>1) events. It does not measure how well the forecast corresponds to the observations.

$$BIAS = \frac{a+b}{a+c} \tag{4.4}$$

Most of the used epidemiological data come from the MILVAR project: these are agronomical tests on varietal susceptibility to late blight in Libramont (2010 to 2017), Ath (2014-2017) and Gembloux (2016). The data for Libramont and Gembloux are provided by the CRA-W (*Centre de recherche agronomique de Wallonie*) while the data for Ath are extracted from a powerpoint presentation from the CARAH [17]. The experimental design of MILVAR assays consists of 4 complete random blocks, each of them testing about twenty different varieties, and no fungicide treatment being applied throughout the season. Data from the WACOBI project (Louvain-la-Neuve, 2016 and 2017) are also used. This project, led by Gil Colau (PhD student at the UCLouvain phytopathology lab), was aimed to test different bacterial biocontrol agents against late blight. The assays used are obviously the untreated control plants. Finally, the Bintje trial conducted in LLN in 2018 as part of the PotatoSMART project is also used. All this epidemiological data consists in regular monitoring (every 2 to 5 days) of the "disease severity", i.e the % of leaf area covered by late blight symptoms. The reference variety for the susceptible class is Bintje. For the intermediate class (moderately susceptible), the varieties Agria, Challenger, Gasore, or Desiree are considered. The reference varieties for the high resistance level are Sarpo Mira, Connect, Bionta, Bionica, or Alouette. For the "moderately susceptible" and "resistant" levels, it is chosen to change the reference variety over years in order to have a better overview of the predictive potential of the models.

Weather data are provided by CRA-W/Pameseb network. For Libramont, Louvain-La-Neuve and Ath, we used data from a weather station on the site itself where epidemiological data were collected. For Gembloux, we used data from the Sombreffe weather station, located 9 km away.

The output of the Guntz-Divoux and Milsol models consists of time series of (non)-sporulation events for each day troughout a season. In addition, the appearance of late blight spots indicates that the fungus is producing spores [51]. Therefore, in the same way as it is done in Duvivier's thesis [24], the variables (a, b and c) used to calculate the contingency scores can be evaluated as follows:

- The model predicted an observed infection (a) if the model forecasted (at least one day of) sporulation in the time interval during which a significant increase in the mean disease severity was observed on the reference variety (depending on the sensitivity level). It will be assumed (as in Duvivier's thesis) that "significant increase" means either an appearance of the first symptoms, an increase >1% in leaf area damaged when the disease level is low (<10%), or an increase >10% when the disease level is high (>10%). When the average disease severity exceeds 85%, the observed data are considered no longer available.

- Infections predicted but not observed (b) are either treatments predicted more than 5 days before the first symptoms appear, or sporulations predicted by the model during time intervals where no significant increase in disease has been observed.

- Observed but not predicted infections (c) are the time intervals during which a significant increase in disease or onset of first symptoms was observed, but no sporulation was predicted by the model.

4.3 Results

The results of the contingency scores and the total number of recommended treatments are presented by year, site, model, and level of disease susceptibility in the table 4.1. Some data are not available or less reliable for the following reasons:

- Libramont, 2012, GD: The review of CARAH warnings for 2012 only included the dates for the most susceptible varieties but did not include details for the other host resistance levels.

- Libramont, 2013, GD & Milsol: Since no infection has been observed on resistant varieties, it is not possible to calculate relevant contingency scores.

- 2016: The review of the 2016 warnings has not been published. Recommended 2016 spraying dates for susceptible varieties were provided by Gil Colau. But those for less susceptible varieties are therefore not available.

- LLN: The field trials (WACOBI and PotatoSMART) conducted from 2016 to 2018 at LLN used here were not intended to compare varietal resistances, it only consisted of sensitive (Bintje) negative controls.

- Ath: The epidemiological data (% of leaf area covered by late blight symptoms) for Ath are less reliable and have a lower temporal resolution because they're extract from a graph from a powerpoint presentation.

For ease of reading, the averages (on all sites and years) validation metrics are presented in the table 4.2 below, according to the model and host susceptibility level.

Table 4.1: Results of the comparison of the prediction efficiency of Milsol and Guntz-Divoux (CARAH) models using the contingency scores method. The metrics presented are: Probability Of Detection (POD), False Alarm Ratio (FAR), Critical Success Index (CSI), tendency to over/underforecast (BIAS), and the total number of treatments recommended by the DSS for the site, the year, and the host varietal resistance level considered: susceptible (susc), moderately susceptible (mod), and resistant (res). The reference varieties used are indicated in brackets : (Ag)=Agria, (Al)=Alouette, (Bioc)=Bionica, (Biot)=Bionta, (Con)=Connect, (Chal)=Challenger, (Des)=Desiree, (Gas)=Gasore, (SM)=Sarpo-Mira.

Site	Year	Model	Suscept.	POD	FAR	CSI	BIAS	# treat.
Libramont	2010	GD	susc	1	0.53	0.46	2.14	15
			mod (Ag)	1	0.58	0.42	2.4	13
			res (Bioc)	1	0.89	0.11	9	9
		Milsol	susc	1	0.36	0.64	1.57	11
			mod (Ag)	1	0.33	0.67	1.5	10
			res (Bioc)	1	0.87	0.12	8	9
Libramont	2011	GD	susc	1	0.54	0.46	2.17	14
			mod (Ag)	1	0.5	0.5	1.5	12
			res (SM)	1	0.89	0.11	9	9
		Milsol	susc	1	0.54	0.45	2.2	14
			mod (Ag)	1	0.54	0.45	2.2	14
			res (SM)	1	0.91	0.09	11	14
Libramont	2012	GD	susc	1	0.4	0.6	1.67	16
		Milsol	susc	1	0.54	0.45	2.2	18
			mod (Ag)	1	0.64	0.36	2.8	18
			res (SM)	1	0.69	0.31	3.25	18
Libramont	2013	GD	susc	0.5	0.6	0.29	1.25	15
			mod (Ag)	0.5	0.57	0.3	1.16	11
		Milsol	susc	0.71	0.58	0.36	1.71	16
			mod (Ag)	0.83	0.54	0.42	1.83	14
Libramont	2014	GD	susc	0.83	0.58	0.38	2	18
			mod (Des)	0.83	0.5	0.45	1.67	16
			res (Al)	0.33	0.8	0.14	1.67	10
		Milsol	susc	1	0.25	0.75	1.33	14
			mod (Des)	1	0.4	0.6	1.67	13
			res (Al)	1	0.57	0.43	2.33	12
Libramont	2015	GD	susc	1	0.75	0.25	4	16
			mod (Ag)	0.67	0.5	0.4	1.33	8
			res (Biot)	0.4	0.6	0.25	1	6
		Milsol	susc	1	0.76	0.23	4.25	17
			mod (Ag)	1	0.71	0.29	3.4	16
			res (Biot)	1	0.64	0.36	2.8	14
Libramont	2016	GD	susc	0.67	0.55	0.36	1.5	14
		Milsol	susc	1	0.4	0.6	1.67	17

Table 4.1: Results of the comparison of the prediction efficiency of Milsol and Guntz-Divoux (CARAH) models using the contingency scores method. The metrics presented are: Probability Of Detection (POD), False Alarm Ratio (FAR), Critical Success Index (CSI), tendency to over/underforecast (BIAS), and the total number of treatments recommended by the DSS for the site, the year, and the host varietal resistance level considered: susceptible (susc), moderately susceptible (mod), and resistant (res). The reference varieties used are indicated in brackets : (Ag)=Agria, (Al)=Alouette, (Bioc)=Bionica, (Biot)=Bionta, (Con)=Connect, (Chal)=Challenger, (Des)=Desiree, (Gas)=Gasore, (SM)=Sarpo-Mira.

Site	**Year**	**Model**	**Suscept.**	**POD**	**FAR**	**CSI**	**BIAS**	**# treat.**
Libramont	2017	GD	susc	0.83	0.5	0.45	1.67	14
			mod (Gas)	1	0.45	0.54	1.83	12
			res (Con)	0.75	0.7	0.27	2.5	12
		Milsol	susc	1	0.33	0.67	1.5	12
			mod (Gas)	1	0.45	0.54	1.83	12
			res (Con)	0.75	0.7	0.27	2.5	12
LLN	2016	GD	susc	1	0.33	0.67	1.5	11
		Milsol	susc	1	0.4	0.6	1.67	11
LLN	2017	GD	susc	0.8	0.6	0.36	2	14
			mod(Chal)	0.83	0.38	0.55	1.33	13
		Milsol	susc	0.6	0.4	0.43	1	9
			mod(Chal)	0.17	0	0.17	0.17	7
LLN	2018	GD	susc	0.5	0.9	0.09	5	12
		Milsol	susc	0.5	0.8	0.17	2.5	5
Gembloux	2016	GD	susc	0.75	0.5	0.43	1.5	11
		Milsol	susc	1	0.43	0.57	1.75	10
Ath	2014	GD	susc	1	0.55	0.44	2.25	19
		Milsol	susc	1	0.43	0.57	1.75	15
	2015	GD	susc	1	0.67	0.33	3	14
		Milsol	susc	1	0.63	0.36	2.75	13
	2016	GD	susc	1	0.33	0.67	1.5	16
		Milsol	susc	1	0.33	0.67	1.5	15
	2017	GD	susc	1	0.67	0.33	3	14
		Milsol	susc	0.67	0.6	0.33	1.67	9

Table 4.2: Average performance measures based on contingency scores of the Guntz-Divoux (CARAH warnings) and Milsol models according to 3 host susceptibility levels : susceptible (susc), moderately susceptible (mod), and resistant (res). The metrics presented are: Probability Of Detection (POD), False Alarm Ratio (FAR), Critical Success Index (CSI), tendency to over/underforecast (BIAS), and the total number of treatments recommended by the decision support system.

Model	**host susceptibility**	**POD**	**FAR**	**CSI**	**BIAS**	**# treatments**
GD (CARAH)	susc	0.87	0.56	0.41	2.26	14.6
	mod	0.83	0.50	0.45	1.60	12.1
	res	0.70	0.78	0.18	4.6	9.2
MILSOL	susc	0.91	0.49	0.49	1.94	12.9
	mod	0.88	0.45	0.44	1.93	13
	res	0.95	0.73	0.26	5.0	13.1

It should be noted in general that results for moderately susceptible and resistant varieties should be viewed with caution as there are only observations for 7 and 5 (respectively) valid site-year pairs data. We will therefore focus instead on the results given for susceptible varieties for which there are data for 16 site-year pairs. Figure 4.1 and 4.2 below shows the results of the model validation metrics (table 4.2) only for susceptible varieties. The first thing to note is that no differences between the two models are statistically significant (cfr confidence interval at 90% on the figures). However, some trends can still be identified and will be discussed in the next section.

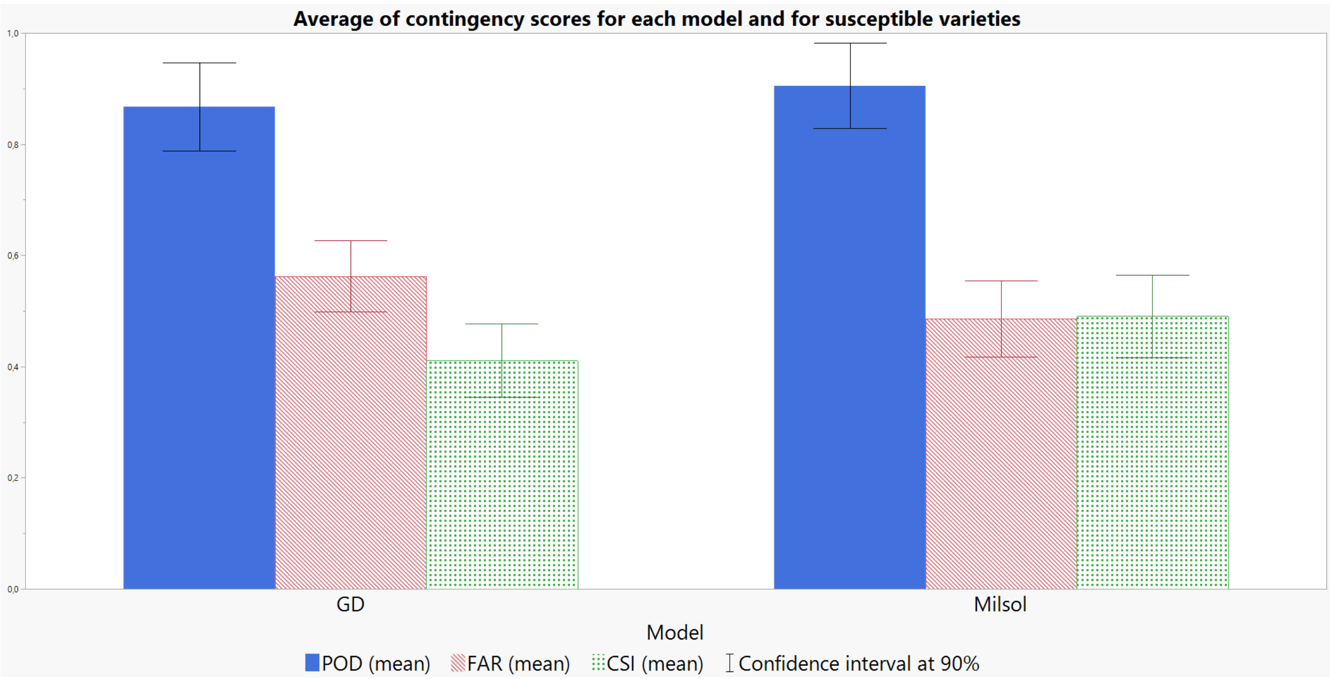


Figure 4.1: Average performance measures based on the contingency scores of the Guntz-Divoux (CARAH warnings) and Milsol models for susceptible potato varieties. The metrics presented are: Probability Of Detection (POD), False Alarm Ratio (FAR), Critical Success Index (CSI), and tendency to over/underforecast (BIAS).

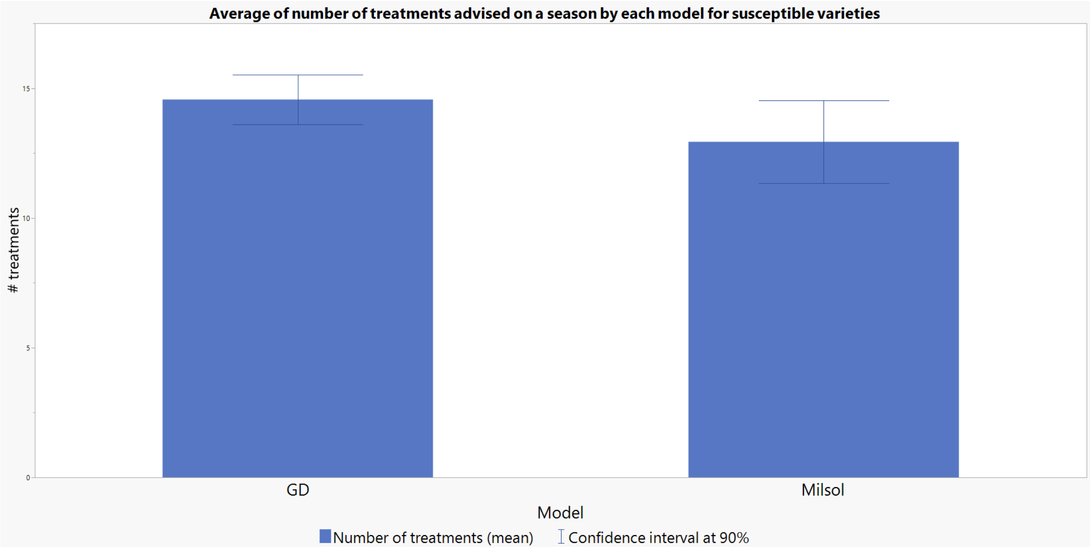


Figure 4.2: Average number of fungicides treatments against potato late blight recommended per season by CARAH warnings (Guntz-Divoux) and Milsol model, for susceptible potato varieties.

4.4 Discussion

First of all, let's remember that all these results presented above must be taken with caution because the majority of the data come from Libramont, a locality where the late blight pressure (in terms of inoculum) is particularly low and not representative of the region where the majority of potatoes are grown (Hainaut and Brabant-Wallon). It should also be remembered that the dataset is also not temporally balanced; some years are more represented than others.

Furthermore, an important thing to note about CARAH warnings is the presence of inconsistencies between the sporulation dates given by the Guntz-Divoux model, and the treatment dates recommended in the late blight warnings (for the same station). These cases of inconsistencies occur a few times a season. The model sometimes simulates sporulation events but no treatment is recommended by the CARAH, or vice-versa (the model does not predict any sporulation during several days but treatment is recommended). The reasons for these inconsistencies may lie in different dimensions of the interpretation step that links the model results to the written warning. First, the consideration of field observations could be a reason (e. g. observation of infection on MILVAR essays and therefore treatment recommended even if the model did not predict sporulation). Cases of particular meteorological events could also be the reason, in particular rainfall (for example, if occasional rainstorms have occurred but could not always be detected by Pameseb stations, CARAH may prefer to recommend treatment for all stations despite the absence of risk according to the model). Another potential reason is that, in order to remove uncertainties related to the position of a field and a station, CARAH takes into account the model outputs for several different stations to give treatment advice for a region (a few nearby stations). Finally, the differences can also come from the calibration of the Guntz-Divoux model by the CARAH.

4.4.1 Varietal resistance

CARAH warnings advised fewer treatments for more resistant varieties but this also reduces the POD, which may mean that some treatments that CARAH advised to avoid for resistant varieties could not have been excluded. This is the case for example in Libramont in 2015. CARAH warnings suggest, for resistant varieties, not to apply treatments during the first half of September. However, at this time in the MILVAR trials, symptoms appear or increase on several resistant varieties (Connect, Bionta, Bionica, Allians), with up to 75% of the leaf area affected on Allians.

Concerning Milsol, the model advises as many treatments for the three host resistance levels. The POD remains very high but so does the number of false alarms.

The very high false alarm ratio value for both models (78 and 73%) for resistant varieties shows that many periods are defined as risk while no infection occurred. The very high BIAS value for both models (4.6 and 5) also shows they are overforecasting infection events. These results suggest that varietal resistance is not yet adequately taken into account in both models, especially for high resistance levels. The next chapter of this thesis (chapter 5) attempts to provide some improving ways to this problem.

An important point must be underlined here regarding the infectivity of resistant varieties, and tempering what has just been said. MILVAR trials are carried out on a test field divided into a large number of plots for each variety. This means that resistant varieties are mixed with (untreated) susceptible varieties which, from the beginning of infection, are an extremely powerful and close source of inoculum. The inoculum pressure on resistant variety plots is therefore abnormally high, and not representative of the reality of an isolated whole field of resistant potatoes. In this sense, it is conceivable that the infection potential of resistant varieties may be overestimated.

4.4.2 CARAH and MILSOL for susceptible varieties

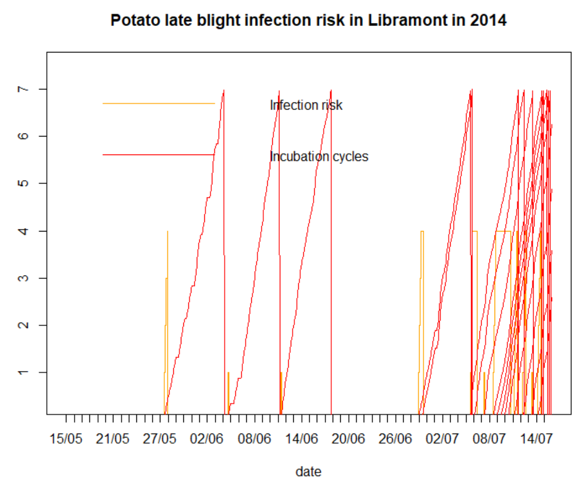
First of all it should be noted that, although no comparison is statistically significant between the two models, concerning the prediction of late blight infections in Bintje, all validation metrics are better for the Milsol model than for CARAH warnings (and Guntz-Divoux model). The mean probability of detection is 4% better for Milsol, which suggests that the French model forecasts slightly better the actual observed sporulation periods. This is essential for the prediction of such a devastating disease, for which a field can be destroyed in a few days if only one infection event is not forecasted. The mean false alarm ratio is 7% better for Milsol, which would mean that it forecasts fewer unobserved infections. Logically, the general accuracy (critical sucess index) of the model is also slightly better for Milsol. The results also suggest that it would be possible to save on average about one more treatment per season by using the French model.

The interannual variability of forecasted risk periods and therefore of the number of treatments is clearly higher for MILSOL than in CARAH warnings. In a year when weather conditions are favourable for late blight (2016 for example), Milsol will recommend as many or even more treatments as CARAH warnings; for Libramont in 2016, Milsol would have recommended 18 treatments while CARAH only 14. On the other hand, in a low pressure year (2018), Milsol will recommend far fewer treatments than the CARAH warnings (5 and 12 respectively at LLN in 2018). This confirms the observation made by Rakotonindraina [53]; in periods of low disease pressure, the quantitative model "Milsol" makes it possible to bypass periods defined as risk by the Guntz-Divoux model.

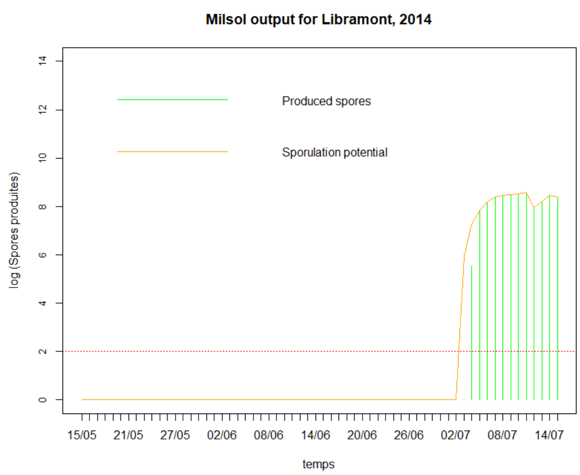
The reason why Milsol is able to bypass periods defined as risky by Guntz-Divoux can be related to the more faithful and rigorous simulation of each step of *P. infestans*'s cycle in the model. Two critical phases of the simulation of *P infestans*'s cycle in Milsol can be highlighted (first the infection step and secondly the sporulation phase), allowing a better monitoring of the pathogen's evolution and therefore a treatment bypass, whereas Guntz-Divoux advises one.

1. **Critical infection phase**: It is the modelling of the infection phase that is decisive for the launch of a cycle. In this type of case, infection is predicted by the Guntz-Divoux model (because the conditions seem favourable to it) so an incubation cycle will be initiated and sporulation will follow. While the Milsol model does not predict infection because the simulated primary inoculum did not survive the conditions at the time of the potential infection. The cycle then stops at the infection stage. Let us take as an example the period from mid-May to the end of June 2014 in Libramont (see figure 4.3).

   During this period, the Guntz-Divoux model predicts three complete disease cycles (infection-incubation-sporulation, see figure 4.3(a)). The first period of infection occurs on May 17. On that day, we observe more than 20 consecutive hours of "wet period" (RH>90% interrupted by periods of 85<RH<90 of maximum 3 hours) to a mean temperature of 11°C. Even if the average temperature is relatively low, the duration of the wet period is so long that Guntz-Divoux predicts a very high risk of infection (4) and therefore launches an incubation cycle (which will end 8 days later with sporulation).



(a) Guntz-Divoux output for Libramont 2014. The infection risk is shown by orange bar and his level is bounded between 0 and 4. Once an infection risk is present, and incubation cycle is launched (red curve). Once the cumulated incubation units has reached the value of "7", the red curve drop to 0 at the vertical, indicating the simulated time of sporulation and therefore a risk period.



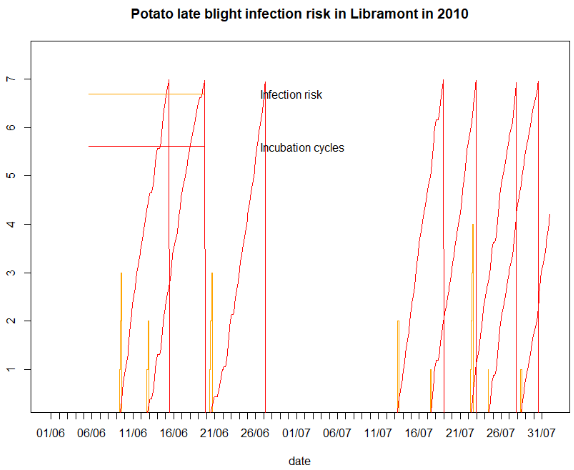
(b) Milsol output for Libramont 2014. The infection risk is not reported in the graph, the only important output is the output $log_{10}(SPORUL)$ which represent simulated sporulation and is indicated by green bars.

Figure 4.3: Output of the Guntz-Divoux and Milsol models for the period from 15/5/2014 to 15/7/2014 in Libramont. Take care in the interpretation of the two graphs, they do not show exactly the same steps of the pathogen's cycle. The time scale (x-axis) is the same, but not the scale of the outputs (y-axis).

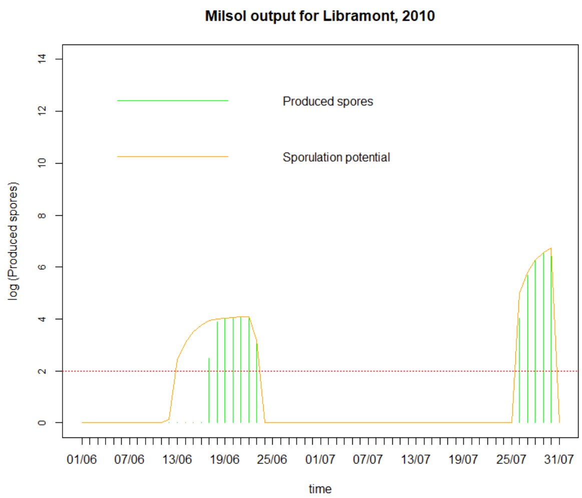
For Milsol during the same period (figure 4.3(b)), the development and germination of spores initiated at 00:00 (midnight) is relatively slow (due to the relatively low temperature of 11°). At about 14-15h, the simulated germination phase is sufficiently far for the spores to be vulnerable but it is not yet complete (100<CUMDDS<150)[1]. At that time, RH falls below the 90% threshold, killing all virtual spores (SURVIE=0 if (CUMDDS>100) & RH<90%) and impeding simulated infection.

2. **Critical sporulation phase**: In this type of case, the simulation of infection and incubation are done more or less at the same time by both models. But in the Guntz-Divoux model, sporulation occurs systematically at the end of the incubation cycle. While in the Milsol model, additional variables simulate the sporulation development and potential in relation to the actual sporulation.

   Let's take for example the month of June 2010 in Libramont. For the Milsol model (see figure 4.4(b)), an infection occurred on 8/6, the subsequent incubation ends around June 13. From June 13 to 16, there is therefore a positive sporulation potential (SPOSPO) BUT this sporulation potential is not expressed in number of spores actually produced (SPORUL) because the proportion of spores actually produced (ACTISPO) is zero. ACTISPO value is null because the simulated cohort did not accumulate enough sporulation development units (TUSPORU) because there were few hours at RH>90% and these "wet hours" were cold (below 10°C). Treatment can therefore be initiated later (around June 16-17) when the sporulation units have been accumulated and the simulated "real" sporulation occurs. In the Guntz-Divoux model (see figure 4.4(b)), these subtleties of sporulation potential and sporulation development units are not taken into account. Sporulation occurs on June 15, 19 and 27, requiring the application of treatments throughout this period.



(a) Guntz-Divoux output for Libramont 2010



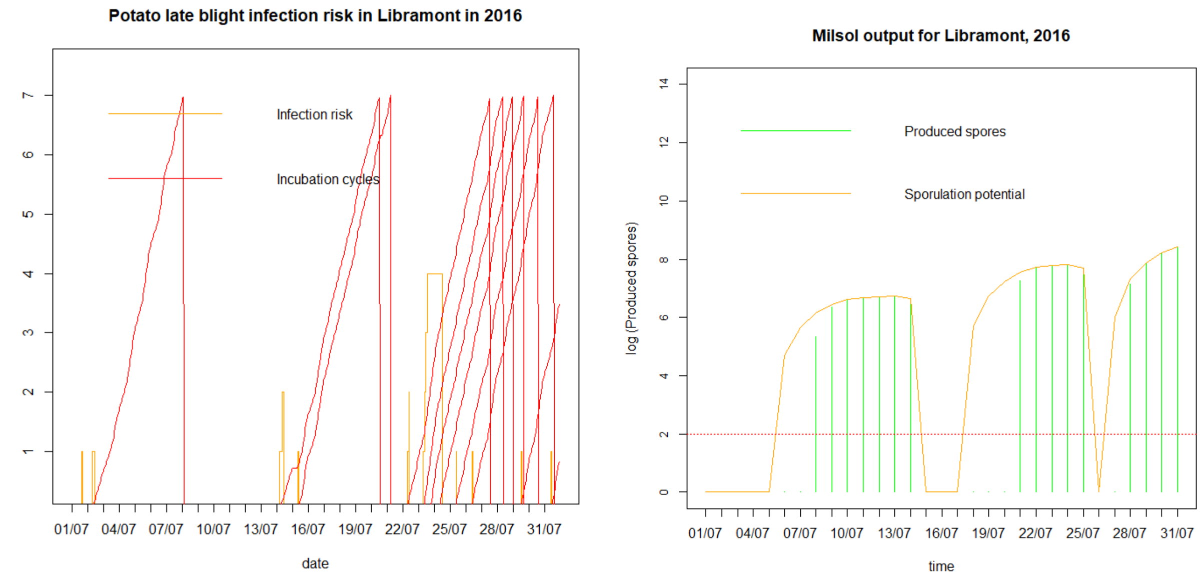
(b) Milsol output for Libramont 2010

Figure 4.4: Output of the Guntz-Divoux and Milsol models for the period from 01/6/2010 to 31/7/2010 in Libramont. The interpretation of the two graphs must be done in the same way as explained in the legend of the figures 4.3 (a) and (b).

[1]See figure 2.1 at section 2.1 for the references of the different variables

The above examples further show why Milsol has a lower false alarm ratio than Guntz-Divoux. But if the French model seems more "selective" about the number of infections (and therefore recommended treatments), how does it manage to have a better POD than Guntz-Divoux? The month of July 2016 in Libramont will be used as an example. According to Guntz-Divoux, only one sporulation (from a low infection) occurs on July-8 and then no sporulation occurs between July 9 and 19 (see figure 4.5(a)). In such cases, CARAH does not recommend treatments because they do not consider that July-8 sporulation will cause any outbreak to the crop due to unfavourable conditions. However, at the same time, there was an explosion of symptoms in the Bintje plots of the MILVAR trials. On the other hand, the Milsol model also predicts sporulation on July-8. However, as soon as the sporulation threshold is exceeded, Milsol recommends treatment, which was necessary in this case.

Finally, it is important to note that while Guntz-Divoux predicts punctual sporulation on a single day, Milsol simulates dynamic sporulation over several days, for which development is dependent on temperature and RH.



(a) Guntz-Divoux output for Libramont 2016

(b) Milsol output for Libramont 2016

Figure 4.5: Output of the Guntz-Divoux and Milsol models for the period from 01/7/2016 to 31/7/2016 in Libramont. The interpretation of the two graphs must be done in the same way as explained in the legend of the figures 4.3 (a) and (b).

4.4.3 Perspectives for Milsol

In the hypothesis of a future practical use of the Milsol model, it should be noted that the high dependence of Milsol outputs on weather variability raises the importance of providing the model with accurate and quality weather data, emphasizing the interest of the AGROMET system. Indeed, since the model is more complex, it is probably more sensitive to weather inputs than the Guntz-Divoux model and the sensitivity analysis performed in this thesis is not valid for Milsol.

A quick tuning of the Milsol model was performed for the conditions of germination, survival, development and sporulation of spores. Instead of considering only a relative humidity threshold of 90% at these stages, it has been set at 89% and the occurrence of rain is also considered as a factor satisfying the moisture conditions of the leaf, even if the humidity threshold is not reached. The tuned Milsol model forecasted 2 out of the 6 infection events that were not identified with conventional Milsol. It should be noted that, even if the Milsol model does not take rainfall as input, it is probably reflected in the relative humidity records. It is indeed expected that, after a rainy period of several hours, the relative humidity will be increased by evaporation.

In addition, it should be noted that a real expertise related to the interpretation of the Guntz-Divoux model has been built for many years and probably allows a better consideration of the outputs of this model. It is conceivable that similar expertise would also develop with the handling of the MILSOL model, further improving its performances.

Finally, it should be noted that in the Mileos decision support system, other factors are taken into account, such as observations in the field, but also the protection status of the crop through the computation of leaching and remanence of the fungicides applied. This last point can be crucial and could make it possible to further reduce the number of sprays in practice if the farmer has treated with some penetrating, translaminar and/or systemic products (for which the persistence is often longer than 7 days).

Chapter 5

Calibration of the Milsol model to identify the effect of host resistance on the disease cycle

5.1 Introduction

As demonstrated in the previous chapter, it seems that the effect of potato varietal resistance to late blight is not yet adequately taken into account in risk prediction models such as Guntz-Divoux or Milsol. Despite the existence for many years of effective potato varieties that are low susceptible to late blight, little is known about the plant-pathogen interactions that restrict infection. These models consider that the pathogen cycle occurs in the same way (same infection process, same incubation period and same sporulation potential), whether the infection of *P. infestans* takes place on susceptible or resistant potato cultivars.

Currently, varietal resistance is taken into account by fixed threshold values that must be reached by the model outputs. These thresholds values differ according to the level of host varietal resistance. For both Milsol and Guntz-Divoux models, two outputs of the models allow to discriminate the risk prediction according to the level of the host plant susceptibility:

- the **infection severity**, represented by a value of 0 to 4 in Guntz-Divoux, and by the SPORUL output variable (0 to 10) in Milsol. The higher the host resistance level, the higher the threshold of infection severity to be reached.
- the **number of simulated generations** of *P. infestans* (complete cycles) to be achieved before considering that a risk of infection is plausible. The higher the host resistance level, the higher the number of generations to be reached.

The objective of this chapter is to vary some model parameters and output thresholds from Milsol model, and to compare simulated outputs with actual observed in-field data in order to:

1. identify the step(s) of *P. infestans*'s cycle on which varietal resistance acts, using the model outputs as a "proof-of-concept".
2. possibly recalibrate the model parameter(s) and/or outputs thresholds (for one two, or the three levels of varietal susceptibility) so that it corresponds better to reality.

5.2 Material and method

The method and data used in this chapter are very similar to those used in the previous chapter. This method is inspired by a chapter from Maxime Duvivier's thesis [24]. His work consisted in assessing the performance of two forecasting models (from meteorological data) for predicting the risk of wheat leaf rust, a wheat disease caused by the fungus *Puccinia triticina*. Given the strong similarities between *P. infestans* and a classical phytopathogenic fungus (cycle, symptoms, etc.), it is considered that Duvivier's method is also relevant in the late blight context.

The epidemiological data observed in-field we will use are the data from the MILVAR trials. These are agronomic assays testing about twenty potato varieties of different resistance levels to late blight, replicated in 4 complete random blocks. The data used were collected from 2010 to 2017 in Libramont, and in 2016 in Gembloux. The evolution of the disease is monitored every 3-4 days by measuring disease severity, the percentage of leaf area affected by late blight.

The reference variety for the susceptible class is Bintje. For the intermediate class (moderately susceptible), the varieties Agria, Challenger, Gasore, or Desiree are considered. The reference varieties for the high resistance level are Sarpo Mira, Connect, Bionta, Bionica, or Alouette. For the "moderately susceptible" and "resistant" levels, it is chosen to change the reference variety over years in order to have a better overview of the predictive potential of the models.

As in the previous chapter, the matching between the model outputs and the observed data is assessed by contingency scores:

- a = observed and forecasted sporulation.
- b = forecasted but not osberved sporulation.
- c = observed sporulation but not forecasted.

Unlike the previous chapter, these contingency scores are calculated at the daily time step [1] while in the previous chapter, these contingency scores were calculated on the scale of the fungicide treatment (several days). For a given day, sporulation is simulated by Milsol if the number of late blight generations and threshold value of the simulated SPORUL variable are reached on that day. Sporulation is considered to occur on observed data if that day falls within a time interval during which symptoms onset has been spotted or mean disease severity in the reference variety has "significantly increased". As Duviver proposed, a "significant increase" is considered to occur when an increase of at least 1% in disease severity is measured when it is low (<10%) or an increase of at least 10% in disease severity is recorded when it is high (>10%). When the average disease severity exceeds 85%, the data are considered no longer available.

Using the contingency scores, the following metrics can then be calculated: Probability Of Detection (POD), False Alarm Ratio (FAR), and Critical Success Index (CSI) (see section 4.2 for the meaning and equations of these metrics.).

Given the large number of parameters included in the Milsol model and for computation time reasons [2], it is necessary to wisely choose the parameters that will be adjusted. The diagram of the structure of the Milsol model is shown again in the figure 5.1.

[1] It is indeed easier to implement an automatic computation of contingency scores at the daily time step.

[2] A single Milsol simulation with a given set of parameters, in a given location, and for one growing season (April to September), takes about 6 minutes to run on a standard laptop computer.

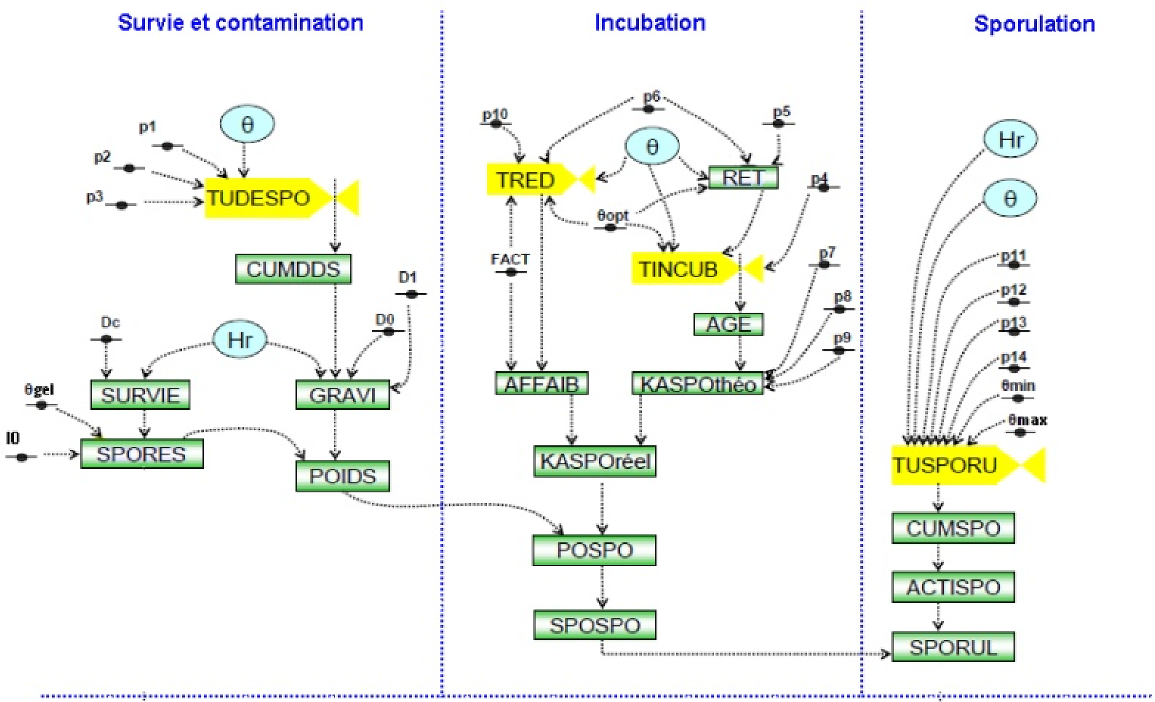


Figure 5.1: Forester diagram of the Milsol model [15]. Variable CUMDDS simulate the degree of spore development. Variable SURVIE models the survival of primary inoculum (SPORES). Variables GRAVI and POIDS compute the infection potential. Variable AGE represents the incubation degree, depending on incubation rate (TINCUB) and mitigated when temperature is too hot (RET). Variable KASPOréel simulates the sporulation potential depending on incubation degree (AGE) and attenuated when temperature is too hot (AFFAIB). Variables POSPO and SPOSPO compute the sporulation potential depending on the infection level (POIDS). Variable CUMSPO correspond to the degree of sporulation development. ACTISPO is the fraction of spores actually released. SPORUL is the final output variable representing the number of spores actually released.

The first compartment of the model (survival and contamination) mainly models processes inherent to *P. infestans* spores; the variables CUMDDS, SURVIE and SPORES model the development, survival and germination of spores, so varietal resistance probably does not influence these processes. GRAVI and POIDS variables represent the potential for contamination, i.e. the penetration of plant tissues by zoospores or sporangia, and could therefore be influenced by varietal resistance. However, a high value of the contamination potential would be reflected in the SPORUL variable (GRAVI -> WEIGHT -> POSPO -> SPOSPO -> SPORUL). It is therefore more efficient to adjust the SPORUL threshold value to be reached, rather than the calculation of GRAVI and POIDS variables, as this allows the model to be run only once. Note that the variable output SPORUL depends both on the severity of the infection, the potential for sporulation in relation to incubation, and the effective simulated sporulation.

The second compartment (incubation), on the other hand, involves strong relationships between the plant and *P. infestans* because it simulates mycelium development in plant tissues. RET, TRED and AFFAIB simulate incubation delay due to over-optimal temperatures (>18°C), so they link the climate to the pathogen growth but is probably not linked with the plant genotype. We therefore first wanted to modify the parameter p4, which corresponds to the temperature multiplication factor to get the incubation rate (TINCUB). The problem is that Milsol models a continuous sporulation period over several (degree-)days and not a punctual one. A decrease in the p4 parameter therefore results in a slight delay in sporulation, but also extends this period, increasing the number of forecasted sporulating days (see figure 5.8 in Annex 6). It is not expected that the incubation process will occur in this way in more resistant varieties.

Considering the "side effect" of parameter p4, it is chosen instead to modify the values of parameters p7 and p8. p7 corresponds to the degree of incubation (AGE) from which the sporulation potential begins, and p8 corresponds to the degree of incubation at which the sporulation potential is maximum. By modifying these parameters, in particular p7, incubation is delayed but without extending the sporulation period (see figure 5.9 in Annex 7), which would represent the fact that more tolerant cultivars would set up defence mechanisms to limit the development of mycelium in their tissues. Parameter p9, which corresponds to the degree of incubation at which sporulation is over ("too old" cohort), remains fixed (at 225).

The third compartment of Milsol models the effective sporulation. Once the degree of incubation has been reached the p9 value, sporangiophores have developed on the leaf surface and sporulation (production and release of sporangia) depend on weather conditions, and maybe the plant genotype (cultivar). It is however expected that the plant will have little impact on this part of the cycle.

Considering what has been discussed above, here are the parameters and output thresholds that will be varied as well as the values that will be tested. The values in bold correspond to the original ones.

- p7 : incubation degree at which sporulation potential begins. Tested values : **75** - 95 - 115.

- p8 : incubation degree at which sporulation reach its maximum potential. Tested values : **150** - 170 - 190.

- sporul threshold : threshold on the common logarithm of the SPORUL variable to be reached to consider that there is a disease risk. Tested values : **2 (susc)** - **3 (mod)** - **4 (res)** - 5 - 6 - 7.

- generation threshold : number of cycles of *P. infestans* to be achieved before considering a potential for infection. Tested values : 2 - **3 (susc)** - **4 (mod)** - **5 (res)** - 6 - 7 - 8 - 9 - 10 - 11 - 12 - 13 - 14 - 15.

Weather data to supply Milsol model are provided by CRA-W/Pameseb network. For Libramont, we use data from a weather station on the site itself where epidemiological data were collected. For Gembloux, we used data from the Sombreffe weather station, located 9km away.

For each combination of parameters and each of the three levels of host susceptibility to late blight (susceptible, moderately susceptible, and resistant), the contingency scores (and the performance metrics) are calculated over the 9 MILVAR trials (2010-2017 for Libramont and 2016 for Gembloux). The R code implementing this calibration method is available in Annex 8.

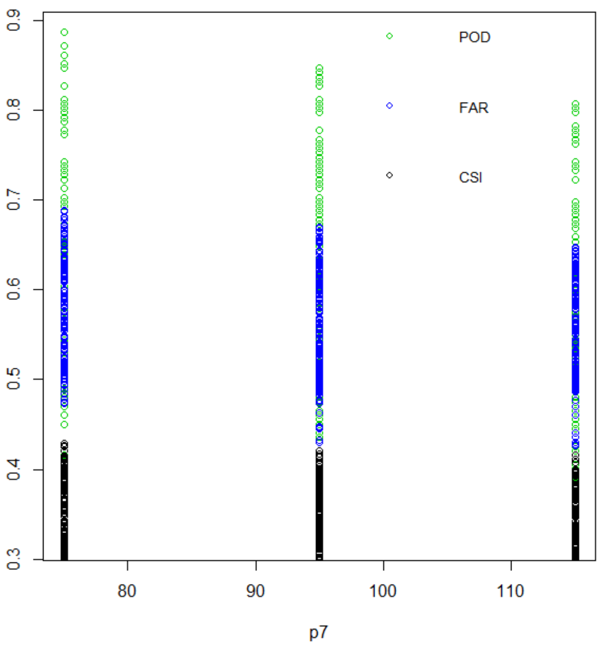
5.3 Results

The table 5.1 below shows the optimal parameter combinations (for the 4 parameters that have been varied), for each of the three host resistance levels, and according to the performance metric of interest (the one we want to optimize). It also shows the values of the three metrics for each set of parameters. When the maximum value of the metric of interest is reached for different sets of parameters, the combination of parameter that optimizes the other two metrics is indicated.

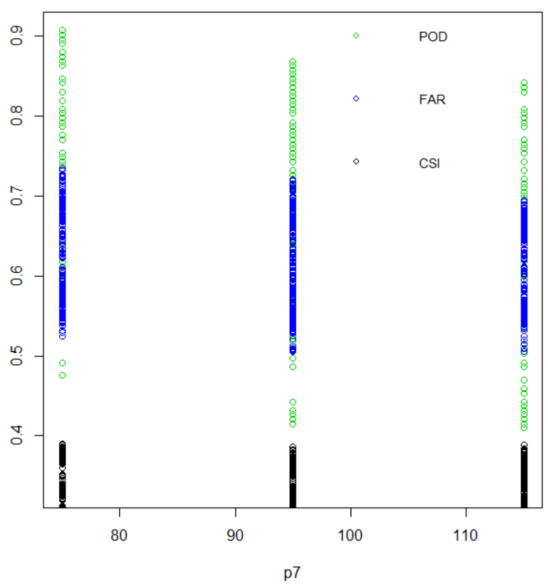
Table 5.1: Table of optimal combinations of Milsol model parameters according to the performance metric of interest, by comparing Milsol outputs and in-field observations from MILVAR assays from 2010 to 2017. The performance metrics are Probability of Detection (POD), False Alarm Ratio (FAR), and Critical Success Index (CSI). Calibration was performed for the following parameters: p7 (degree of incubation from which the sporulation potential begins), p8 (degree of incubation at which the sporulation potential is maximum), sporul threshold (threshold of the output variable SPORUL to be reached to consider that there is a risk of infection) and gen threshold (number of generations to reach before considering that there is a risk of infection).

Resistance level	**Interest metric**	**Other metrics**		**p7**	**p8**	**sporul threshold**	**gen threshold**
Susceptible	POD=88.6	FAR=60.0	CSI=38.1	75	150,170,190	2	6
	FAR=42.6	POD=32.7	CSI=26.3	115	170	7	15
	CSI=42.9	POD=80.2	FAR=52.1	75	150,170,190	2	9
Moderately susceptible	POD=90.7	FAR=66.8	CSI=32.1	75	150,170,190	2	6
	FAR=50.5	POD=50.8	CSI=33.4	95	170	5	15
	CSI=39.0	POD=86.9	FAR=58.6	75	150,170	3	9
Resistant	POD=91.1	FAR=79.5	CSI=20.1	75	150,170,190	2	9
	FAR=72.9	POD=50.0	CSI=21.3	115	150,170,190	6	15
	CSI=21.9	POD=68.9	FAR=75.7	115	150	6	9

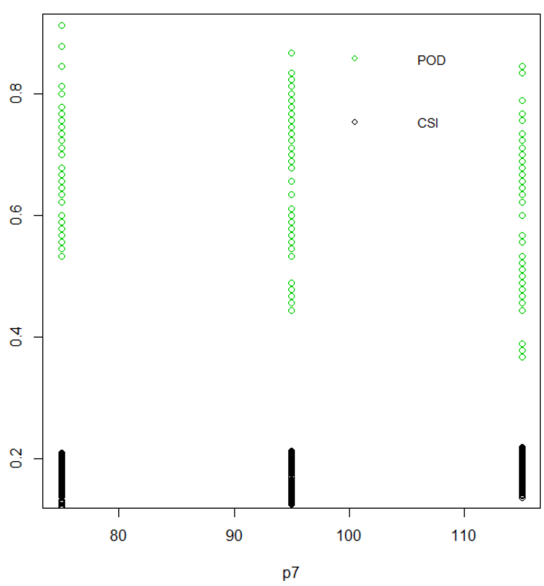
Figure 5.2 shows the evolution of the three metrics (POD, FAR and CSI) according to the value taken by the parameter p7 and by level of host varietal resistance. Given the decrease in the POD obtained when the level of parameter p7 increases, and so for the three levels of resistance, it can be said that in this range of values (75 to 115), the variation of parameter p7 does not seem to be a good way to adapt Milsol to varietal resistance.



(a) Susceptible variety (Bintje)



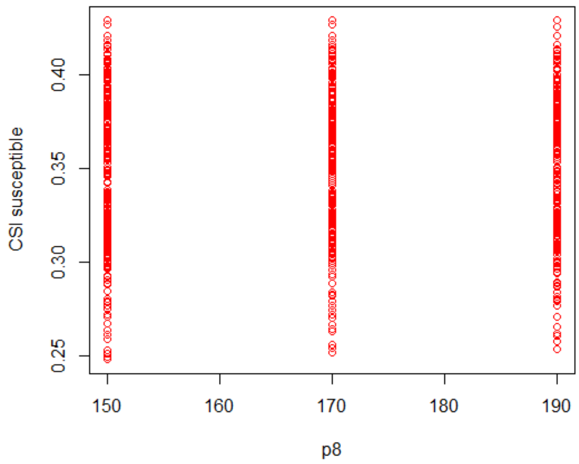
(b) Moderately susceptible varieties (Agria, Challenger, Gasore, Desiree)



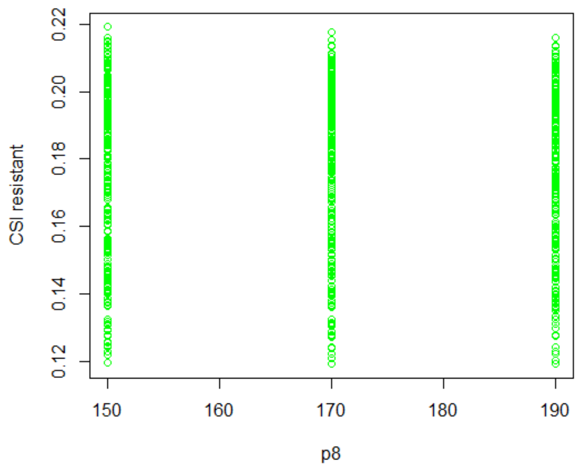
(c) Resistant varieties (Sarpo Mira, Connect, Bionta, Bionica, Alouette)

Figure 5.2: Milsol metrics: Probability Of Detection (POD), False Alarm Ratio (FAR), and Critical Success Index (CSI) obtained according to the value taken by the parameter p7 and for all simulations of the calibration (for all values of other parameters) comparing Milsol outputs with in-field observations from MILVAR assays from 2010 to 2017.

Figure 5.3 shows the critical success index measured in relation to the variation of the parameter p8. We can see that no particular pattern emerges from the graphs, proving that the variation of the p8 parameter in the 150-190 range has very little impact on the model response.



(a) CSI for susceptible variety (Bintje)

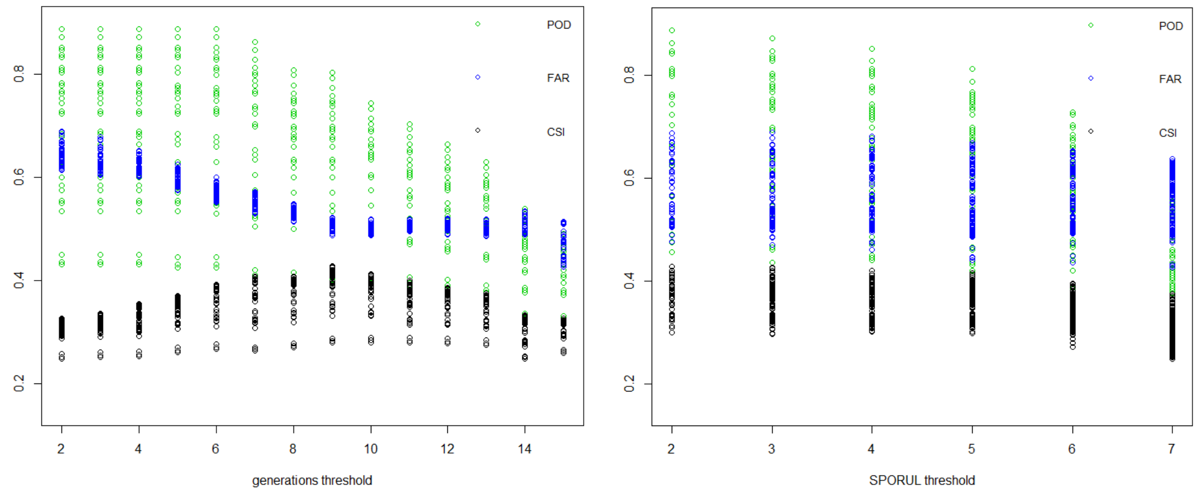


(b) CSI for resistant varieties (Sarpo Mira, Connect, Bionta, Bionica, Alouette)

Figure 5.3: Critical success index (CSI) of the Milsol model obtained according to the value taken by the parameter p8, for susceptible and resistant cultivars, and for all simulations of the calibration (all values of other parameters). The calibration is done by comparing Milsol outputs with in-field observations from MILVAR assays from 2010 to 2017.

Figure 5.4(a) shows the evolution of the three metrics for susceptible variety (Bintje) as a function of the value taken by the generation threshold to be reached. We can see that we can afford to increase the threshold of simulated generations to reach the value of 6 for Bintje, without reducing the probability of detection but well the false alarm ratio. Between 7 and 9 generations, the POD decreases but the FAR decreases more quickly, so the CSI is still increasing. Figure 5.4(b) shows the evolution of the three metrics for susceptible variety (Bintje) as a function of the value taken by the SPORUL threshold to be reached. It can be seen that we cannot afford to increase the SPORUL treshold above the value of "2" without decreasing the POD. In addition, increasing the SPORUL threshold in the range of value 2 to 5 does not seem to allow to decrease the FAR.

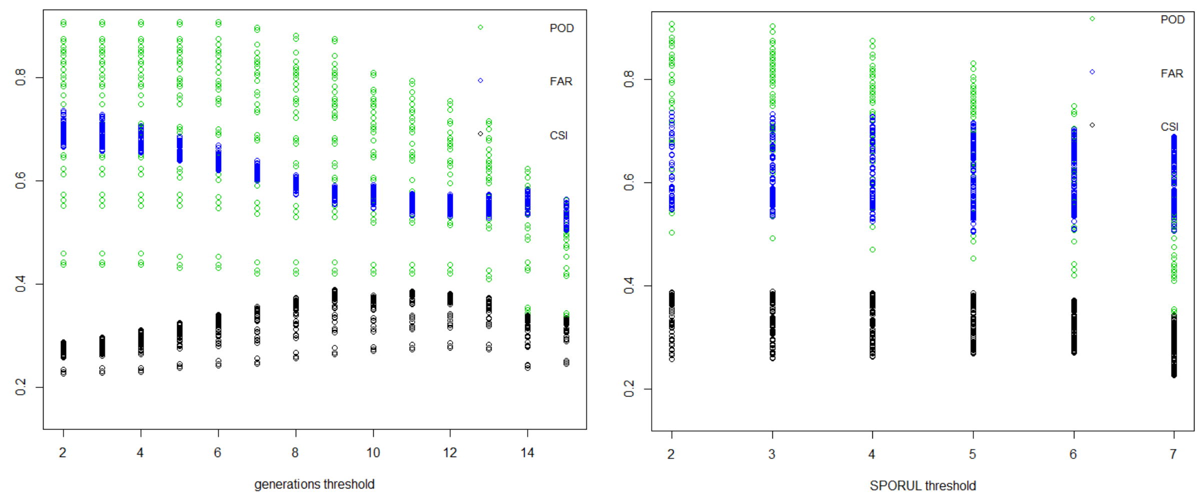
Figure 5.5(b) shows the evolution of the three metrics for moderately susceptible varieties as a function of the value taken by the SPORUL threshold to be reached by the model to consider an infection risk. For this host susceptibility level, it is possible to increase the SPORUL threshold to 3 (without decreasing the POD) but it does not especially decrease the FAR. Figure 5.5(a) shows it is possible to reach the generations threshold to 6 to 9. Between 6 and 9, the POD decrease but not so much (and the FAR is also decreasing, which is positive), while above the 9 value, FAR do no decrease a lot while POD does well.



(a) Milsol metrics depending on generation threshold

(b) Milsol metrics depending on SPORUL threshold

Figure 5.4: Probability of Detection (POD) , False Alarm Ratio (FAR), and Critical Success Index (CSI) obtained for the Milsol model, for susceptible variety (Bintje), according to the number of simulated late blight generations and SPORUL thresholds to be reached before considering there is an infection risk, and for all simulations of the calibration (all values of other parameters). The calibration is done by comparing Milsol simulated outputs with in-field observations from MILVAR assays from 2010 to 2017.

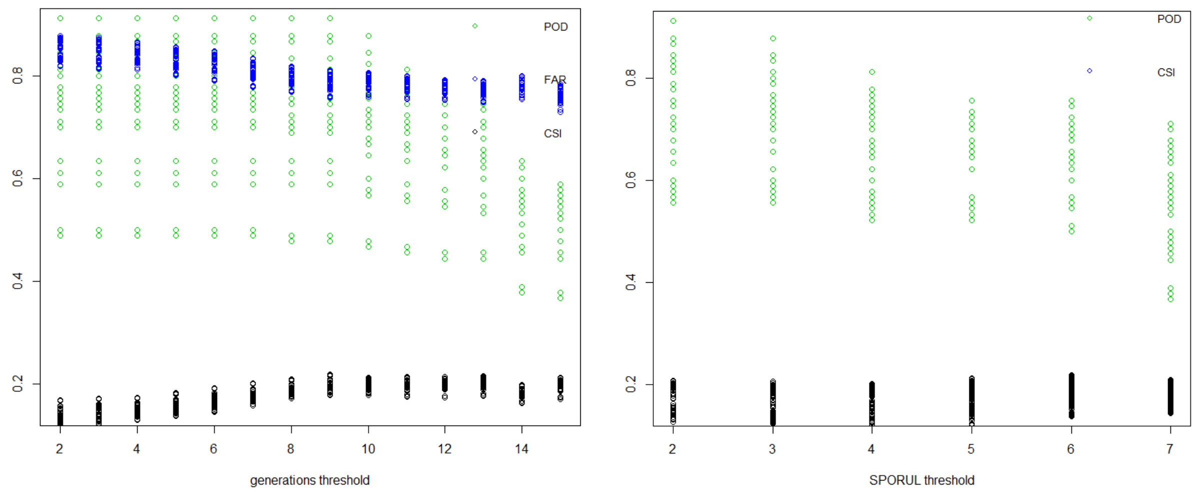


(a) Milsol metrics depending on generation threshold

(b) Milsol metrics depending on SPORUL threshold

Figure 5.5: Probability of Detection (POD) , False Alarm Ratio (FAR), and Critical Success Index (CSI) obtained for the Milsol model and for moderately susceptible varieties (Agria, Challenger, Gasore, Desiree), according to the number of simulated late blight generations and SPORUL thresholds to be reached before considering there is an infection risk, and for all simulations of the calibration (all values of other parameters). The calibration is done by comparing Milsol simulated outputs with in-field observations from MILVAR assays from 2010 to 2017.

At last, figure 5.6(a) shows the evolution of the metrics for resistant varieties as a function of the value taken by the generations threshold to be reached by the model to consider an infection risk. It seems that the number of "latent" generations for this sensitivity class can be increased to 9, without decreasing the POD but rather the FAR. Figure 5.6(b) shows the evolution of POD and CSI (FAR has not been displayed for clearness reasons) in relation to the SPORUL threshold. This graph suggests that the SPORUL threshold can be brought to the value of 3, as for moderately susceptible varieties, but not higher, otherwise the POD would be affected.



(a) Milsol metrics depending on generation threshold

(b) Milsol metrics depending on SPORUL threshold

Figure 5.6: Probability of Detection (POD) , False Alarm Ratio (FAR), and Critical Success Index (CSI) obtained for the Milsol model, for resistant varieties (Sarpo Mira, Connect, Bionta, Bionica, Alouette), according to the number of simulated late blight generations and SPORUL thresholds to be reached before considering there is an infection risk, for all simulations of the calibration (all values of other parameters). The calibration is done by comparing Milsol simulated outputs with in-field observations from MILVAR assays from 2010 to 2017.

5.4 Discussion

It has been tested to change the values of some parameters of the Milsol model in order to better adapt the model to the host varietal susceptibility level. The table 5.1 shows a results summary although these need to be qualified by the figures 5.2, 5.4, 5.5 and 5.6.

First, it seems that in the range of values tested here (150 - 190), variation of the p8 parameter value has a very small (or even non-existent) influence on the performance measurements, and therefore on the outputs of the Milsol model, and so regardless of the resistance level. Indeed, for most of the rows in the table 5.1, regardless of the level taken by parameter p8, the values of the three metrics are exactly the same. This suggestion is supported by the graph 5.3.

Secondly, the combinations of parameters that minimizes the False Alarm Ratio are not realistic for any level of resistance. Indeed, they consider thresholds (sporul and generations) and values of parameters p7 and p8 that are not relevant, but rather minimize the total number of predicted days with a risk of sporulation in general. We see that, when we try to minimize the FAR, the Probability of Detection drops by several tens of percents, which is unacceptable for the model.

On susceptible varieties (in this case Bintje), the maximization of the CSI as well as the POD suggests that the ideal parameters values would be p7=75 and sporul threshold=2 (original values of the Milsol model). For a threshold generation of 9 (best CSI), the probability of detection is about 8% lower than the POD for a threshold generation of 6 (best POD). For this reason, and given the high destruction rate of late blight, particularly with susceptible cultivars, the priority must be given to the probability of detection, therefore a threshold generation=6.

On moderately susceptible cultivars, again if we focus on optimizing the POD and CSI, and based on the evolution of these metrics in the figures 5.5, the combinations of optimal parameters are almost identical to those for susceptible varieties; p7=75, generation threshold = 6 or 7. The optimization of the CSI also suggests that, for this moderately susceptible susceptibility class, it would be possible to increase the sporul threshold to 3. This is confirmed by the trend of the POD on graph 5.5(b). For the combination of parameters p7=75, p8=150, generation threshold=7 and SPORUL threshold=3, the performance metrics take the following values: POD=89.1 and CSI=35.1, which makes of this set of parameters a good trade-off between best POD and best CSI.

On resistant varieties, the situation is a little more complex. If we want to maximize the CSI, we can afford to set all the parameters to a very high value (cfr table 5.6: p7=115, sporul threshold= 6 and generations threshold=9). However, given the very low POD obtained for this set of parameters, as well as the very low gain of CSI allowed by this set compared to the CSI obtained when maximizing the POD, it seems more appropriate and reasonable to consider the parameter set that maximizes the POD: p7=75, p8=150, sporul threshold=2 or 3, and generations threshold=9.

All these results as well as the figures 5.2 suggest that, for the range of values tested for the parameter p7 (75 - 115), the incubation period of *P. infestans* is not delayed in potato varieties more resistant to late blight. However, these results indicate that the number of late blight generations spent before the risk of infection is present, as well as the threshold of sporulation intensity (which reflects the severity of the cycle as a whole; infection, incubative age of the cohort, and sporulation) are indeed higher among the more resistant varieties. These two thresholds already change according to the varietal resistance in the original Milsol model, which reinforces the validity of these results.

Note that the reason we obtain higher generations thresholds (6 to 9) than those of the original Milsol model (3 to 5) is because we have computed the number of generations here automatically for each season since April 1st. While in the original Milsol model, they start calculating the number of generations at the "beginning of the season" (i.e. probably when planting begins).

It should be noted in general that the increase in SPORUL threshold does not seem to reduce the FAR significantly (much less than what the increase in generations threshold does), see figure 5.4(b), 5.5(b) or 5.6(b). This is explained by the fact that in the "high" season (June to September), high SPORUL values (>7) are reached during most of the days at positive infection risk.

Except for the number of late blight generations to be achieved (which is not a stage in the cycle per se), we have therefore not been able to identify a specific step in *P. infestans*'s cycle that is restricted by potato variety resistance. The still high false alarm ratio value (even for a threshold generation=9) for resistant varieties indicates that there is still a lot of work to be done to improve the fit between model outputs and observations for these varieties. It is possible that the value of p7 is much higher than that of the original model, which has not been tested here. It is also possible that a more unexpected stage of the cycle is involved, such as sporulation (development of sporangiophores on the leaf surface). One could also imagine that it would be necessary to add a variable to the model that would simulate the penetration of plant tissues by *P. infestans* as a function of varietal resistance and infection severity for example. There are therefore many potentials areas of study but few clues to give directions to take.

As in the previous chapter, an important point must be underlined here regarding the infectivity of less susceptible varieties, and tempering what has been discussed here. MILVAR tests are carried out on a test field divided into a large number of plots for each variety. This means that resistant varieties are mixed with susceptible varieties which, from the beginning of infection, are an extremely powerful and close source of inoculum. The inoculum pressure on resistant variety plots is therefore abnormally high, and not representative of the reality of an isolated whole field of resistant potatoes. In this sense, it is conceivable that the infection potential of moderately susceptible and resistant varieties may be overestimated.

A second important point probably distorts the results obtained here and refers to the method used. In order to be able to compare the data observed in fields (monitoring of disease severity, i.e. % of leaf area affected by symptoms) with the outputs of the Milsol model (simulated sporulation or not), we considered that thresholds of observed disease severity increase corresponded to an effective sporulation (see method at section 5.2). By this rather simplifying method, once these thresholds are exceeded, information related to the degree of severity of the disease severity evolution is lost. However, when we look at any disease severity curves (see for example figure 5.10 at Annex 9), we can see that foliage infection appears on resistant varieties a little later (10-15 days) than on susceptible ones, but especially disease severity increases at a lower rate, and stabilizes at a certain ceiling. It seems, however, that the observed increases in disease severity in less susceptible cultivars are often sufficient to exceed the thresholds used in this method, identifying these periods as effective sporulation periods, but information on the amount of the increase in disease severity is lost. This information is nevertheless decisive and is precisely the great interest of more tolerant varieties.

In addition, it should be reminded that the reference variety considered for in-fields observation changed from year to year for moderately susceptible and resistant cultivars. In order to be able to compute the contingency scores, a reference variety must be selected for each year on which at least symptom onset has been observed on the test plot (e. g. 2010 Bionica, 2011 Sarpo-Mira, 2014 Alouette, etc). Varieties (especially resistant ones) on which no symptoms were observed during the monitoring period could therefore not be used. This implies that varieties are actually not randomly chosen every year, leading to an overestimation of the infection capacity on less susceptible varieties.

Finally, and until the effect of varietal resistance on the disease cycle is better characterized, studies conducted to exploit varietal resistance [45] suggest that it is possible to reduce the doses applied for more resistant varieties (provided that the level of resistance to tuber blight follows the level of resistance to foliage blight). The higher the disease pressure (case of Belgium), the lower the dose reduction ; in high disease pressure, doses can be decreased by only 20% compared to the recommended dose.

Conclusion

The literature review of this thesis showed that Belgium is the European country that sprays the most fungicide treatments (about an average of 19) in potato farming per season, three to four times more than the countries that spray the least (about 5 in Northern countries), but also more than neigbouring countries (11, 14 and 15 respectively for England, The Netherlands and France). The reasons for these disparities between European countries are not well-known. It is indeed not clear how combinations of blight weather conditions, the importance of different inoculum sources (i.e. dumps, volunteers and oospores), the use of resistant cultivars, varying pathogen populations, the use of DSS's and the density of potato fields influence differences in fungicide use between European countries [31]. Through strong exchanges between national institutes in these areas, the relative importance of these different drivers should be identified in order to better target the levers to be exploited to reduce the application of plant protection products in our regions.

It is also currently observed that, despite the existence of potato cultivars sustainably resistant to late blight, these are not used on a large scale. The reasons given are related to the qualities (morphology, culinary, and yield) of the susceptible varieties, as well as the high risk of disease perceived by the farmer by reducing the amount of treatments on resistant varieties [16]. It therefore seems that work needs to be done both at the level of farmers, traders and processing industries to encourage the use of these resistant varieties. This can be achieved for example through economic incentives for the use of resistant varieties for the processing industry (taking care that the consequences do not fall back on the farmer). In the context of this thesis, this also means taking better account of host varietal resistance in decision support systems in order to better exploit the potential of these cultivars, and also to earn the farmer's confidence for their use. Indeed, it was demonstrated in the chapter 4 for the two models tested that, either the decrease in treatments recommended by these DSS's was not done at the right time (because treatments were avoided but disease was observed on untreated trials), or no decrease in recommended treatments was done, which discredits all the interest of these cultivars. The new calibration attempts of the Milsol model made in this thesis at chapter 5 have also failed to save periods forecasted as "at risk", without reducing the detection of actual infection periods, even for high level of varietal resistance. It is possible that these results may be fooled by the overestimation of infectivity on less susceptible varieties because of their proximity to infected susceptible cultivars, acting as a very close and powerful source of inoculum. In order to avoid this side effect and to measure the resistance capacity of cultivars under more standard growing conditions, it may be appropriate to distribute trials with different varietal resistance levels to separate fields.

The epidemiological model used in France "Milsol" was tested in the Walloon context retrospectively on observed in-field data monitoring the disease. The performance metrics of this model, based on contingency score computations, suggest that it would provide better results than the current warnings issued by the CARAH, especially for susceptible varieties (Bintje). It should be noted, however, that this difference is not statistically significant. In addition, most of the observed data came from a trial field at Libramont, a site where late blight inoculum pressure is low because it is not located in the main Walloon potato growing area. On the one hand, before the Milsol model is hypothetically used to predict the risk of late blight in Wallonia, field trials would have to be launched in Hainaut province and/or Brabant-Wallon to compare a weekly treatment schedule, a treatment schedule based on CARAH warnings, and one based on Milsol's advices. On the other hand, the integration of rainfall (missing in the original model) could be easily done, in a similar way to the integration of rainfall in the Guntz-Divoux model. It would also be wise to contact the team at *Arvalis-Institut du végétal* who developed this model in order to benefit from their expertise. Finally, it should be noted that the Milsol model simulates the pathogen cycle more rigorously than the Guntz-Divoux model. It is therefore likely that Milsol's outputs are more sensitive to meteorological data than Guntz-Divoux model, which supports the need for accurate meteorological data (AGROMET), and raises the relevance of a sensitivity analysis on the Milsol model.

Most epidemiological models used to predict the risk of potato late blight (including Guntz-Divoux and Milsol) are based solely on meteorological data. They assume that inoculum is always present on the field, and in unlimited quantities. At best, they estimate qualitatively the presence of inoculum by observing symptoms (e. g. on cull piles) in the region. It is possible that the current models have reached the maximum accuracy that can be achieved with a model based only on meteorological data. And that, if we want to further increase the accuracy of the prediction to avoid unnecessary treatment, other information must be provided as an input into the model. In this sense, the PotatoSMART project is relevant because one of its objectives is to monitor the flight of late blight spores using sensors distributed throughout the region. If the results of the project are successful, and it turns out that it is possible to predict the amount of spores present at a location, it is conceivable that this information could be integrated into a future decision support system as limiting information for the disease's development. In other words, even if the model predicts a high risk of infection depending on weather conditions, this infection cannot occur if the inoculum is not present.

If the "Guntz-Divoux-like" model remains the reference model in Wallonia, the sensitivity analysis performed in the chapter 3 showed that the Guntz-Divoux model is much more sensitive to variations in relative humidity than to variations in temperature, in the uncertainty ranges of the AGROMET project, i. e. $\pm 1°C$ for temperature, and $\pm 5\%$ for relative humidity. This observation leads us to invest as many resources as possible to minimize the error made on the relative humidity interpolations in the future AGROMET system, so that the output of the Guntz-Divoux model on which the farmer is based corresponds best to his situation (meteorologically speaking). Actually, this observation is probably also valid for most late blight risk prediction models (including Milsol), since they are based mostly on periods of high relative humidity, i.e. above 90 %. This threshold, required for infection risk to be present, is probably the reason for the high sensitivity of these models to variations in relative humidity data.

It has also been proven that, in years of low late blight pressure (meteorologically speaking), uncertainties in meteorological data have a greater effect on the deviation of (Guntz-Divoux) model outputs, and therefore on the inappropriateness (meteorologically speaking) of a treatment recommended by the model, than in years of high pressure. This finding seems difficult to resolve, but it may be necessary to share it with farmers so that they can be even more vigilant in monitoring their potato fields in years of low disease pressure (dry and hot).

Finally and more generally, it should be reminded that the principle of integrated protection management is to combine all the elements, knowledge and techniques available to control the disease (varietal resistance, prophylactic measures, cultivation techniques, types of protection products, etc). Decision support systems are only one component of the integrated protection strategy, but they must be designed to integrate all the other elements of this strategy, since their purpose is to provide farmers with a final advice adapted to their situation. And that is where the difficulty lies. The stakes for the future are therefore complex, since the challenge is to build a system that is able to predict the strategy to be adopted, while crop conditions are heterogeneous (organic vs conventional farming) and dynamic; global warming, appearance of new strains of *P. infestans* by sexual reproduction, changes in the products used (emergence of fungicides resistance, perhaps soon emergence of biological control products, e. g. bacterial), changes (additions/removals) in the list of potato varieties resistant to late blight,...

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Field-scale modelling of the potato late blight infection risk in Wallonia

Validation and sensitivity analysis of the current model, test and calibration of the French model "Milsol", and effect of host resistance on the disease cycle

Timothée Clément

Late blight (*Phytophthora infestans*) is the main disease in potato farming. The extremely powerful and fast destructive potential, as well as the limited number of systemic active ingredients and the emergence of resistance to them in the pathogen, make the use of preventive fungicide treatments essential to control this endemic disease. In Belgium, 15 to 20 fungicide sprays are applied each season to control it, which is more than any other European country. First, a sensitivity analysis with regard to meteorological data was carried out on the Guntz-Divoux model, an epidemiological model similar to that used for late blight warnings in Wallonia by the CARAH (Centre for Agronomy and Agro-industry of Hainaut Province). It was concluded that the future supply of the model with data from the AGROMET system (supply of interpolated meteorological data at a very small spatial and temporal scale) will allow a prediction of the late blight risk more suitable (meteorologically speaking) for a farmer's location than if the model is supplied by data from a "close" (10 to 20km) meteorological station from his field. In addition, the model outputs (and therefore the accuracy of a treatment prediction) are more sensitive to uncertainties in meteorological data during years of low late blight pressure (hot and dry) than during years of high pressure. Secondly, the epidemiological model used in France "Milsol" and CARAH warnings were evaluated retrospectively on observed in-field data monitoring the disease severity, by calculating contingency scores. For susceptible varieties (Bintje), the performance of the Milsol model appears to be slightly better than the warnings provided by the CARAH, although this difference is not statistically significant. For both models, consideration of varietal resistance does not seem appropriate; CARAH warnings skip periods when the disease appears, while Milsol model does not reduce the number of fungicide treatments, discrediting the use of less susceptible varieties. Finally, an attempt was made to calibrate the parameters of the Milsol model to better understand the effect of host varietal resistance on the pathogen cycle. Apart from the number of simulated late blight generations spent before the infection risk is actually present, no particular step of *P. infestans*'s cycle could be identified as inhibited by host varietal resistance. More specific analyses under controlled conditions should be undertaken to identify the critical phases of the pathogen's cycle which are impacted by varietal resistance.

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