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Modeling the Main Fungal Diseases of Winter Wheat: Constraints and Possible Solutions

Moussa El Jarroudi, Louis Kouadio, Bernard Tychon, Mustapha El Jarroudi, Jürgen Junk, Clive Bock and Philippe Delfosse

Additional information is available at the end of the chapter

Abstract

The first step in the formulation of disease management strategy for any cropping system is to identify the most important risk factors. This is facilitated by basic epidemiological studies of pathogen life cycles, and an understanding of the way in which weather and cropping factors affect the quantity of initial inoculum and the rate at which the epidemic develops. Weather conditions are important factors in the development of fungal diseases in winter wheat, and constitute the main inputs of the decision support systems used to forecast disease and thus determine the timing for efficacious fungicide application. Crop protection often relies on preventive fungicide applications. Considering the slim cost–revenue ratio for winter wheat and the negative environmental impacts of fungicide overuse, necessity for applying only sprays that are critical for disease control becomes paramount for a sustainable and environmentally friendly crop production. Thus, fungicides should only be applied at critical stages for disease development, and only after the pathogen has been correctly identified. This chapter provides an overview of different weather-based disease models developed for assessing the real-time risk of epidemic development of the major fungal diseases (Septoria leaf blotch, leaf rusts and Fusarium head blight) of winter wheat in Luxembourg.

Keywords: mechanistic model, stochastic model, integrated pest management

1. Introduction

Plant disease epidemics involve changes in disease intensity in a host population over time and space. Acquiring comprehensive information on this process is necessary to understanding

the factors that cause epidemics. However, even a complete set of data on disease intensity does not automatically lead to insights into the epidemic process. Furthermore, the information regarding risk of disease needs to be communicated stakeholders who can subsequently take management decisions to protect the crop when risk of an epidemic is deemed high. Various mathematical models are used to summarize the essential features of the data or measurements of interest regarding disease development. Models for biological or physical processes can be developed using several methods. Empirical models are developed to describe an observed process, phenomenon, or relationship between variables using established statistical principles, and do not use previously developed theory or concepts to establish the relationship between the response variable and predictor variables. In contrast, mechanistic models are developed based on a theory, hypothesis, or concept of how a phenomenon or process occurs. Data are later considered after the mechanistic model is developed and might be used to improve the theory on which the model is based.

2. Challenges in predicting plant disease epidemic development

In many of the models that are discussed in this chapter, diseased individuals are grouped in three categories. After infection of the host takes place, the infected individual first goes through a phase where the disease develops and "grows" in the individual, but the infected individual does not produce propagules or infectious units. The infected individual is in a latent state. After the latent period, the infected individual becomes an infectious individual, meaning that it now produces infectious units that have the potential to cause subsequent infections. "Disease forecasting," "disease prediction," and the development of "disease warning systems" are activities familiar to plant disease epidemiologists [1–6]. Having identified the factors that lead to epidemics, it is of great importance to use this information to provide a basis for the management of plant disease. The level of disease risk to which a crop is exposed may be influenced by many factors, some of these are beyond the control of growers, but some factors are integral components of crop production systems and can be managed to minimize that risk.

2.1. Seasonality and the disease cycle

Many cropping systems are cyclical or seasonal. With annual plants, the crop is planted and harvested at specific times each year. Planting a specific (or a few) genotype(s) results in an abrupt increase in population of susceptible individuals. While harvesting immediately decreases both the population of susceptible individuals and the population of latent, infectious individuals. In the period between harvest and planting, the pathogen has to survive either as propagules or on living or dead plant material left in the field, in the soil, or in other locations. Crops are exposed to a risk of infection from pathogens, the outcome of which is economic loss when the epidemic increases above a certain threshold, which results from reduction in both the quantity and quality of crop yield. In this chapter, we are interested in quantifying the risk of infection to which a crop is exposed as a basis for deciding whether intervention aimed at

disease suppression is justified. Aspects of this process differ from pathogen to pathogen, from crop to crop, and from location to location [4]. Goulds and Polly [7] and Binns et al. [8] draw a distinction between crop protection based on either curative or preventative action. Without necessarily wishing to adhere rigidly to this dichotomy, it is nevertheless clear that in some cases, sample data are the most important components of the information on which decision making is based. In others, data relating to the host and the environment often play a more important role, and the evidence on which a decision is made about the need for appropriate control action is therefore likely to be more wide ranging. The first step in the formulation of a disease management strategy for any cropping system is to identify the most important risk factors among those on the long list of possible candidates. This is facilitated by basic epidemiological studies of pathogen life cycles, and an understanding of the way in which weather and cropping factors affect the quantity of initial inoculum and the rate of the pathogen life cycle. To be able to identify risk factors, we need information both on the candidate risk factors and on the definitive status of the crops in which they are studied.

2.2. Basis of decision making

Jones [9] discussed a decision-making guideline based on impact on yield for fungicidal control of eyespot disease of winter wheat (*Triticum aestivum* L.). Treatment was considered to be worthwhile if ≥20% of tillers were diseased at growth stage (GS) 30–31. Accordingly, the recommendation was for a sample of tillers to be collected at the appropriate growth stage and a decision of whether to treat was made based on the percentage of tillers with symptoms of eyespot disease, in relation to the specified threshold. Decision making was based on a two-stage cluster sampling procedure, collecting a total of 50 tillers for the assessment [7]. The economic threshold is the level of risk exposure at which crop protection measures should be applied, in order to prevent the economic injury level from being reached. An economic threshold may be used to identify circumstances in which it becomes economically advantageous to apply crop protection measures. The economic threshold is a discrete choice threshold: the only options are to apply crop protection measures or to withhold them. However, the choice between these two options must be made before it is known for sure whether a crop will sustain economic loss resulting from reductions in the quantity and quality of yield. Thus, the economic threshold may be used as a basis for deciding whether or not crop protection measures are required, at a time when it is still possible to keep damage below the economic injury level. Weather-based systems, or weather-based systems combined with other disease or agronomic variables have been developed in various areas in Europe to determine whether fungicide sprays should be applied to prevent the risk of epidemics that might otherwise lead to yield loss. For example, Audsley et al. [10] developed a model in the UK based on weather, host resistance and inoculum pressure to project effects on green leaf area, which was coupled with effects on yield loss as a decision support system for Septoria leaf blotch, powdery mildew, and yellow and brown rusts.

In this chapter we specifically provide an overview of different weather-based disease models developed and used for assessing in real time the risk of epidemic development for the major fungal diseases (i.e., Septoria leaf blotch, powdery mildew, leaf rusts and Fusarium head

blight) of winter wheat in Luxembourg. A description of the models is provided along with the constraints associated with their use for in-season disease monitoring. The challenges faced using weather-based models in a changing climate are also discussed.

3. Main fungal diseases of wheat in Luxembourg and associated decision support systems

Wheat represents one of the most widely cultivated cereals with a production area of 215 million ha worldwide [11]. Unfortunately, wheat diseases remain a major constraint to wheat production [12]. Crop protection often relies on calendar-date applied, preventive fungicide applications, and small grain cereals are typically treated with two or three foliar fungicide applications in Luxembourg and Belgium [13, 14]. The marginal cost/revenue ratio for winter wheat and the potential negative impacts that overuse of pesticides can have on the environment are compelling arguments to minimize inputs, including fungicides. Effective estimation of the risk of disease epidemic development can minimize the number of fungicide spray applied, leading to a more sustainable and environmentally friendly system of wheat production. Using tools to develop integrated pest management can lead to fungicides being applied only at particular stages that are at risk of infection, and only when the pathogen has been correctly identified (accurate identification and/or estimation of severity of disease can be critical to effective management). Diseases of wheat that have become economically important in Luxembourg include Septoria leaf blotch (SLB) caused by *Zymoseptoria tritici Roberge in Desmaz.*, wheat leaf rust (WLR) caused by *Puccinia triticina Eriks.*, wheat stripe rust (WSR) caused by *Puccinia striiformis Westend. f. sp. Tritici Eriks.*, and Fusarium Head Blight (FHB) caused mainly by *Fusarium graminearum*. The control of the diseases caused by these pathogens is a high priority to minimize yield and grain quality losses.

3.1. Septoria leaf blotch

The majority of the SLB disease prediction systems proposed for the management of *Z. tritici* assume that the main risk of infection of the upper leaves (the most critical for grain fill [15]) comes from the inoculum that developed on the leaves during the winter and spring before the extension of the stem [16]. These prediction systems are based solely on rainfall occurring during stem extension, without considering the development of individual leaves [17–19]. The importance of rain and splash dispersal for development of severe SLB has been demonstrated in several studies (e.g., [16, 20–22]). Shaw and Royle [19] suggested that the amount of Septoria inoculum at GS31 (first node detectable) [23] was only a partial guide to forecast the inoculum available during the expansion of the last two leaves. The progression of the disease on the upper leaves depends on the sensitivity of the cultivar, and the period of infection (infections occurring during and/or just after the emergence of these leaves could lead to severe impacts if the weather conditions are favorable) [24]. The mechanisms by which the pathogen population increases on the upper leaves are determined by the interaction of plant growth, the meteorological conditions allowing the dispersal of the inoculum and thus opportunity for new infections, and the availability of that inoculum in sufficient proximity to the upper leaves [19]. El Jarroudi et al. [20] suggested that the greatest risk to a wheat crop occurs

from infections arising between the emergences of leaf 2 (L2) and the flag leaf and roughly two latent periods before these leaves would naturally begin senescence. If the upper leaves are infected early in the cropping season, they are likely to suffer much more severe disease for two reasons: a) there is sufficient time for the pathogen to have more than one multiplication cycle on the leaves, with a longer time during which dissemination and infection may occur, resulting in premature loss of leaf area; b) these leaves are closer to the sources of the inoculum and extreme splashing events will no longer be necessary to disperse sufficient number of spore onto a susceptible tissue that is higher in the crop canopy. Furthermore, the structure of the wheat plants and the position of the source of the inoculum on specific leaves relative to each other are constantly changing and thus the risk of disease progression is dynamically complex and specific to each crop, cultivar and season [22]. In addition, the life of the upper leaves is considerably shortened by secondary infections resulting from the inoculum produced by primary lesions in the same leaf layer [19]. The detection of spores of *Z. tritici* during the season demonstrates the need for a predictive model [25, 26]. Both asexually produced pycnidiospores and sexually produced ascospores of *Z. tritici* are known to cause disease in wheat [22, 27], with ascospores being aerially dispersed over relatively long distances, and the pycnidiospores being primarily splash dispersed. Furthermore, the ascospores have an impact not only as primary inoculum in autumn and winter [27], but also as secondary inoculum at the end of spring and in summer. This airborne inoculum could help to colonize the upper leaves without the need for splash-dispersed pycnidiospores or could exacerbate the damage caused by splash-dispersed *Z. tritici* (**Photo 1**) due to the presence of the additional ascospore inoculum [28].

Due to the potential for yield loss from SLB, growers tend to spray fungicides several times during the winter wheat season to protect their crops. The development of resistance in

Photo 1. Symptoms of Septoria leaf blotch caused by *Zymoseptoria tritici* on leaf L3 of the cultivar Achat. The black dots in the tan lesions are the pycnidia that produce the splash dispersed pycnidiospores (photo taken on May 30, 2007 at Everlange, Luxembourg; photo credit: El Jarroudi M.).

Z. tritici to the main fungicides used for its control [20] has been demonstrated in many countries. Moreover, actual disease severity does not always justify a fungicide spray. In years with a low disease risk, a lower fungicide dose could be used [29]. There are several weather-based Decision Support Systems (DSSs) available to help a grower decide whether a fungicide application is required [30–32]. These models rely mainly on rainfall measurement, or in some case more comprehensively on weather data, without considering the development of the different leaf layers during stem elongation [18, 33–37].

However, many models neglect the periods of interruption of acceptable temperature or humidity for infection which are important factors in disease development, and can be an indispensable element in developing more accurate models. According to Shaw [38], interruptions in periods at 75% relative humidity for 48 h slightly reduced the efficiency of the infection process, but interruptions at 50% relative humidity resulted in major effects, but still allowed infection to occur. To simulate infection, some models take daily conditions [39, 40], while others, for example the PROCULTURE model are based on hourly weather conditions [14, 20].

3.1.1. The PROCULTURE model

The PROCULTURE model is an interactive web-based, field-specific, DSS based on the mechanistic modeling of the development of the last five leaf layers of the wheat plant coupled with the progress of SLB on these layers [14, 20, 41, 42]. A descriptive flowchart of the model is presented in **Figure 1**. The main inputs include weather data (hourly air temperature, rainfall and relative humidity) and field-specific data including the location, sowing date and cultivar susceptibility. Field observations are also important since a fine-tuning of the model may be required based on the actual growth stage (around the first node stage, GS32) and the severity of SLB on the particular leaf layer as specified by the model. The model considers infection to have occurred when, during a 2 h rainfall event, precipitation for the first hour is at least 0.1 mm (to allow for the swelling of pycnidia), followed by a second hour with at least 0.5 mm precipitation (**Figure 1**), leading to the release and splash dispersal of the conidia [14, 20]. In addition, after rainfall, relative humidity should be higher than 60% during the following 16 h [20, 43] and the temperature should remain above 4°C for 24 h [20] for germination and infection.

The evaluation of the PROCULTURE model at several sites in Belgium [14, 44] and Luxembourg [20] demonstrated that the model can explain disease progression in the canopy (**Figure 2**) and can be used to advise farmers when to apply fungicides during stem elongation, as the three upper leaves emerge. The need for and timing of a single fungicide spray using the PROCULTURE model is based on the observed disease severity earlier in the cropping season (i.e., severity on the lower leaves L5-L4 at GS 31–37, L1 being the flag leaf), the susceptibility of the cultivar, past and forecasted weather conditions, and the predicted development of leaves based on the output of the PROCULTURE model. Furthermore, historical data (weather and disease incidence and severities) were used as a basis for similarity analysis to further evaluate the risk of severe disease development. Given the threshold level of observed disease severity (namely on the lower leaves) and weather conditions (actual and forecasted), an advice for fungicide treatment was taken and fungicides applied only if required to protect the upper leaves. For example, a 5% of emergence of L3 coinciding with SLB symptoms on L5 and a rainfall event, results in a greater risk that L3 will be affected by

SLB during full emergence. Consequently, a fungicide treatment against the risk of SLB is recommended if a latency period of the disease is completed at 75% emergence and favorable weather conditions forecasted. Overall, the assessment of the infection periods achieved an accuracy of 85%. The results showed that the PROCULTURE model satisfactorily recommended none or a single fungicide treatment at each study site, regardless of geographical location or possible variability among the fungal diseases involved [45].

### 3.1.2. Spatialization of PROCULTURE alerts using radar rainfall

The PROCULTURE model is being used in early warning systems in Belgium and Luxembourg to define, in real time, the risk of SLB developing on the upper leaves of winter wheat during stem elongation. However, setting up an operational network for recommending the optimal time for fungicide application requires a representative network of weather stations throughout the region where the DSS will be used. In our studies (e.g., [20, 46]) overestimation or underestimation of the risk of SLB progression could often be traced back to differences in rain events captured by the tipping-bucket rain-gauges at the weather station compared with the rainfall to which a particular field was actually exposed. Rainfall data could be interpolated between weather stations, but precipitation between fields are characterized by high spatial and temporal variability [47, 48], making the interpolation unreliable [49, 50].

Radar may provide a solution for improving the interpolation of precipitation data [51, 52]. Over the past few years, radar-derived estimates have been increasingly used in disease forecasting applications as an alternative to gauge-derived measurements [51, 53].
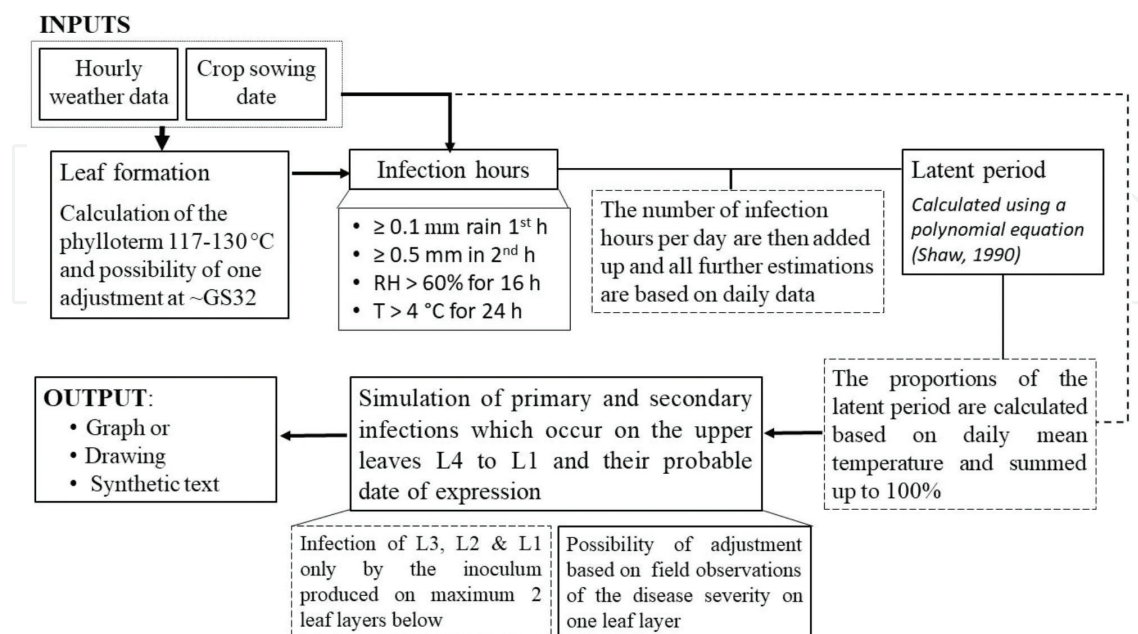
Figure 1. Descriptive flowchart of the PROCULTURE model for predicting the risk of Septoria leaf blotch (SLB) infection events. T: Air temperature; RH: Relative humidity.
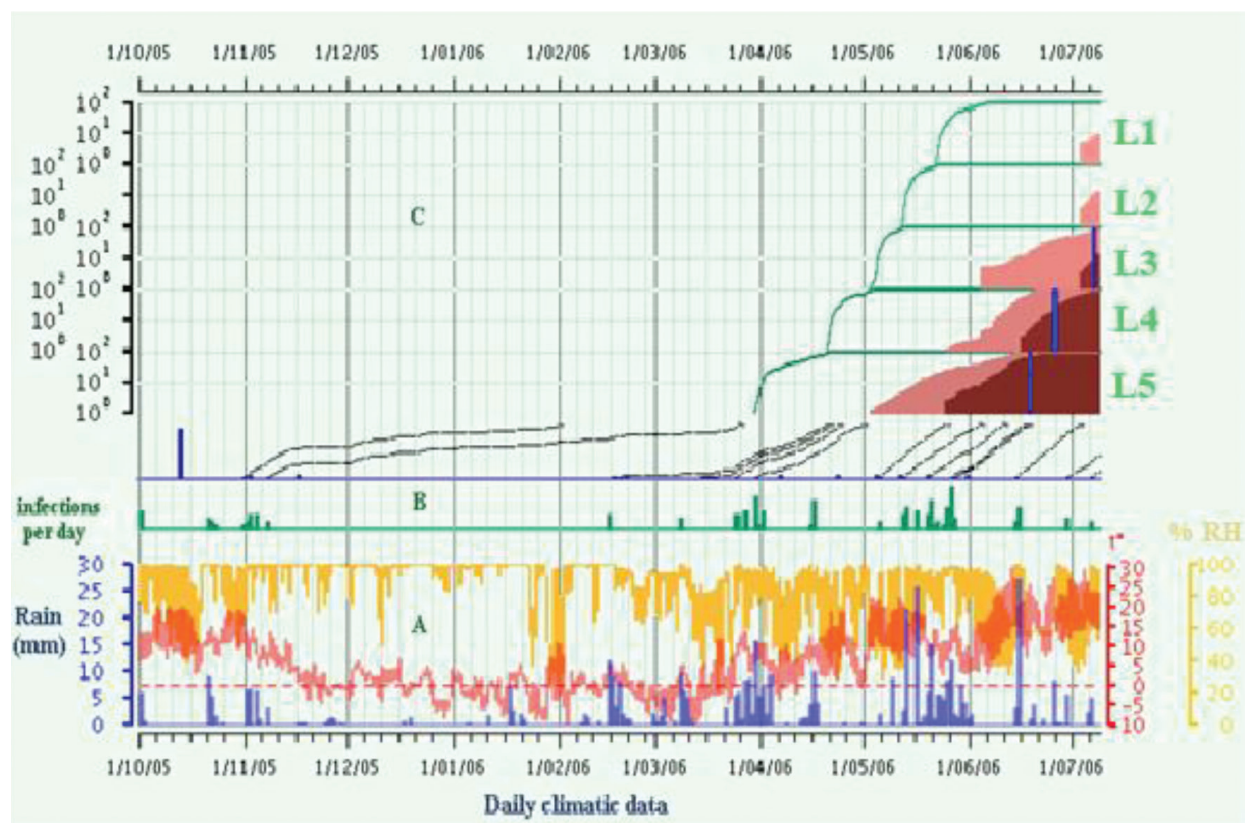
Figure 2. Output of the Septoria risk simulation model from 2006 in winter wheat fields at Reuler Luxembourg. A: Observed daily values of air mean temperature (°C) and rainfall (mm). B: Number of hours per day with a > 80% probability of infection. C: Lines: Leaf area development (0–100%) of leaves L5–L1 (flag leaf is L1). Gray: Accumulation of hours of primary infection expressed on leaves L5–L1 (maximum of 100 h) (Reuler is one of the representative sites of winter wheat cropping regions in Luxembourg selected for field experiments in the framework of the SENTINELLE project. It is located in the northern part of Luxembourg).

Mahtour et al. [42] validated the simulation of infection periods for *Z. tritici* calculated by PROCULTURE using radar-based rainfall measurements. The duration of periods with a high probability of infection by *Z. tritici* was calculated by PROCULTURE and using radar rainfall data for these trials was similar to that based on gauge measurements (**Table 1**). A better spatial representation of precipitation will inevitably improve present DSSs. Consequently, the DSSs could more accurately be the basis for recommending appropriate fungicide applications. If the results of the radar-based rainfall measurements combined with PROCULTURE are confirmed for a larger precipitation dataset and a larger number of stations, the sole use of radar data in the disease-warning system will be considered in the future. The results from this work should encourage research on additional radar-based rainfall applications for diseases of other crops.

3.2. Wheat leaf rust

WLR is of major historical significance and is of economic importance worldwide. It is the most widespread of the three species of rusts causing significant yield losses over large geographical areas [54–59]. Several studies in major cereal-producing areas have revealed

Field sites	Observation period	Year	Events[a]	Duration of infection period[b]		POD$_{so}$[c]		FAR$_{so}$[d]		CSI$_{so}$[e]	
				Gauge	Radar	Gauge	Radar	Gauge	Radar	Gauge	Radar
HUMAIN[f]	21/05 to 05/07	2003	18	60	62	0.93	0.83	0	0	0.93	0.83
	03/05 to 28/06	2004	16	46	40	0.73	0.87	0	0	0.73	0.87
	20/05 to 15/07	2005	8	24	27	0.86	1.00	0	0.12	0.85	0.87
			42	130	129	**0.84**[h]	**0.90**	**0**	**0.04**	**0.84**	**0.86**
USELDANGE[g]	13/05 to 29/06	2003	15	56	44	0.87	0.80	0	0	0.87	0.80
	16/05 to 09/07	2004	18	48	48	0.72	0.78	0	0	0.72	0.78
	14/05 to 12/07	2005	15	33	32	0.71	0.86	0.09	0.07	0.67	0.81
			48	137	124	**0.77**	**0.81**	**0.03**	**0.02**	**0.75**	**0.80**
BURMERANGE[g]	17/05 to 03/07	2003	10	30	22	0.70	0.70	0	0	0.70	0.70
	05/05 to 13/07	2004	15	43	55	0.73	0.93	0	0	0.73	0.93
	12/05 to 04/07	2005	12	24	28	0.91	0.83	0	0	0.91	0.83
			37	97	105	**0.78**	**0.82**	**0**	**0**	**0.78**	**0.82**
REULER[g]	—	2003	—	—	—	—	—	—	—	—	—
	27/05 to 05/07	2004	10	45	32	0.70	0.70	0	0	0.70	0.70
	16/05 to 11/07	2005	11	24	23	0.82	1.00	0	0	0.82	1.00
			21	69	55	**0.76**	**0.85**	**0**	**0**	**0.76**	**0.85**
All			148	433	413	0.79	0.84	0.01	0.02	0.77	0.83

[a]Number of infection events deduced from visually observed symptoms in the field sites on the upper three leaves.

[b]Total number of hours with a high probability of infection simulated by PROCULTURE.

[c]Probability of Detection of infection by *Z. tritici* is the number of cases where infections are both simulated and observed against the number of infections observed. Perfect forecast = 1.

[d]False Alarms Ratio of infection by *Z. tritici* is the number of observed infections not simulated against the number of infections observed in the field. Perfect forecast = 0.

[e]Critical Success Index of *Z. tritici* infection takes into account both false alarms and missed events. The POD$_{so}$, FAR$_{so}$ and CSI$_{so}$ show the infection occurrence comparison between infection periods (on the last 3 leaves) determined by visual observations and simulated by the PROCULTURE model using measurements from four rain-gauges or radar-based estimates. Perfect value = 1.

[f]Site in Belgium.

[g]Site in Luxembourg.

[h]Average for each field site over three cropping seasons indicated in bold.

- No data.

Table 1. Comparison of the performance when using rain-gauge or radar-based rainfall measurements in the PROCULTURE model for estimating the risk of infection events in winter wheat by *Zymoseptoria tritici* at four sites during three cropping seasons in Luxembourg and Belgium [42].

that epidemics of WLR occur under (i) favorable conditions for overwintering spores as a source of primary inoculum, (ii) rapid and abundant production of wind-dispersed urediniospores, and (iii) a complex interaction between environmental conditions and host resistance [54, 60]. The dispersal of foliar pathogens and WLR in particular around a spore source has been described in many studies, sometimes confirming dispersal over large distances [61] but most often at the spatial scale of an infected plant or group of plants [62, 63], or even a single leaf [64]. Although these studies give valuable insights to allow understanding of epidemic spread of diseases like WLR and to parameterize simulation models, they most often do not take into account the local structure of the host crop and its potential effect on disease distribution [64].

Two different approaches have been used to forecast development of epidemics of WLR. Some forecasting systems consider the effect of weather on the disease by means of empirical rules, flow charts [65], disease indices [66, 67], or regression equations [68, 69]. Other models forecast severity of WLR on the basis of the dynamic of the epidemic, using a fixed relative growth rate of the disease [70–72].

Moisture and temperature are reported to be the most important meteorological parameters influencing the development of epidemics of WLR [73]. Nevertheless, the genetic resistance of wheat cultivars is critically important factor in determining the impact of the disease [74]. Urediniospores are deposited by wind or rain on the adaxial and abaxial surfaces of wheat leaves. Rain on, or turbulence around the leaf surface allows the dispersal of urediniospores. In addition, wet deposition (spore scavenged from the air by rain) is considered an important mechanism of crop contamination by some rusts [75]. Although most rainfall events promote spore dispersal in the field, heavy rain may also induce the leaching of spores deposited on leaves and may totally deplete the lesions in the process [76]. When the urediniospores of WLR are in contact with susceptible wheat leaves, the success of infection requires a minimal duration of surface wetness, which varies as a function of temperature [50, 77]. De Vallavieille-Pope et al. [77] showed that optimum temperatures for uredospore germination ranged from 12 to 15°C and that the germination process ceased above 35°C. As noted, the presence of free water on the leaf surface is essential for urediniospore germination. In an earlier study, Eversmeyer [78] proposed an optimum temperature of 16°C for completion of the infection process by uredinisospores of *P. triticina*, with infection needing a dew period of at least 3–4 h. In the same study, it was shown that the latent period for WLR ranged from 8 to 20 days for air temperatures between 10 and 20°C. The process of infection has an approximately linear relationship with the sum of base 0 degree-days. It has also been demonstrated that germination of urediniospores of *P. triticina* could be delayed or inhibited by increasing light intensity [78, 79]. For this reason, infections occur preferentially at night (**Photo 2**).

Considering these data, an empirical approach for simulating infection by WLR and progress of the disease on the upper three leaf layers has been proposed and validated in Luxembourg [2]. The model used only weather data logged between 8 pm to 5 am based on the assumption that spore germination is inhibited by light. Each infection event was deemed to require a period of at least 12 consecutive hours counted on at least two nights with air temperatures ranging between 8 and 16°C and a relative humidity greater than 60% (**Figure 3**). Moreover, the hourly rainfall totals during these 12-hour periods must be less than 1 mm to avoid the leaching of spores present on leaves. Furthermore, the primary infection in a field requires a

Photo 2. A leaf showing symptoms of infection by *Puccinia triticina,* causing pathogen of wheat leaf rust (photo taken on June 2009 at Burmerange, South Luxembourg; photo credit: El Jarroudi M.).

light rain (0.1–1.0 mm) in the first hour of an infection event supposing that this rainfall allows the first deposition of the inoculum in the field. This light rain event is not a necessity once the primary infection has occurred. The model has led to a DSS that allows optimizing timing of applications of the fungicide for controlling WLR in fields in Luxembourg.
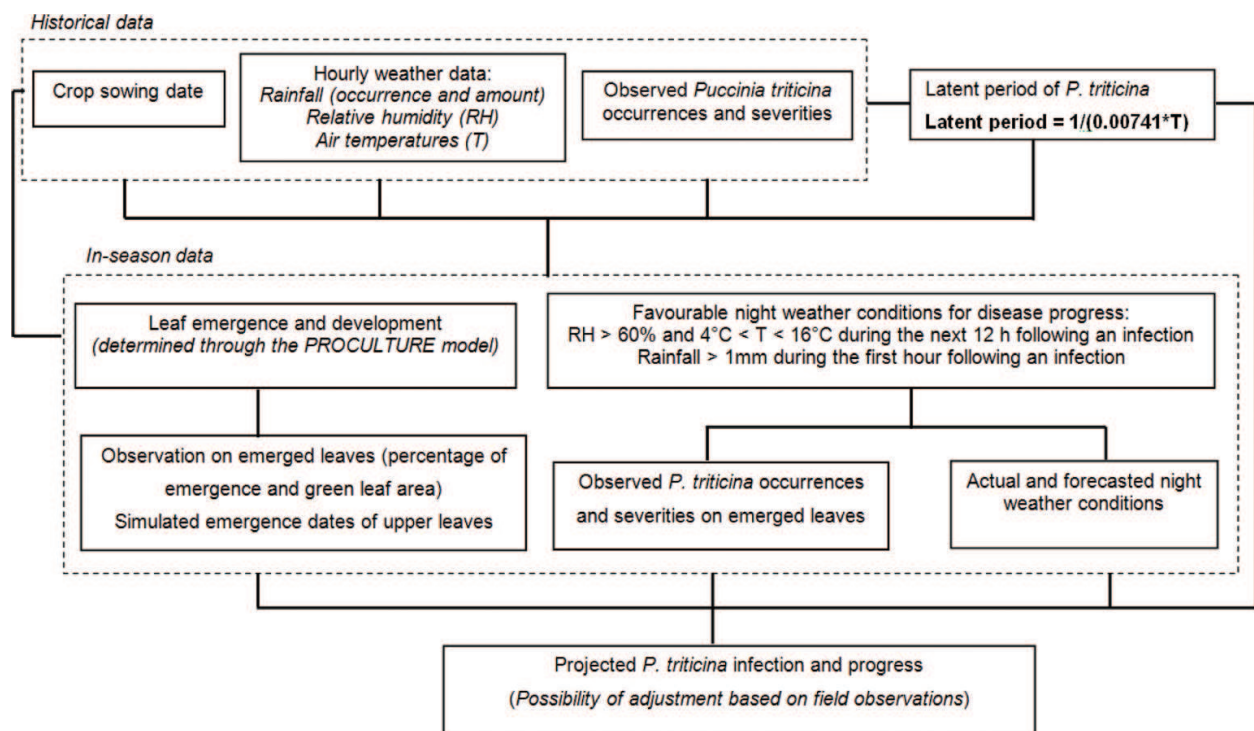
Figure 3. Descriptive flowchart of the model used for predicting wheat leaf rust (WLR) infection events caused by *Puccinia triticina* [80].

The presence of primary inoculum in the air is not considered as a limited factor in this model. We assumed that spores of *P. triticina* are already present in fields during the period of study. A fine-tuning of the DSS will include an effective assessment (i.e., spore dispersion estimates) for the spores in the same field, since spores from outside the field are only required to initiate the first infection (exogenous inoculum). Indeed, the assessment of the model coupled with detection of spores showed that the infection periods on susceptible cultivars (**Figure 4**) were well predicted [81].

Thus, the detection of airborne inoculum by sensors and its coupling to a reliable model of dispersion could help improve forecasting the occurrence of WLR. In Belgium, a recent study on the spatio-temporal distribution of the airborne inoculum of *P. triticina* indicated that infection on the three youngest leaf layers could originate from endogenous and/or exogenous inoculum. The first symptoms observed on crops can be the result of either infection by urediniospores carried upwind by air masses from distant infected fields or the consequence of sporulating lesions occurring in the fall and remaining active after the winter [82]. Airborne inoculum was generally detected in fields during the growing season between March and May (during the spring green-up). Various densities of airborne inoculum were observed depending of the site and the year, and the severity of WLR on the upper leaf layers during the grain filling was strongly influenced by the density of spores collected during the development of these leaf layers [83].

Molecular diagnostics combined with sampling of airborne inoculum could be exploited to more accurately predict the risk of epidemics in wheat agro-ecosystems. Strategies for controlling WLR in fields include the use of resistant cultivars. But a prolonged period of monitoring WLR involving susceptible cultivars and favorable night conditions conducive to spore production, dispersal of, and infection by *P. triticina* with subsequent development of WLR should demonstrate the capability of the DSS in these situations. Junk et al. [84] studied the potential infection periods of WLR in a changing climate at two selected sites in Luxembourg (Burmerange and Christnach) using a weather threshold-based model for infection and development and progress of WLR that involved hourly night-time data for air temperature, relative humidity and rainfall. Their findings revealed that highest proportions of favorable days for infection with *P. triticina* and development of WLR in the future would occur during spring and summer at both sites, with the proportions more marked at Burmerange.

3.3. Wheat stripe rust

WSR is an example of a disease of world-wide importance and ability for long distance dispersal. Crop pathogens with worldwide prevalence and potential for long distance migration and thus invasions into new areas may pose a serious threat to food security regionally or globally [85]. WSR of wheat is among the most important crop diseases causing a continuous threat to crop production [86, 87]. Worldwide. the virulence and race diversity of populations of *P. striiformis* is apparent. Races from regionally prevalent lineages cause epidemic outbreaks resulting in widespread economic losses in wheat production [85, 88]. Virulence to most of the characterized resistance genes has been observed in Europe, reflecting the large-scale deployment of these genes in Europe in the past [89–93]. More recently, the footprint of epidemics of WSR appears to be moving into non-traditional, warmer and dryer areas suggesting a wider range of adaption [85]. Based on an ostensibly representative selection of isolates of WSR collected from the United States (and genetically similar isolates from Denmark, Mexico and
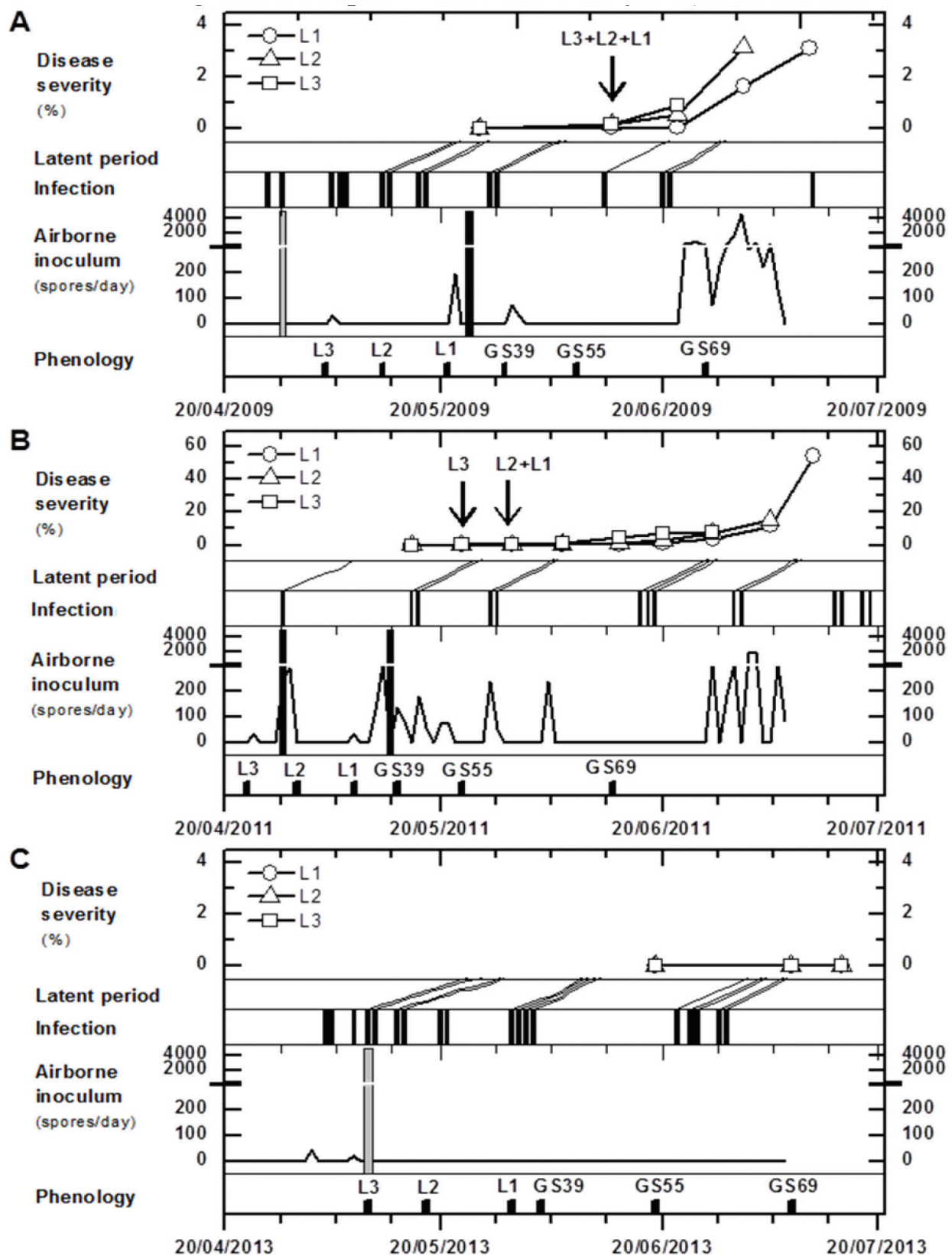
Figure 4. Severity of wheat leaf rust (WLR) on the three upper leaves in wheat plants. Severity of WLR, infection by, and latent periods of *P. triticina* were determined based on favorable night weather conditions at Perwez, Belgium in 2009 (a), 2011 (B) and 2013 (C). The arrows show the time of the first disease observation in the field. Phenology of the plants including the appearance of the three upper leaves is represented at the bottom of each figure. The airborne inoculum trapped in the field allows determination of when the "inoculum condition" was reached (black bars). The gray bars symbolize the moment when the "rain conditions" of the original model were reached. (source: [81]).

Eritrea) before and after 2000 [94], it was demonstrated that isolates collected after 2000 were more aggressive and had adapted to produce more urediniospores in a shorter time period, and at higher temperatures. The pathogen has been highly mobile and the geography of its genetics has changed and expanded, especially since 2000. Multiple new incursions of the pathogen have been reported in Australia and South Africa [95, 96] and international movement of spores of *P. striiformis* from Europe (in 1979) and North America (in 2002) has been implicated on the clothing of travelers [97]. Indeed, in 2011 a new race of *P. striiformis*, named "Warrior," was detected in various European countries including France, Germany and the UK [93]. Since urediniospores of P. striiformis can spread over large distances [98], the race Warrior is probably already present in Luxembourg. Confirming the existence of Warrior in commercial Luxembourgish wheat fields was not part of this study.

In most seasons, environmental conditions during spring and early summer are conducive to the production of large quantities of spores of *P. striiformis*, which are dispersed from distances of a few centimeters to thousands of kilometers (**Photo 3**), where they might reach a susceptible host plant [76, 98]. The sporulation capacity and infection efficiency of *P. striiformis* are affected mainly by air temperature, leaf-wetness duration and light intensity [77]. Urediniospores of *P. striiformis* require a relative humidity near saturation for at least three hours to germinate [99] and are sensitive to an interruption of the wet period during germination [77]. The presence of free water on the leaf surface is also essential for spore germination [77, 99, 100]. Thus, rain is often considered conductive to disease spread because rain events are generally followed by extended periods of leaf wetness [76, 99].

The model developed is based on a stepwise approach (**Figure 5**) consisting of (1) the determination of the potential range of weather conditions conducive to WSR in Luxembourg using a stochastic approach, and (2) the determination of optimum classes of combined weather variables
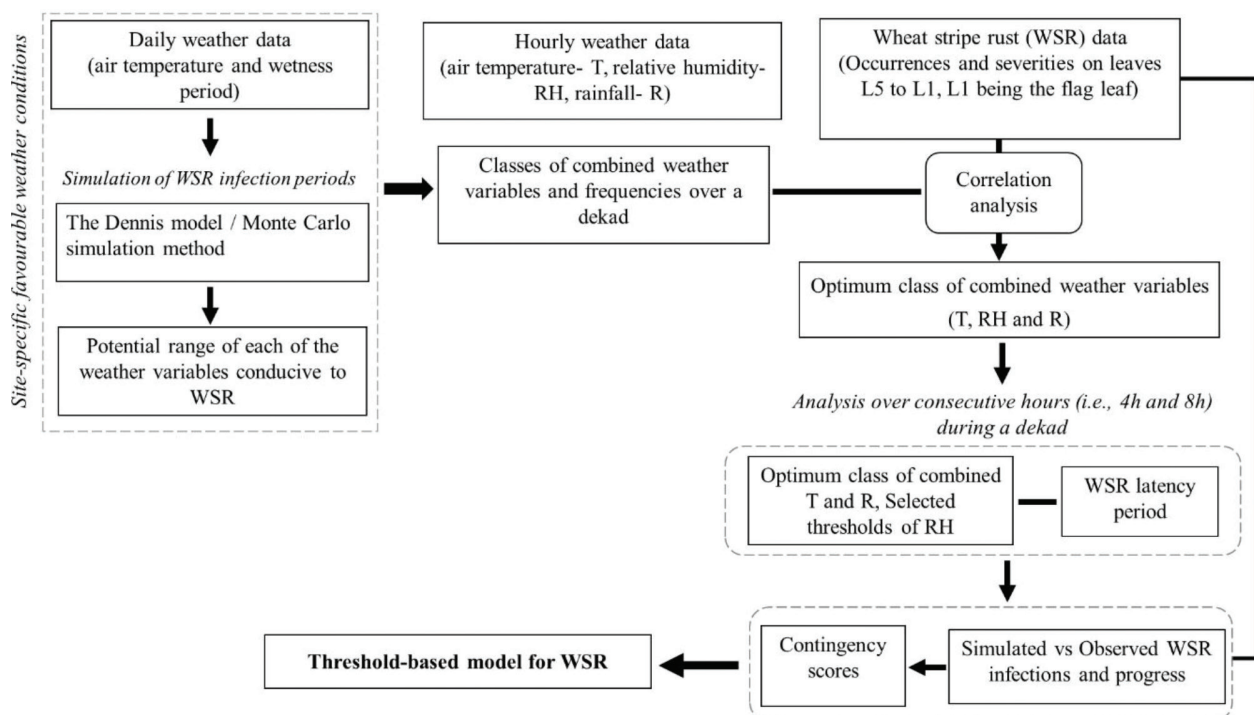
Figure 5. Descriptive flowchart of the modeling approach for predicting infection events of wheat stripe rust caused by *Puccinia striiformis* [13]. Air temperature (T), relative humidity (RH) and rainfall (R).

Photo 3. Fungicide treated and non-treated plots of winter wheat and a leaf (inset) showing symptoms of wheat stripe rust caused by *Puccinia striiformis* (photo taken on 2015 in Burmerange, South Luxembourg. Photo credit: Beyer M.).
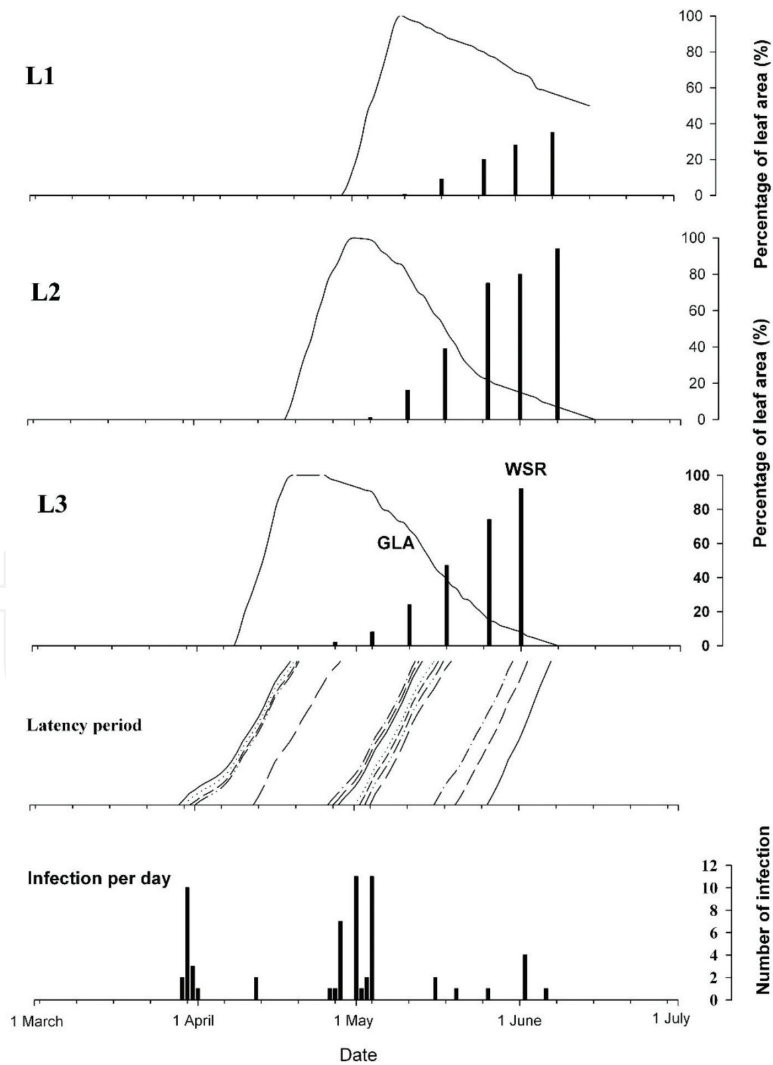
Figure 6. Example of simulated infection events by *Puccinia striiformis* (cause of wheat stripe rust (WSR)), observed green leaf area (GLA) and severity of WSR on the three upper leaves (L3 to L1, L1 being flag leaf) at Burmerange, Luxembourg during the 2015 cropping season. The severity of WSR is expressed as percentage leaf area diseased [13].

(air temperature (T), relative humidity (RH) and rainfall (R)) conducive to the disease and building of a weather threshold based model for predicting WSR infection events [13].

The threshold-based model for development of WSR was evaluated using independent data from experiments in Luxembourg in 2002–2015 [13]. Infection days and latency periods for *P. striiformis* (**Figure 6**) were calculated based on periods when the combined favorable weather variables (4°C < T < 16°C, RH > 92% and R ≤ 0.1 mm) were met. The overall performance of the threshold-based weather model developed in this study is quite similar to that developed for WLR across the same geographical region. Although the findings are area-specific and may differ in other geographic regions, the underlying hypothesis and approach can be extended to different locations and/or explored for other economically important fungal diseases of other crops.

3.4. Fusarium head blight

Besides the yield loss that it can cause, FHB can negatively affect the entire human food and animal feed chain through the contamination of wheat grains with mycotoxins. Contamination with fumonisins can result in grains unusable for consumption or for further processing into bakery products, breakfast cereals, pasta, snacks, beer or animal feed, etc., [101–106].


**Photo 4.** Fusarium growth on wheat (Photo credit: Giraud F.).

Weather is a critical factor influencing FHB. Frequent rainfall, high humidity and warm temperatures, coinciding with flowering and early kernel filling, favor infection by *Fusarium* spp. and development of the disease [107]. Numerous research and survey reports have shown that the main environmental factors influencing the development of FHB (**Photo 4**) are temperature and humidity/wetness [108, 109] It has been speculated that the difference observed in severity of FHB between 2007 and 2008 (**Figure 7**) (21.0 ± 17.8% versus 13.5 ± 16.2%) may, at least in part, be explained by the warmer temperature observed in 2007 (11.9°C) compared to 2008 (9.4°C) [103, 110]. Climatic factors can also influence the impact of fungicide application and its effect on Fusarium strain population [111].

Many studies have highlighted the relationship between the severity of FHB in specific fields where certain cereals particularly maize, were the previous crop [103, 112]. Maize residues are a host for several *Fusarium* species and thus provide a source of inoculum for infection of any susceptible crops planted in that land [113, 114]. Suitable cultural practices (e.g., crop rotation) aiming to reduce inoculum borne plant residues could be effective in controlling FHB in winter wheat fields.

A simulation model for predicting the periods of infection by *Fusarium* spp. was developed and evaluated at various sites in Luxembourg during 2007–2009 [115]. Like the models developed for other fungal diseases, the main inputs are T, R and RH. Information on the cultivar and the previous crop are also considered while using the model outputs for recommending fungicide sprays (i.e., the model is only used when sensitive cultivars are planted after maize or sorghum).
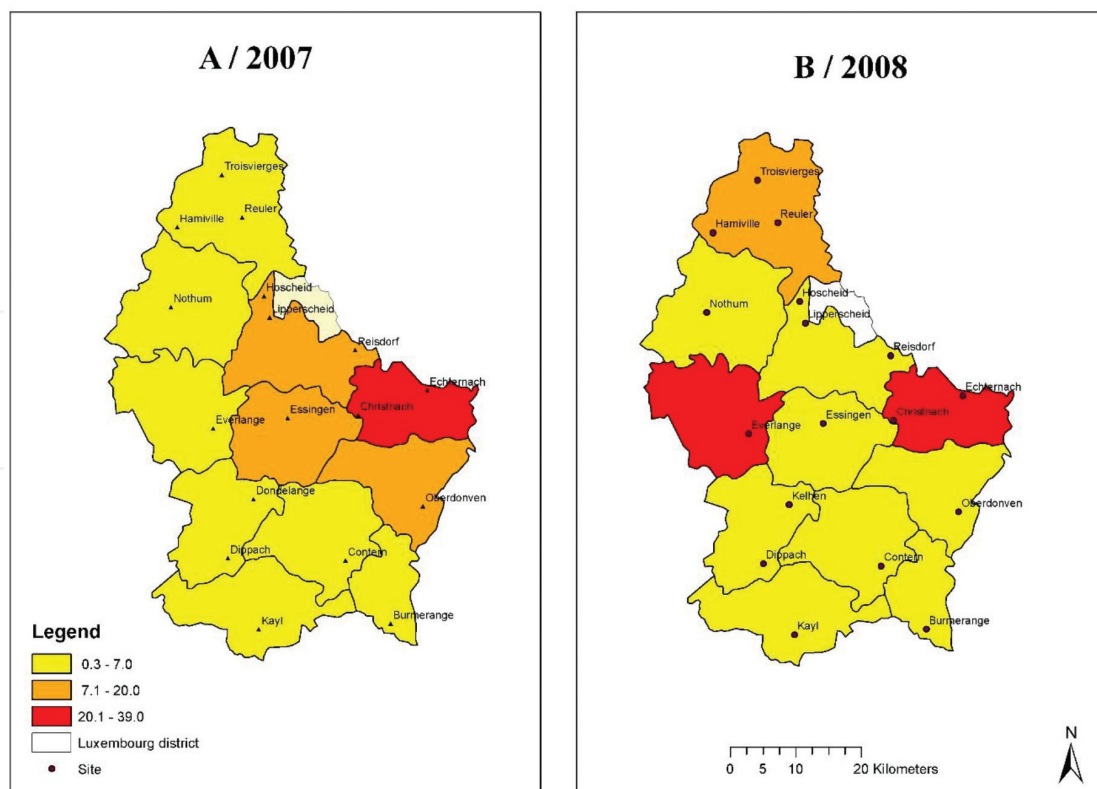
Figure 7. Incidence of fusarium head blight (% infected wheat spikes), caused by *Fusarium* spp. in various districts of Luxembourg (n = 17) in 2007 (a) and 2008 (B) as assessed between GS 77 and GS 87 ([45]).
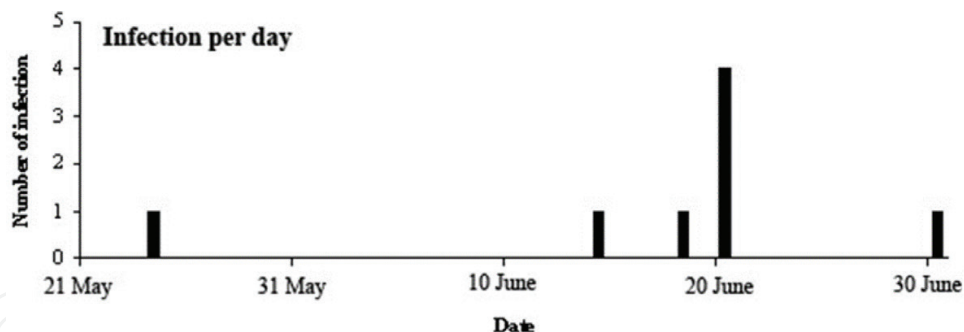
Figure 8. Example of simulated infection events by *Fusarium spp.* at Reuler, Luxembourg during the 2007 cropping season.

An example of the number of infection events by *Fusarium* spp. is depicted in **Figure 8**. Because of the changes in the composition of Fusarium population across sites and other site-specific characteristics related to the climate and topography, a mixed performance of the model. Thus, knowledge of the spatial patterns of epidemics of FHB, along with information on the Fusarium species involved are crucial to developing improved control and management measures relevant to each region, as in Luxembourg [116]. Furthermore, management strategies based on fungicide application should also take into account the effect chemical treatments may have on toxin induction by Fusarium species [103, 111]. Management tools in the future might include a weather-based DSS to help predict and eventually manage FHB.

4. Concluding remarks

Meteorological variables are most often used as the input data for disease forecasting models of fungal diseases of winter wheat in Luxembourg and elsewhere. For disease risk assessments at the regional scale, the meteorological data in these forecasting models must originate from local weather stations which are part of a meteorological networks consisting of automatic weather stations (AWSs). However, the choice of location for an AWS within a field or the distance between AWSs locations are both factors that hamper accurate forecasting of fungal diseases at regional scales. Moreover, techniques used to interpolate weather data from a set of neighboring sites suffer from some potential sources of error, e.g., difficulty in capturing small scale variation, failure to account for local topographical features, etc.

With the changes in the patterns of world climate expected during the coming decades [117], the pattern of corresponding distributions of fungal diseases will be affected accordingly. Thus, new challenges are emerging that need to be addressed. Climate change affects pathogen biology not only directly but also indirectly through effects on host development and phenology. Modeling to predict new disease threats is expected to be beneficial since many years of data are needed to prepare appropriate solutions to developing issues. However, although the impacts of climate change on crop disease are being studied, uncertainties inherent in crop disease models remain largely unexplored and unreported [118]. Moreover, acclimation to future climatic conditions by both the pathogen and the host can significantly alter the outcome of the plant–pathogen interaction [119].

Wheat diseases present a constant and evolving threat to food security. Decision-support tools based on in-season disease monitoring and disease progress models in relation to weather variables present various advantages for managing the development of epidemics of those diseases, while limiting potentially harmful side effects of excessive fungicide applications while ensuring economic benefit. Embedded in operational warning systems for plant disease monitoring, DSSs could provide a valuable service to the farmer community for pest and disease management through integrated and environmentally friendly methods.

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