IPSIM-Web, An Online Resource for Promoting Qualitative Aggregative Hierarchical Network Models to Predict Plant Disease Risk: Application to Brown Rust on Wheat

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Abstract

A qualitative pest modeling platform, named Injury Profile Simulator (IPSIM), provides a tool to design aggregative hierarchical network models to predict the risk of pest injuries, including diseases, on a given crop based on variables related to cropping practices as well as soil and weather environment at the field level. The IPSIM platform enables modelers to combine data from various sources (literature, survey, experiments, and so on), expert knowledge, and simulation to build a network-based model. The overall structure of the platform is fully described at the IPSIM-Web website (www6.inra.fr/ipsim). A new module called IPSIM-Wheat-brown rust is reported in this article as an example of how to use the system to build

and test the predictive quality of a prediction model. Model performance was evaluated for a dataset comprising 1,788 disease observations at 13 French cereal-growing regions over 15 years. Accuracy of the predictions was 85% and the agreement with actual values was 0.66 based on Cohen's κ . The new model provides risk information for farmers and agronomists to make scientifically sound tactical (within-season) decisions. In addition, the model may be of use for ex post diagnoses of diseases in commercial fields. The limitations of the model such as low precision and threshold effects as well as the benefits, including the integration of different sources of information, transparency, flexibility, and a user-friendly interface, are discussed.

Farmers are counting on innovations to reduce the reliance on pesticides to protect yield from pest and disease injuries (Lamichhane et al. 2016). Among them, modeling tools can aid in improving management of agroecosystems based on the concepts of agroecology (Deguine et al. 2017) and create decision support systems that may optimize (often reduce) pesticide use (Shtienberg 2013).

The Injury Profile Simulator (IPSIM) modeling platform was designed to build qualitative models for predicting injury profiles (i.e., a combination of injury levels caused by multiple pests) (Savary et al. 2000) as a function of cropping practices and production situations (PS) (Aubertot and Robin 2013). The IPSIM can be used to (i) help design cropping systems less exposed to the risk of pest damage, (ii) help perform diagnoses of agronomic problems in commercial fields, and (iii) support teaching and training activities. The approach is innovative by combining various sources of information: knowledge from scientific and technical literature, expert knowledge, simulation models, and datasets obtained from experiments or diagnoses in commercial fields. As a proof of concept, the model IPSIM-Wheat-eyespot was developed for an important soilborne stem disease and its predictive quality was judged fair (Robin et al. 2013). A website, named IPSIM-Web, was recently designed to present the concepts of the IPSIM platform. It provides recommendations for the development of IPSIM models, along with access to a collection of existing IPSIM models.

In order to demonstrate how to use of the platform, the design and development of a new IPSIM-based model and the evaluation of its predictive quality are described. The model concerns a major worldwide airborne disease, leaf rust, caused by *Puccinia triticina* Erikss., the most common rust disease on wheat (*Triticum aestivum* L.).

Crop protection in the context of agroecology relies on prophylactic measures and complementary, partially effective methods. They have to be developed, adapted, combined, and applied in a wide range of PS, defined here as the set of physical, chemical, and biological components of a given field or agroecosystem (excluding the crop) along with the field environment and socioeconomic drivers that may affect the farmer's decisions (Aubertot and Robin 2013; Savary et al. 2000). In this definition, the term "environment" refers to the landscape and the associated factors that can directly or indirectly influence the field concerned (Aubertot and Robin 2013).

Few epidemiological models for wheat diseases integrate the effects of multiple cropping practices (e.g., fungicide treatments, cultivar resistance, sowing date and rate, crop sequence, tillage, and fertilization) (Aubertot et al. 2005), mainly because it is difficult to describe their numerous effects on agroecosystems. Several models have been developed for predicting brown rust epidemics, often to aid decision making on fungicide applications, and are generally based on within-season weather variables and crop phenology (El Jarroudi et al. 2010). Wheat rust epidemics have been successfully predicted using two kinds of models: simulation models (Audsley et al. 2005; Benizri and Projetti 1992; El Jarroudi et al. 2010; Räder et al. 2007; Rocque 1991; Rossi et al. 1997) or statistical models (Burleigh et al. 1972; Daamen 1991; Eversmeyer 1970; Eversmeyer and Kramer 1996, 1998; Moschini and Perez 1999; Thepot and Gouache 2009). Among these models, very few take both weather and agricultural practices into account. The influence of sowing date or host resistance has been considered in only a few models (Audsley et al. 2005; Benizri and Projetti 1992; Moschini and Perez 1999). Other models describe the effect of brown

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*The e-Xtra logo stands for "electronic extra" and indicates that eight appendices are published online.

rust on wheat yields (Moschini and Perez 1999; Robert et al. 2004b; Seck et al. 1988). Our article first describes IPSIM-Web, a website to promote qualitative aggregative hierarchical networks. The development of IPSIM-Wheat-brown rust is then detailed as an example of its functionalities. Finally, a sensitivity analysis and the evaluation of its predictive quality are presented, along with a discussion on the limitations and benefits from using the tool.

IPSIM-Web

IPSIM-Web is an online resource that enables methodological advances with regards to the qualitative modeling of crop pest injury profiles. The main page of the website (www6.inra.fr/ipsim) shows the objectives and its structure, composed of seven sections (Fig. 1). The user can select English or French language. The content of each of the seven sections of the website is shown in Table 1.

IPSIM-Wheat-brown rust: background, model building, and evaluation. *Brown rust epidemiology and control.* Brown rust is caused by *P. triticina*, a rust fungus found in most agroecological regions where wheat is grown and that is now recognized as a prevalent pathogen in wheat production areas where it causes significant yield losses (Kolmer 2005; Roelfs et al. 1992). Yield losses of up to 70% in wheat caused due to brown rust usually result from a decrease in kernel number per spikelet and lower kernel mass (Huerta-Espino et al. 2011). At the end of the 20th century, brown rust was considered the most damaging foliar disease in Europe (Dean et al. 2012; Goyeau and Lannou 2011; Kolmer et al. 2013). The main strategies for leaf rust control rely on the use of cultivars with genetic resistance to leaf rust and the application of fungicides. The use of resistant cultivars is the preferable and most economical method to reduce losses from leaf rust. *P. triticina* is an airborne pathogen and is slightly endocyclic as opposed to highly endocyclic pest, as defined by Aubertot and Robin (2013). The term “endocyclic” refers to an organism whose development is mostly restricted to a particular field and which depends highly on the field’s endoinoculum (Aubertot and Robin 2013). Consequently, the

main control methods used against this pathogen are (i) genetic resistance (mainly the use of resistant cultivar alone or in a cultivar mixture; Bolton et al. 2008; Cox et al. 2004; Goyeau and Lannou 2011), (ii) use of fungicides (Roelfs et al. 1992; Samborski 1985), (iii) mitigation through crop status (balanced nitrogen [N] fertilization and reasonable sowing rate) (Robert et al. 2002, 2004a), (iv) escape (late sowing date) (Mishra et al. 1994), and (v) management of primary inoculum sources at the landscape level (i.e., management of wheat volunteers and the spatial distribution of wheat fields) (Anderson and Soper 2003; Papaix et al. 2011).

IPSIM-Wheat-brown rust construction. The IPSIM-Wheat-brown rust model was built using the method described on the IPSIM website. This model can be defined as a hierarchical deterministic Bayesian network (the oxymoron results from the fact that the considered probabilities have only two values: 0 or 1). IPSIM-Wheat-brown rust was designed in three stages, which are detailed in the following sections (Bohanec 2003): (i) identification and organization of model attributes, (ii) definition of the scale of the attribute, and (iii) definition of aggregative tables.

Definition of the model attributes. This qualitative multiattribute model aims to predict the final severity of brown rust in a given field based on the cropping practices performed in a given PS. The spatial scale addressed by the model is the field, under the influence of allo-inoculum sources at the landscape level. The temporal scale addressed by the model is the wheat growing season, although some input variables encompass crop sequence (going back to the pre-season). The final severity of brown rust has been divided into three main types of explanatory variables. The adaptation to brown rust of the generic IPSIM model structure presented by Aubertot and Robin (2013) is shown in Figure 2. The first step involves the choice of attributes to be taken into account and their hierarchical position in the tree. All attributes were chosen using the knowledge available in peer-reviewed literature combined with the knowledge of a panel of experts: five researchers and engineers, two faculty people, and three crop consultants from Agricultural Chambers, a cooperative and technical institute (Table 2).

Fig. 1. Structure of the IPSIM website.

We have chosen and organized them in a hierarchical tree. This resulted in an IPSIM-brown rust tree with a total of 18 attributes, 11 basic (i.e., input attributes) and 7 aggregated, including the final attribute. The 11 basic attributes are the terminal leaves or inputs of the model. In IPSIM-brown rust, they describe i) cropping practices, ii) spring weather, and iii) interactions with the rest of the landscape in terms of the proportion of wheat fields and wheat volunteer density in the landscape. The seven aggregated attributes result from the combination of immediate descendant attributes, aggregation rules being described in the “aggregative tables” section. The output of IPSIM-Wheat-brown rust is represented by the attribute “Final severity of brown rust” (brown rust severity on the leaf flag at stage 7, “milky grain”; development of fruit on the BBCH scale) (Lancashire et al. 1991).

Nine basic attributes describing the cropping practices (and affecting the final severity) are grouped together in the main “Cropping practices” subtree. This illustrates the complexity of the effects of cropping practices and the need to consider a combination of practices in order to evaluate the final brown rust severity. All the attributes, within or between subtrees, can interact with each other via the aggregating tables. The structure combines attributes based on tactical (within-season) or strategic (between-seasons) decisions (Kropff et al. 1995) that affect the final disease severity. These decisions can affect the agroecosystem at several stages (Aubertot and Robin 2013). The main “Cropping practices” subtree is composed of four levels: 1 = primary inoculum control, 2 = avoidance, 3 = mitigation through crop status and host resistance, 4 = chemical control.

Primary inoculum control. *P. triticipina* is an obligate fungus dependent on living plant tissue for its growth and propagation (Bolton et al. 2008). Cumulative effects of the crop sequence on the disease in a given field are presumably less important than for endocyclic diseases. Leaf rust survives during the summer on wheat volunteers (bread wheat, durum wheat, or triticale) which serve as inoculum reservoirs for the autumn-planted winter wheat (Bolton et al. 2008). Wheat volunteers are generally favored by reduced tillage rather than conventional tillage with plowing (Blackshaw et al. 2001; Derksen et al. 1993; Ogg and Parker 1989; Pickett 1993). Survival of the pathogen depends on a “green bridge” (on self-sown wheat volunteers) after harvest and before the emergence of cultivated wheat at the landscape level (Roelfs et al. 1992). Drastic reductions in pathogen populations will follow severe summer droughts that kill green bridge volunteers (Anderson and Soper 2003). Insufficient rain or abnormally high temperatures may prevent the establishment of wheat volunteers after harvest, which prevents the survival of *P. triticipina* inoculum from previous wheat crops (Eversmeyer and Kramer 2000). Nevertheless, urediniospores can be wind dispersed and infect host plants hundreds of kilometers away from their source plant (Bolton

et al. 2008). This exogenous (or airborne) inoculum is a major source of inoculum in agricultural production areas where a host is absent or where the environment during part of the year is too severe for pathogen survival (Roelfs et al. 1992). Therefore, the fields neighboring a given field with infected wheat volunteers are certainly more exposed to higher levels of inoculum than those situated further away from any primary inoculum sources. Most epidemics are the result of endogenous (or local) inoculum (Roelfs et al. 1992; Samborski 1985; Zadoks and Bouwman 1985). Tillage and seedbed preparation (such as plowing and, to a lesser extent, shallow tillage) and mechanical or chemical weeding aimed at destroying wheat volunteers (and thus preventing the green bridge) help manage and reduce primary endogenous inoculum of *P. triticipina* (Bailey et al. 2001; Ogg and Parker 1989; Roelfs et al. 1992). Primary inoculum control (i.e., wheat volunteer management) has a significant impact on brown rust epidemics and, thus, is explicitly taken into account in the IPSIM-Wheat-brown rust model. The attribute describing the level of control of wheat volunteers depends on two basic attributes: (i) “rainfall amount during the fallow period” because it affects volunteer emergence and physical destruction and (ii) “soil preparation after harvest of the preceding crop”, the efficacy of which depends on the level of rainfall during the fallow period.

Avoidance. In general, avoidance consists of practices that lead to uncoupling of crop vulnerability and the presence of inoculum. For brown rust, late sowing is a way of controlling the disease because early sowing will be longer exposed to early-season inoculum. Indeed, brown rust has often been reported to be more severe for early-sown crops because rust incidence generally decreases with later sowing (Eversmeyer and Kramer 2000; Mishra et al. 1994; Moschini and Perez 1999). This effect of the sowing date was included in the model.

Mitigation through crop status and host resistance. Host resistance. This is considered the most economically and biologically effective control method for brown rust (German et al. 2009; Kolmer 1996). At present, 76 leaf rust resistance genes (designated *Lr1* to *Lr76*) have been identified in wheat (Goyeau and Lannou 2011; McIntosh 2015). However, new races of *P. triticipina* regularly emerge (e.g., 40 to 60 new races are identified in North America every year). These are wind dispersed over thousands of kilometers across continents and oceans and challenge breeders to achieve durable resistance to cereal rusts (Ordoñez and Kolmer 2007). Genetic control of brown rust is one of the main methods used to contain the disease. Therefore, it was factored in as a priority in our model.

Fertilization. In general, applications of N fertilizers may influence plant health by altering the susceptibility to plant pathogens (Agrios 1997). This is the case for brown rust on wheat. A high level of N favors brown rust by increasing leaf area and, consequently,

Table 1. Structure of IPSIM-Web

Section	Content
Presentation of IPSIM	In the first subsection, the context of the IPSIM platform is described. A second subsection outlining the general objectives follows this page. A third subsection presents the specificities of the approach.
Designing IPSIM models	This section contains five subsections. The first describes the steps to design the conceptual model. The second explains how to combine literature and expert knowledge to create hierarchical networks. The third presents the offline implementation using the DEXi software method (Bohanec 2009), and provides a link to download the software. The fourth subsection provides the generic structure of an IPSIM model, along with the aggregative table for a multiple pest model (Aubertot and Robin 2013). The fifth and final section describes how to design a converter in order to translate nominal (e.g., cultivar names) or quantitative (e.g., sowing rate) variables into ordinal ones.
Sensitivity analysis	This section describes how to perform a sensitivity analysis of IPSIM models, using reports provided by the DEXi software (Bohanec 2009).
Assessment of the predictive quality of IPSIM models	This section explains how to assess the predictive quality of IPSIM models. It is divided into two parts. The first provides recommendations on the collection and organization of appropriate datasets. The second details the statistical method used to rigorously assess the predictive quality of IPSIM models when applied to independent data.
Application to different crop-pest systems	This section presents the published models designed using the IPSIM platform and offers a link to download them for use with the DEXi software (Bohanec 2009).
References	A list of useful references for anyone wishing to implement an IPSIM approach.
Acknowledgments	This section acknowledges the financial and institutional support, obtained from various sources, and provides the names of all those who have contributed to the development of IPSIM.

producing a dense canopy and humid microclimate. For instance, increasing N rates (from 67 to 134 kg ha⁻¹) were found to be associated with increased leaf rust severity (from 5.8 to 9.4%) (Mascagni et al. 1997). On the other hand, N deficiency tends to delay the development of most foliar diseases (Flint and Gouveia 2001) as reported for brown rust (de Vallavieille-Pope et al. 2000). Robert et al. (2002, 2004a) suggested that, when the leaf N content of the host is restricted, spore production per lesion is reduced. However, the lack of certainty discouraged us from giving a great weight to this process in the model.

Plant density. In general, low plant density limits disease development by restricting the contact between plant organs or lowering humidity within the canopy (Burdon and Chilvers 1982). However, sowing density rarely influences brown rust severity significantly, probably because of the compensation caused by increased tillering at low sowing densities (Chester 1946). Some studies suggested that microclimatic changes resulting from higher plant densities favored disease development (Pfleege and Mundt 1998). These adverse effects may partly explain the year-to-year variability of epidemic durations and severities (Pfleege and Mundt 1998). The effect of plant density on brown rust was included in the model structure but given a low weight.

Chemical control. The fallback solution of fungicide applications against multiple fungi (e.g., brown rust, yellow rust, and *Septoria tritici*) can be used when other control methods are not sufficient. Fungicides are an effective control method for many rust diseases (German et al. 2009; Samborski 1985). Fungicides of two chemical classes, quinone outside inhibitor and the demethylation inhibitor, achieve excellent control (70 to 97%), especially because brown rust has not yet developed resistance (Arvalis 2016b; FRAC 2016). This very effective control method was included in our model.

The two other subtrees of IPSIM-Wheat-brown rust describe the weather and the field environment. Details of each factor are discussed below.

Weather effects. Of these two subtrees, weather conditions are key factors affecting brown rust development (Bolton et al. 2008; de Vallavieille-Pope et al. 2000; Eversmeyer and Kramer 2000; Roelfs 1989; Sache 2000; Samborski 1985). We decided to take only spring weather into consideration because it is the most critical period for leaf rust infections (Table 2). In the model, wet and mild spring weathers are considered favorable to the disease (temperatures of 12 to 25°C and long free water periods are favorable to spore germination) (Bolton et al. 2008; de Vallavieille-Pope et al. 1995; El Jarroudi et al. 2014). Consequently, this attribute has a high weight in the model.

Landscape effect. The effect of the landscape structure, especially the proportion of the wheat area in the microregion of interest, can influence brown rust epidemics. Indeed, brown rust, like most airborne diseases, produces a large number of spores ready to be removed from host plants and transported over a few centimeters (to neighboring plants of the same field) or over thousands of kilometers (Bolton et al. 2008; Frezal et al. 2009; Sache 2000). However, qualitatively, higher densities of wheat volunteers in the surrounding fields and a higher proportion of wheat fields in the microregion (because the disease is polycyclic) increases the likelihood of the deposit of exogenous inoculum in a given wheat field. Moreover, the varietal composition of the landscape influences the resistance level of the most-grown wheat varieties by altering the structure of the pathogen populations (Papaix et al. 2011). Therefore, the effect of the landscape was included in the model but with a low weight, because it is difficult to quantify its impact. In conclusion, epidemics of brown rust appear to be influenced more by the environmental conditions favorable to their development than by primary inoculum management (Charles et al. 2011). These different effects were used to design the structure of IPSIM-Wheat-brown rust and to rank the respective influence of its attributes (Fig. 2).

Definition of the Scales of the Attributes

The second step in the design of a DEXi model is the choice of qualitative scales for the basic and aggregated attributes. Sets of

possible qualitative values are assigned to each attribute (Fig. 3). The value scale is discrete and is described using words (e.g., low, normal, or high) rather than numbers. Depending on the attribute and on the precision of available information, two to four qualitative values were considered. For example, the aggregated attribute “primary inoculum management” is described using a two-grade value scale (i.e., favorable or unfavorable), identifying whether this form of management is favorable or unfavorable to the development of the disease. The method used to define the ordinal values of a given attribute relies on expert knowledge and information available in peer-reviewed and technical literature (Table 2). The number of levels considered in the scale associated with a given attribute generally depends on the knowledge available: the deeper the knowledge, the higher the number of levels. In order to achieve a certain resolution for the output of the model, we chose to use a five-level scale for the final aggregated attribute (i.e., brown rust severity). In order to deal with a reasonable number of lines in the aggregative tables, we limited the number of levels per scale to two to four for input attribute and intermediate aggregated attributes.

Some of the values of the basic attributes are estimated quantitatively and then translated into ordinal qualitative values using technical publications, data from experiments or simulation models, and expert knowledge. This conversion factors in the regional context. For example, the three-grade value scale for the attribute “Effects of the sowing date” (from early sowing to late sowing) depends on the sowing date distribution in the given region (Arvalis 2016a). Similarly, the chemical control efficacy is described using a three-level scale (good efficacy, average efficacy, and low efficacy) as defined by Arvalis, the French extension institute specializing in cereals (Arvalis 2016b).

Other attributes are directly estimated qualitatively. For instance, the attributes “soil preparation” or “preceding crop” are nominal variables. The level of cultivar resistance was described using the official list provided by the French National Seed Testing Station (Groupe d’Etude et de contrôle des Variétés et des Semences; <http://cat.geves.info/Page/ListeNationale>) and published by Arvalis-Institut du végétal (<http://www.fiches.arvalis-infos.fr/>). The level of the susceptibility of the cultivar is expressed using a 1-to-9 scale, ranging from very susceptible to resistant. Sometimes, a two-value scale is sufficient to represent the value of an attribute (e.g., the

Attribute tree

Attribute

Final severity of brown rust

Fig. 2. Hierarchical structure of IPSIM-Wheat-brown rust. Bold and nonbold terms represent aggregated and basic attributes, respectively. (11 basic attributes and 7 aggregated attributes) (screenshot of the DEXi software).

preceding crop is host or nonhost). However, other attributes usually need a three-value scale to describe the diversity of cropping practices or field environment (e.g., the sowing date attribute requires three grades to describe farmers' practices: the sowing date can

be early, normal, or late). Initial quantitative attributes (e.g., "level of N fertilization" described with a quantitative value such as 180 kg/ha) were translated into ordinal values (i.e., high, normal, and low) based on threshold values defined using regional technical references.

Table 2. Knowledge available in the literature on the effects of cropping practices and the production situation on the severity of brown rust on wheat^a

Factor	Dir	Int	Impact on brown rust development	References
Tillage	0	0	No conclusion on the precise effect of soil tillage. Nevertheless, tillage seemed to be unfavorable for rotations with continuous wheat because volunteer wheat emergence is greater than with a no-till system.	Anderson and Soper 2003; Derksen et al. 1993; Ogg and Parker 1989; Pickett 1993; Roelfs et al. 1992
Destruction of volunteer wheat	+	+	Presence of wheat volunteers, as reservoirs of inoculum for the autumn-planted winter wheat, favors the conservation of the disease during summer. The destruction of all volunteer wheat would significantly reduce the survival of primary inoculum.	Anderson and Soper 2003; Blackshaw et al. 2001; Bolton et al. 2008; Derksen et al. 1993; Eversmeyer and Kramer 2000; Ogg and Parker 1989; Pickett 1993; Roelfs et al. 1992
Preceding crop	0	0	Effect of rotation is very poorly described and its impact is presumably a lot less important (no conservation on residues).	Anderson and Soper 2003
Sowing date	+	++	Brown rust has often been reported to be more severe in early sown crops.	Eversmeyer and Kramer 2000; Mishra et al. 1994; Moschini and Perez 1999
N fertilization rate	+	++	N favors brown rust by increasing foliar area and creating a dense canopy and a wet microclimate. When N available in the host is limited, spore production is reduced. N deficiency tends to delay the epidemic development of most foliar diseases such as powdery mildew and brown and yellow rusts.	de Vallavieille-Pope et al. 2000; Mascagni et al. 1997; Robert et al. 2002; Robert et al. 2004a, b
Sowing rate	+	+/-	Contradictory results. For some authors, seeding density rarely had a significant influence on rust severity. Others suggested that microclimatic changes resulting from higher plant densities led to improved conditions for disease development.	Chester 1946; Pfleeger and Mundt 1998
Cultivar choice	+	+++	Genetic resistance is the most economical method of reducing yield losses due to leaf rust. To date, 76 leaf rust resistance genes have been designated and mapped in wheat. However, new races of brown rust have been introduced in different continents and reduce the number of effective rust-resistance genes available for use.	Azzimonti 2013; Eversmeyer and Kramer 2000; German et al. 2009; Goyeau and Lannou 2011; Goyeau et al. 2009, 2012; Kolmer 1996, 2005; Ordoñez and Kolmer 2007
Cultivar mixture	+	+	Severity of leaf rust is lower in mixtures than in single-cultivar crops. Impact of cultivar mixtures on leaf rust depends on the properties and proportions of the cultivars used in the mixture.	Cox et al. 2004; Jackson and Wennig 1997; Lannou et al. 1994a,b; Mahmood et al. 1991; Mille and de Vallavieille-Pope 2001; Pfleeger and Mundt 1998; Vilich-Meller 1992
Weather interactions with the territory	+	++	Urediniospores infect the telial host with free water on the leaf surface and temperatures of 5 or 10 (depending on the authors) to 25°C. Germination occurs after 4 to 8 h at 20°C under 100% humidity. The uredinal stage was thought to be unable to survive the hot, dry summers because susceptible host plants were not available.	Bolton et al. 2008; de Vallavieille-Pope et al. 1995, 2000; Eversmeyer and Kramer 2000; Roelfs 1989; Roelfs et al. 1992; Sache 2000; Samborski 1985
	+	+/-	Rusts of wheat are fungal plant pathogens that can be disseminated thousands of kilometers across continents and oceans by the wind. The varietal composition of the landscape influences the resistance level of the most-grown wheat varieties by altering the structure of the pathogen population.	Bolton et al. 2008; Frezal et al. 2009; Kolmer 1996; Papaix et al. 2011 Sache 2000
Interactions with the territory	+	+/-	Rusts of wheat are fungal plant pathogens that can be disseminated thousands of kilometers across continents and oceans by wind. The landscape varietal composition influences the resistance level of the most grown wheat varieties by altering the structure of the pathogen population.	Bolton et al. 2008

^a Dir = direction and Int = intensity of the effect. Cropping practices and weather can be favorable (+), unfavorable (-), or neutral (0) to the development of brown rust. The intensity of the considered factor is summarized using four classes: 0 = no effect, + = slight, ++ = significant, and +++ = crucial.

For the weather attribute, three qualitative values were chosen (unfavorable, favorable, and very favorable) using knowledge from weather-based epidemiological models (Caubel et al. 2012; Räder et al. 2007) and the database from the national report on wheat disease development (M. Délos, personal communication). In principle, the scale can be preferentially ordered (from “bad” to “good” values) or unordered (for nominal attributes). In Figure 3, all scales are ordered.

Definition of Aggregative Tables

The third step in the design of a DEXi model consists of defining aggregative tables that determine how to aggregate several attributes. They consist of a set of “if-then” decision rules that are grouped together to fix the value of an aggregated attribute as a function of the value of the immediate descendant attributes. In DEX, aggregative tables (so-called “utility functions”) are represented by decision rules, which are provided by the model developer, grouped together for each aggregated attribute, and presented in tabular format. Based on the scores of lower-level attributes, the model calculates the scores of all of the aggregated attributes as well as the final attribute value.

An example of an aggregative table is shown in Figure 4. It defines the influence of cultivar choice, level of N fertilization, and sowing rate on genetic resistance and mitigation through crop status. Basically, each row in Figure 4 represents a simple if-then rule that determines the value of the aggregated attribute as a function of combinations of the three possible cultivar choices, the two possible levels of fertilization, and the possible three sowing rates. Interpreting the rules in Figure 4, one can see that the “cultivar choice” attribute is much more influential than the two others and that brown rust severity will decrease with a resistant cultivar, balanced fertilization, and a low sowing rate.

The seven aggregative tables of IPSIM-Wheat-brown rust were established using knowledge available in international literature (Table 2, with the specific use of the two columns: direction and intensity of the factors considered), plus the panel of experts. They can be found in Appendices 1, 2, 3, 4, 5, 6, and 7 and online at www6.inra.fr/ipsim.

Converter. IPSIM-Wheat-brown rust is based on qualitative attributes and aggregative tables. In order to transform quantitative or nominal variables that are usually available to potential users for their situation, a converter was designed to transform nominal or quantitative variables into ordinal ones. It uses regional references adapted to the local features of cropping practices or PS (e.g., recommended sowing date and rate, and N fertilization). It was developed using Excel and is available on the IPSIM website (E Application to different crop-pest systems, <https://www6.inra.fr/ipsim/Application-to-different-crop-pest-systems>). If required, it allows fast and easy adaptations of the model to new PS and cropping practices.

IPSIM-Wheat-Brown Rust Simulation Examples

The model was applied to three hypothetical (but typical) cropping systems. This application was conducted mainly to illustrate how the model can be used. The attribute tree and output results obtained (i.e., final aggregated attribute, brown rust severity) are provided in Figure 5. They represent the values of all the basic input attributes and aggregated attributes for an organic wheat field, a high-input field, and a conventional wheat field.

Sensitivity analysis and predictive quality. *Sensitivity analysis of IPSIM-Wheat-brown rust.* A sensitivity analysis of IPSIM-Wheat-brown rust was conducted using the automatic procedure embedded in the DEXi software (Bohanec 2009) and described by Bohanec (2015). This procedure calculates the standardized local and global weights of each attribute as a function of the aggregative tables using a linear regression method (Bohanec 2009; Robin et al. 2013). They are approximated and express the influence of each attribute on the value of the output variable or aggregated attribute immediately above. The use of standardized values is recommended because they take into account the fact that the various attributes are associated with scales with various numbers of classes (Bohanec 2009). The attribute weights are presented in Figure 6 according to the method described by Bohanec (2015). For example, the attribute “Genetic resistance and mitigation through crop status” is determined at 83% by “cultivar choice”, at 12% by “level of N fertilization”, and at 5% by “sowing rate” (Fig. 6). These weights can be seen as an equivalent to a sensitivity analysis for quantitative models (Aubertot and Robin 2013).

Description of the dataset. A large independent dataset was established using a national survey conducted to identify relevant data from various research and extension institutes in France. Studies were selected based on having complete datasets (input and final attributes): description of cropping practices, weather, and field environment along with brown rust severity at stage 7, milky grain, and development of fruit on BBCH scale. The dataset obtained is presented in Table 3 and described below.

S1. The dataset used to assess the predictive quality of IPSIM-Wheat-brown rust comprises results from a multienvironment experimental network consisting of several combinations of cultivars and crop management (CM) systems (Loyce et al. 2008, 2012). Four rule-based CM plans were defined, with a decrease in input level from CM1 (a high-input system) to CM4 (a low-input system), and cultivars were clustered into three groups according to their scores for resistance to diseases. This was done to analyze the effects of interactions between genotype and management on diseases and on yield. These trials were not specific studies on brown rust diseases but addressed major fungal wheat diseases.

Attribute	Scale
Final severity of brown rust	50-100; 20-50; 10-20; 5-10; 0-5
Effect of cropping practices	Favorable; Moderately favorable; Unfavorable
Primary inoculum management	Favorable; Unfavorable
Preceding crop	Host; Non host
Rainfall amount during the fallow period	Favorable; Unfavorable
Soil preparation	Non destruction of volunteers; Destruction of volunteers
Escape: effects of the sowing date	Early sowing; Normal sowing date; Late sowing
Mitigation through crop status	Very favorable; Favorable; Moderately favorable; Unfavorable
Cultivar choice	Very susceptible to susceptible; Moderately susceptible; Moderately resistant to resistant
Level of N fertilisation	Excess level; Balanced level
Sowing rate	High; Normal; Low
Chemical control efficacy	Very good control efficacy; Good control efficacy; Average control efficacy; Low control efficacy
Fungicide T2 efficacy	Good efficacy; Average efficacy; Low efficacy or 0 treatment
Number of fungicide treatment further T2	0; 1; 2
Effects of soil and weather	Very favorable; Favorable; Unfavorable
Spring weather	Very favorable; Favorable; Unfavorable
Interactions with the rest of the landscape	Favorable; Neutral
Primary inoculum sources	Very important; Normal

Fig. 3. Attribute scales of IPSIM-Wheat-brown rust. All of the scales are ordered from values favorable to brown rust (i.e., detrimental to the crop) on the left-hand side to values unfavorable to brown rust (i.e., beneficial to the crop) on the right-hand side. In the DEXi software, this difference is clearly visible because, by convention, different shades are used to indicate values beneficial, detrimental, or neutral to the user (screenshot of the DEXi software).

- S2. Other data originated from the MicMac-Design Project, the aim of which was to design and assess cropping systems managed in low input farming, according to Integrated Crop Management principles.
- S3. Data from the “SGCI integrated systems for arable crops” system experiment were used. Three systems representing crop management choices for southwestern France were specified by their objectives and constraints: A, water and labor fully available; B,

input and labor reduction; and C, drastic input reductions (Nolot and Debaeke 2003). The main wheat pests were monitored on plots approximately 1.5 ha in size (Nolot and Debaeke 2003).

- S4. The installation experiment INRA-ASTER Mirecourt (Coquil et al. 2009) also provided data. Since 2005, two organic dairy systems have been prototyped. The evolution of the main diseases on the different crops of the studied cropping systems has been monitored.

	Cultivar choice	Level of N fertilisation	Sowing rate	Mitigation through crop status
1	Very susceptible to susceptible	Excess level	High	Very favorable
2	Very susceptible to susceptible	Excess level	Normal	Very favorable
3	Very susceptible to susceptible	Excess level	Low	Very favorable
4	Very susceptible to susceptible	Balanced level	High	Very favorable
5	Very susceptible to susceptible	Balanced level	Normal	Very favorable
6	Very susceptible to susceptible	Balanced level	Low	Very favorable
7	Moderately susceptible	Excess level	High	Favorable
8	Moderately susceptible	Excess level	Normal	Favorable
9	Moderately susceptible	Excess level	Low	Moderately favorable
10	Moderately susceptible	Balanced level	High	Moderately favorable
11	Moderately susceptible	Balanced level	Normal	Moderately favorable
12	Moderately susceptible	Balanced level	Low	Moderately favorable
13	Moderately resistant to resistant	Excess level	High	Unfavorable
14	Moderately resistant to resistant	Excess level	Normal	Unfavorable
15	Moderately resistant to resistant	Excess level	Low	Unfavorable
16	Moderately resistant to resistant	Balanced level	High	Unfavorable
17	Moderately resistant to resistant	Balanced level	Normal	Unfavorable
18	Moderately resistant to resistant	Balanced level	Low	Unfavorable

Fig. 4. Aggregative table for the “Genetic resistance and mitigation through crop status” aggregated attribute. Aggregation rules (for the 18 possible combinations of three cultivar choices, two levels of fertilization, and three sowing rates) and the resulting weights for each input attribute calculated as described by Bohanec (2015).

Option	Conventional field	High-input field	Organic field
. Final severity of brown rust	10-20	0-5	0-5
.. Effect of cropping practices	Moderately favorable	Unfavorable	Unfavorable
... Primary inoculum management	Unfavorable	Favorable	Unfavorable
.... Preceding crop	Non host	Host	Non host
.... Rainfall amount during the fallow period	Favorable	Favorable	Favorable
.... Soil preparation	Destruction of volunteers	Non destruction of volunteers	Destruction of volunteers
... Escape: effects of the sowing date	Normal sowing date	Early sowing	Late sowing
... Mitigation through crop status	Moderately favorable	Very favorable	Unfavorable
.... Cultivar choice	Moderately susceptible	Very susceptible to susceptible	Moderately resistant to resistant
.... Level of N fertilisation	Balanced level	Excess level	Balanced level
.... Sowing rate	Normal	Normal	High
... Chemical control efficacy	Average control efficacy	Very good control efficacy	Low control efficacy
.... Fungicide T2 efficacy	Good efficacy	Good efficacy	Low efficacy or 0 treatment
.... Number of fungicide treatment further T2	0	2	0
.. Effects of soil and weather	Very favorable	Very favorable	Very favorable
... Spring weather	Very favorable	Very favorable	Very favorable
.. Interactions with the rest of the landscape	Neutral	Neutral	Neutral
... Primary inoculum sources	Normal	Normal	Normal

Fig. 5. Example of three simulations (screenshot of the DEXi software) carried out with IPSIM-Wheat-brown rust in a given production situation: favorable amount of rainfall during the fallow period, spring weather very favorable to the disease, and normal sources of inoculum at the landscape level (i.e., departmental proportion of wheat field area lower or equal to the national wheat field area proportion). Cropping practices (conventional, high-input, and organic fields) of the three simulations are described by the values of eight attributes.

S5. Data were used from fungicide trials undertaken by the members of In Vivo AgroSolutions, a subsidiary of Union InVivo, the biggest French group of cooperatives. The goal of these trials,

carried out in all the French wheat production regions, is to assess the efficacy of single fungicides and fungicide programs on main wheat diseases: brown rust, yellow rust, Septoria tritici blotch,

Attribute	Local level 1	Local level 2	Local level 3	Global level 1	Global level 2	Global level 3
Final incidence of brown rust						
1. Effects of cropping practices	40			40		
1.1. Primary inoculum management		2			1	
1.1.1. Preceding crop			34			1
1.1.2. Rainfall amount during the fallow period			33			0
1.1.3. Soil preparation			33			0
1.2. Escape: effects of Sowing date		2			1	
1.3. Mitigation through crop status		53			22	
1.3.1. Cultivar choice			83			18
1.3.2. Level of N fertilisation			12			3
1.3.3. Sowing rate			5			1
1.4. Chemical control efficacy		43			16	
1.4.1. Fungicide T2 efficacy			50			8
1.4.2. Number of fungicide treatment further T2			50			8
2. Effects of soil and weather	37			37		
Spring weather		100			37	
3. Interactions with the rest of the territory	23			23		
Primary inoculum sources		100			23	

Fig. 6. Respective normalized weights of the attributes of IPSIM-Wheat-brown rust calculated by DEXi (Bohanec 2015). Local weights represent the impact of each attribute on the value of the immediate descendant attribute in the hierarchy. Global weights represent the influence of each attribute on the value of the final attribute. Local and global weights are distributed in three levels of aggregation.

Table 3. Main features of the datasets used for the evaluation of the predictive quality of IPSIM-Wheat-brown rust

Code	Studied impact of cropping practices on brown rust	Design	Year	Location	Number of site-years	References
S1	Effects of crop management and cultivar on winter wheat diseases	Network of multifactorial field trials	1999–2012	13 locations (12 regions)	1,026	Loyce et al. 2008, 2012
S2	Design of innovative prototypes in low-input cropping systems (Mic-Mac design)	Multifactorial field trials	2010–2013	2 locations (Toulouse, Midi-Pyrénées)	23	http://institut.inra.fr/Organisation/Annuaire-des-sites/Agriculture/Agronomie/Systeme-de-culture/Agriculture-integree/Projet-MicMac-Design
S3	Design and evaluation of arable crop systems (SGCI)	Multifactorial field trials	1995–2002	1 location (Toulouse, Midi-Pyrénées)	43	Nolot and Debaeke 2003
S4	Design of environmentally friendly organic dairy systems	Multifactorial field trials	1997–2011	1 location (Mirecourt, Vosges)	11	Coquil et al. 2009
S5	Cropping year trials for fungicides	Monofactorial field trials	2007–2012	5 locations (4 regions)	10	InVivo AgroSolutions 2013 (unpublished data)
S6	Effects of cultural practices and climate on winter wheat diseases	Survey in commercial fields	2011–2013	2 locations (Midi-Pyrénées and Languedoc Roussillon)	132	Magnard 2012

Fusarium head blight, and powdery mildew (InVivo AgroSolutions 2013).

S6. Finally, diagnoses in 44 commercial fields were conducted in two regions of southern France (Midi-Pyrénées and Languedoc-Roussillon) where diseases, animal pests, and weeds have been monitored in wheat fields since 2011.

In all, 1,788 site-years (commercial or experimental fields) were used for the evaluation of the predictive quality of the model. They are composed of a large number of combinations of cropping practices and PS (in 13 French cereal-growing regions over 15 years) (Table 3).

Despite the significant size of the database, all possible combinations of the input attributes of the model ($2^5 \times 3^6 = 23,328$) could not be observed in experiments or diagnoses in commercial fields. For example, the model was tested almost solely for nonhost preceding crops (99.7% of observed fields), balanced level of N fertilization (99.6%), moderately or quite to very resistant cultivar (87%), and at 68% for unfavorable spring weather (a large proportion of data comes from northern France, where brown rust is less frequent than in the south). Consequently, the model was essentially tested for low severities: the database is unbalanced, with 85% of the observed final severities in the 0-to-5% severity class (Fig. 7, marginal distribution of the observed instances of the confusion matrix).

Statistical analyses. The model was assessed for its ability to predict severity classes. In order to do so, quantitative observed data severities were transformed into ordinal values, using the same discretization as the model (i.e., 0 to 5, 5 to 10, 10 to 20, 20 to 50, and 50 to 100%). Each of the observed brown rust severities was associated with a value simulated by the model using the corresponding observed input attributes. In order to characterize the predictive quality of the model, a confusion matrix was calculated as a table layout, in which each column represents the instances in a predicted class and each row represents the instances in an observed class. The associated accuracy (proportion of correctly predicted situations) was calculated along with the Cohen's quadratic weighted κ (Agresti 2010) that can be interpreted as the proportion of variability explained by the model (Fleiss and Cohen 1973), the Kendall's τ_b (Kendall

1938), and the Spearman's rank correlation coefficient ρ_s (Spearman 1904). These calculations were performed using Mathematica 10.1.0.0 (Wolfram Research, Inc. 2015).

Evaluation of the Predictive Quality

The calculated accuracy of the confusion matrix (Fig. 7) indicates that the model correctly predicted most of the observations (85%). The quadratic weighted κ criterion indicated that the model explained approximately 66% of the variability of the dataset. The Kendall's τ_b and the Spearman's rank correlation coefficient ρ_s were 0.59 and 0.61, respectively. Therefore, the overall predictive quality of IPSIM-Wheat-brown rust was judged satisfactory. The predictive quality was good for the lowest class (the most frequently observed class in the dataset): 82% of the observed values between 0 and 5% were correctly simulated. The model underestimated final severities for observations higher than 5% (267 instances): 205 of 267 instances were underestimated by the model (0.768 ratio), whereas 11 instances were overestimated (0.041 ratio).

Discussion

The IPSIM website provides detailed information for users who wish to design their own models using the IPSIM platform (Aubertot and Robin 2013) based on the DEXi system (Bohanec 2009). An example application of the IPSIM platform is provided for an important foliar disease on wheat. IPSIM-Wheat-brown rust offers new possibilities for the design of innovative cropping systems less reliant on fungicides. This is the first wheat brown rust model to consider simultaneously the effects of weather, cropping practices, and landscape. This is done by running the model for a wide range of cropping practices in various PS, enabling the identification of a combination of agricultural practices limiting the epidemics. The example presented is innovative in several ways: (i) it considers a longer time frame than the cropping season, because it includes the effect of the preceding crop; (ii) no other simulation model factors in as many cropping practices affecting the development of the disease; (iii) interactions between these practices, as well as detrimental or beneficial interactions between practices and weather, are also considered; and (iv) interactions at the landscape level are taken into account (i.e., the proportion of wheat in the considered region), although this spatial representation is rather limited as compared with the generic conceptual scheme of IPSIM (Aubertot and Robin 2013). The qualitative nature of the IPSIM method is well suited to the modeling of complex systems for which no high level of precision is required. The DEXi software offers a suitable environment for the organization of available knowledge and a rapid development of models similar to IPSIM-Wheat-brown rust. The main strength of the IPSIM approach is that it offers a simple method for handling complexity while taking into account a wide range of drivers and permitting a high level of generality (Aubertot and Robin 2013).

A major innovation of the IPSIM modeling approach is that it aggregates information from various sources (i.e., technical and scientific literature, expert knowledge, experimental data, data from diagnoses in commercial fields, or other simulation models). The main characteristic of the approach is that it deals with qualitative variables (sometimes derived from quantitative variables). This implies a loss of precision but makes it possible to represent a high level of complexity. The relatively limited number of attributes and scales allows the representation of the complex underlying mechanisms to be kept as simple as possible. Increasing the number of classes of the various IPSIM scales could lead to improved precision of the model. However, this would result in more complicated aggregative tables, which would be more difficult to complete. Attributes and scales were selected from literature, experimental data, and expert knowledge. Sometimes, there is a lack of knowledge in existing literature or a lack of consensus on the effects of different factors. Consequently, the model could not yet integrate these factors. For instance, the severity of leaf rust is lower in cultivar mixtures than in single-cultivar crops and decreases with the proportion of resistant cultivars (Cox et al. 2004; Jackson and Wennig 1997; Lannou et al. 1994a,b; Mahmood et al. 1991; Mille and de Vallavieille-Pope 2001; Pfleeger

	Simulated					Total
	0–5%	5–10%	10–20%	20–50%	50–100%	
0–5%	1467 <i>82.0</i>	33 <i>1.85</i>	15 <i>0.839</i>	6 <i>0.336</i>	0 <i>0</i>	1521 <i>85.1</i>
5–10%	64 <i>3.58</i>	20 <i>1.12</i>	5 <i>0.280</i>	0 <i>0</i>	1 <i>0.0559</i>	90 <i>5.03</i>
10–20%	28 <i>1.57</i>	15 <i>0.839</i>	12 <i>0.671</i>	2 <i>0.112</i>	0 <i>0</i>	57 <i>3.19</i>
20–50%	21 <i>1.17</i>	12 <i>0.671</i>	14 <i>0.783</i>	16 <i>0.895</i>	3 <i>0.168</i>	66 <i>3.69</i>
50–100%	7 <i>0.391</i>	5 <i>0.280</i>	9 <i>0.503</i>	30 <i>1.68</i>	3 <i>0.168</i>	54 <i>3.02</i>
Total	1587 <i>88.8</i>	85 <i>4.75</i>	55 <i>3.08</i>	54 <i>3.02</i>	7 <i>0.391</i>	1788 <i>100</i>

Fig. 7. Confusion matrix of the IPSIM-Wheat-brown rust model and marginal distributions. Numbers in italic are overall percentages calculated as the ratio of the number of instances in a given situation, or marginal sums, to the total number of observations $\times 100$ ($n = 1,788$). Color codes represent the distance between observed and simulated values. The color gradient was calculated using green to indicate situations where simulations match observations (the diagonal of the matrix) and red where the differences are maximum. Intermediate colors were arbitrarily defined by the ColorFunction option in Mathematica (Wolfram Research, Inc. 2015), according to the number of the classes considered (five in this case).

and Mundt 1998; Vilich-Meller 1992). However, this important factor could not yet be integrated into the model because of the lack of experimental references to adequately describe it. Both the choice of the number of classes and the definition of thresholds are crucial for the overall development of the model. The use of thresholds (e.g., level of N fertilization or sowing rate) leads to abrupt switches between classes when variables are close to thresholds. This can be a source of serious error for the cut-off values, particularly if the threshold discriminates between the contradictory effects of an attribute (e.g., 100 mm of rainfall during the fallow period differentiates between a favorable or unfavorable possible destruction of volunteers and, consequently, a favorable or unfavorable management of primary inoculum). To remediate this situation, fuzzy logic could be used to account for the uncertainty in the input variables by avoiding the knife-edge effect of a given class (Bockstaller et al. 2008). Instead of a threshold value, which distinguishes a favorable class from an unfavorable class, partial or fuzzy classes could be defined between them. In this approach, the estimation of attributes is continuous, leading to potentially higher sensitivity. However, it is harder to use and weights associated with each attribute are not as explicit as in the DEXi models (Fragoulis et al. 2009; Pelzer et al. 2012; van der Werf and Zimmer 1998).

Finally, some values of the basic indicators are difficult to estimate objectively. For example, the presence of volunteers in the field margins, or the genetic structure of *P. trititica* (e.g., impact of new races, or regional evolution of races) is difficult for users to provide. In this case, the corresponding variables were not factored into the model. Moreover, all values of the basic attributes have to be defined qualitatively, and some of them have to be derived from quantitative values. This can be tedious and sometimes questionable. For instance, it can be difficult to determine whether the N fertilization level is in excess or balanced. In this case, the use of a crop model embedding the effect of N availability in soil could be foreseen. However, since the early stages of IPSIM development, it has been clear that precision was not an objective of the model (Aubertot and Robin 2013). It is this approach that was applied for modeling the effects of cropping practices and weather on brown rust.

How accurate the assessment of the predictive quality of IPSIM-Wheat-brown rust is depends not only on the model itself but also on the diversity of the data used. These data should represent a variety of soils, weather conditions, and cropping systems as well as final severities. The large dataset used in this study partially satisfied the three former conditions but did not fully satisfy the latter because of a lack of data for moderate or severe brown rust epidemics. This is consistent with French historical data that illustrate that the disease occurs mostly in southwestern France, where levels of risks are highly dependent on weather scenarios and cropping practices (Appendix 8). Farmers usually use resistant cultivars or fungicides, which explains the generally low severities in the dataset and, thus, the predictive quality of the model could not be thoroughly evaluated for medium or high levels of severities. Therefore, it seems important to complete the dataset used for the assessment of the IPSIM model's predictive quality by adding PS with moderate and severe brown rust epidemics. This can be achieved by (i) setting up specific experiments, (ii) performing agronomic diagnoses in commercial fields, and (iii) integrating data from other countries. Nevertheless, IPSIM-Wheat-brown rust reasonably represented the variability of the 1,788 fields used to test its predictive quality over a wide range of regions and for many years (Table 3).

Further improvements can be made in the future while maintaining the modeling platform's accuracy and simplicity. Now that the first version of IPSIM-Wheat-brown rust is available, it will be possible to improve its predictive quality by optimizing the aggregative tables. In order to do so, a specific algorithm will be developed and used with powerful computational resources to cope with the huge size of the domain to be explored. It will be made available to IPSIM modelers on the IPSIM website.

A major innovation of the IPSIM platform is its flexibility and adaptability because it easily integrates local factors such as the local climate or locally used cultivars. The simple and user-friendly interface of

DEXi makes this tool an efficient support for communication, teaching, and training for researchers, advisers, extension workers, teachers, or even farmers. This can be a means to exchange knowledge and experience in an iterative assessment approach between model-makers and users, because the model offers the possibility of adjusting certain scales or aggregative rules.

Free sharing of the underlying methodological breakthroughs can potentially affect any agricultural region worldwide because IPSIM models apply to a wide range of agricultural productions and PS. The approach can help the ex-ante assessment of the biotic risk for new cropping systems in a given PS, based on the impact of cropping practices factored into the model. It can also be used for the ex-post assessment of cropping systems, regarding the risk of multiple pests. Therefore, it can be used to help decision making for farmers, advisers, or experimenters, even if some variables such as weather or landscape are independent from farmers' choices. Thus, the model will aid in decision making for new cropping practices. The new IPSIM website will also be used for teaching and training.

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Literature Cited

- Agresti, A. 2002. Categorical Data Analysis. 2nd ed. Wiley Series in Probability and Mathematical Statistics. Wiley, Hoboken, NJ.
- Agrios, G. N. 1997. Plant Pathology, 4th ed. Elsevier, Burlington, MA.
- Anderson, R. L., and Soper, G. 2003. Review of volunteer wheat (*Triticum aestivum*) seedling emergence and seed longevity in soil. Weed Technol. 17:620-626.
- Arvalis. 2016a. Blé tendre. Quand semer mes céréales et à quelle densité? Online publication. <https://www.arvalis-infos.fr/view-22990-arvarticle.html?region=Arvalis>.
- Arvalis. 2016b. Interventions de printemps 2016-2017. SYNTHÈSE NATIONALE. Online publication. https://www.arvalis-infos.fr/file/galleryelement/pj/08/96/3a/c5/choisir_2_national_7696807478995285377.pdf
- Aubertot, J. N., Dore, T., Ennaifar, S., Ferre, F., Fourbet, J. F., and Schneider, O. 2005. Integrated Crop Management requires to better take into account cropping systems in epidemiological models. In: Proc. 9th Int. Workshop Plant Dis. Epidemiol. Landemeau, France.
- Aubertot, J. N., and Robin, M. H. 2013. Injury profile SIMulator, a qualitative aggregative modeling framework to predict crop injury profile as a function of cropping practices, and the abiotic and biotic environment. I. Conceptual bases. PLoS One 8:e73202.
- Audley, E., Milne, A., and Paveley, N. 2005. A foliar disease model for use in wheat disease management decision support systems. Ann. Appl. Biol. 147: 161-172.
- Azzimonti, G., Lannou, C., Sache, I., and Goyeau H. 2013. Components of quantitative resistance to leaf rust in wheat cultivars: Diversity, variability and specificity. Plant Pathol. 62:970-981.
- Bailey, K. L., Gossen, B. D., Lafond, G. P., Watson, P. R., and Derksen, D. A. 2001. Effect of tillage and crop rotation on root and foliar diseases of wheat and pea in Saskatchewan from 1991 to 1998: Univariate and multivariate analyses. Can. J. Plant Sci. 81:789-803.
- Benizri, E., and Progetti, F. 1992. Mise au point d'un modele de simulation de la rouille brune du ble [A model of simulation of wheat leaf rust]. Agronomie 12: 97-104.
- Blackshaw, R. E., Larney, F. J., Lindwall, C. W., Watson, P. R., and Derksen, D. A. 2001. Tillage intensity and crop rotation affect weed community dynamics in a winter wheat cropping system. Can. J. Plant Sci. 81:805-813.
- Bockstaller, C., Guichard, L., Makowski, D., Aveline, A., Girardin, P., and Plantureux, S. 2008. Agri-environmental indicators to assess cropping and farming systems. A review. Agron. Sustain. Dev. 28:139-149.
- Bohanec, M. 2009. DEXi: Program for Multi-Attribute Decision Making, Version 3.02. Online publication. Jozef Stefan Institute, Ljubljana, Slovenia. <http://kt.ijs.si/MarkoBohanec/dexi.html>

- Bohanec, M. 2015. DEXi: Program for Multi-Attribute Decision Making, User's Manual, Version 5.00. IJS Report DP-11897, Jožef Stefan Institute, Ljubljana, Slovenia. <http://kt.ijs.si/MarkoBohanec/pub/DEXiManual500.pdf>
- Bolton, M. D., Kolmer, J. A., and Garvin, D. F. 2008. Wheat leaf rust caused by *Puccinia triticina*. *Mol. Plant Pathol.* 9:563-575.
- Burdon, J. J., and Chilvers, G. A. 1982. Host density as a factor in plant disease ecology. *Annu. Rev. Phytopathol.* 20:143-166.
- Caubel, J., Launay, M., Lannou, C., and Brisson, N. 2012. Generic response functions to simulate climate-based processes in models for the development of airborne fungal crop pathogens. *Ecol. Model.* 242:92-104.
- Chester, K. S. 1946. The Nature and Prevention of Cereal Rusts as Exemplified in the Leaf Rust of Wheat, 2nd ed. *Chronica Botanica*, Waltham, MA.
- Coquil, X., Blouet, A., Fiorelli, J. L., Bazard, C., and Trommenschlager, J. M. 2009. Conception de systèmes laitiers en agriculture biologique: Une entree agronomique [Designing organic dairy systems based on agronomic principles]. *INRA Prod. Anim.* 22:221-234.
- Cox, C. M., Garrett, K. A., Giosue, S., Munk, L., Newton, A. C., Nicks, R. E., Ostergard, H., Pons-Kuhnemann, J., Rossi, V., and Sache, I. 2000. Assessment of epidemiological parameters and their use in epidemiological and forecasting models of cereal airborne diseases. *Agronomie* 20:715-727.
- de Vallavieille-Pope, C., Huber, L., Leconte, M., and Goyeau, H. 1995. Comparative effects of temperature and interrupted wet periods on germination, penetration and infection of *Puccinia recondita* f. sp. *tritici* and *P. striiformis* on wheat seedlings. *Phytopathology* 85:409-415.
- El Jaroudi, M., Giraud, F., Delfosse, P., Hoffmann, L., Maraite, H., and Tychon. B. 2010. Assessment of the night weather parameters and their use in forecasting model of wheat leaf rust. (Abstr.) *Phytopathology* 100:S32.
- El Jaroudi, M., Kouadio, L., Delfosse, P., and Tychon, B. 2014. Brown rust disease control in winter wheat: I. Exploring an approach for disease progression based on night weather conditions. *Environ. Sci. Pollut. Res.* 21:4797-4808.
- Eversmeyer, M. G. 1970. A method of predicting epidemic development of wheat leaf rust. *Phytopathology* 60:805-811.
- Eversmeyer, M. G., and Kramer, C. L. 1996. Modeling winter and early spring survival of *Puccinia recondita* in wheat nurseries during 1890 to 1993. *Plant Dis.* 80:490-493.
- Eversmeyer, M. G., and Kramer, C. L. 1998. Models of early spring survival of wheat leaf rust in the Central Great Plains. *Plant Dis.* 82:987-991.
- Eversmeyer, M. G., and Kramer, C. L. 2000. Epidemiology of wheat leaf and stem rust in the central Great Plains of the USA. *Annu. Rev. Phytopathol.* 38: 491-513.
- Flieiss, J. L., and Cohen, J. 1973. The equivalence of weighted kappa and the intraclass correlation coefficient as measures of reliability. *Educ. Psychol. Meas.* 33:613-619.
- Flint, M. L., and Gouveia, P. 2001. IPM in Practice. Principles and Methods of Integrated Pest Management. University of California, Oakland.
- FRAC. 2016. Protocol of the discussions and recommendations of the SBI working group of the Fungicide Resistance Action Committee (FRAC). [http://www.frac.info/docs/default-source/sbi-wg/sbi-wg-current/minutes-of-the-2015-meeting-recommendations-for-2016-\(april-2016\).pdf?sfvrsn=2](http://www.frac.info/docs/default-source/sbi-wg/sbi-wg-current/minutes-of-the-2015-meeting-recommendations-for-2016-(april-2016).pdf?sfvrsn=2)
- Fragoulis, G., Trevisan, M., Guardo, A. d., Sorce, A., Meer, M. d., Weibel, F., and Capri, E. 2009. Development of a management tool to indicate the environmental impact of organic viticulture. *J. Environ. Qual.* 38:826-835.
- Frezal, L., Robert, C., Bancal, M. O., and Lannou, C. 2009. Local dispersal of *Puccinia triticina* and wheat canopy structure. *Phytopathology* 99:1216-1224.
- German, S., Chaves, M., Campos, P., Viedma, L. d., and Madariaga, R. 2009. Are rust pathogens under control in the Southern Cone of South America? In: Proc. Oral Pap. Posters, Borlaug Global Rust Initiative 2009 Tech. Workshop, Obregon, Sonora, Mexico. R. McIntosh, ed.
- Goyeau, H., Berder, J., Czerepak, C., Gautier, A., Lanen, C., and Lannou, C. 2012. Low diversity and fast evolution in the population of *Puccinia triticina* causing durum wheat leaf rust in France from 1999 to 2009, as revealed by an adapted differential set. *Plant Pathol.* 61:761-772.
- Goyeau, H., and Lannou, C. 2011. Specific resistance to leaf rust expressed at the seedling stage in cultivars grown in France from 1983 to 2007. *Euphytica* 178: 45-62.
- Goyeau, H., Lannou, C., Pariaud, B., Azzimonti, G., Cheyron, P. d., Couleaud, G., and Maumene, C. 2009. Durabilité et gestion de la résistance génétique du blé à la rouille brune causée par *Puccinia triticina* [Durability and management of genetic resistance to wheat leaf rust]. Pages 235-244 in: Association Française de Protection des Plantes, 9ème conférence internationale sur les maladies des plantes, Tours, France.
- Huerta-Espino, J., Singh, R. P., German, S., McCallum, B. D., Park, R. F., Chen, W. Q., Bhardwaj, S. C., and Goyeau, H. 2011. Global status of wheat leaf rust caused by *Puccinia triticina*. *Euphytica* 179:143-160.
- Jackson, L. F., and Wennig, R. W. 1997. Use of wheat cultivar blends to improve grain yield and quality and reduce disease and lodging. *Field Crops Res.* 52: 261-269.
- Kendall, M. 1938. A new measure of rank correlation. *Biometrika* 30:81-93.
- Kolmer, J. A. 1996. Genetics of resistance to wheat leaf rust. *Annu. Rev. Phytopathol.* 34:435-455.
- Kolmer, J. A. 2005. Tracking wheat rust on a continental scale. *Curr. Opin. Plant Biol.* 8:441-449.
- Kropff, M. J., Teng, P. S., and Rabbinge, R. 1995. The challenge of linking pest and crop models. *Agric. Syst.* 49:413-434.
- Lamichhane, J. R., Dachbrodt-Saaydeh, S., Kudsk, P., and Messéan, A. 2016. Toward a reduced reliance on conventional pesticides in European agriculture. *Plant Dis.* 100:10-24.
- Lancashire, P. D., Bleiholder, H., Boom, T. d., Langeluddeke, P., Stauss, R., Weber, E., and Witzengerber, A. 1991. A uniform decimal code for growth stages of crops and weeds. *Ann. Appl. Biol.* 119:561-601.
- Lannou, C., de Vallavieille-Pope, C., Biass, C., and Goyeau, H. 1994a. The efficacy of mixtures of susceptible and resistant hosts to two wheat rusts of different lesion size: Controlled condition experiments and computerized simulations. *J. Phytopathol.* 140:227-237.
- Lannou, C., de Vallavieille-Pope, C., and Goyeau, H. 1994b. Host mixture efficacy in disease control: Effects of lesion growth analyzed through computer-simulated epidemics. *Plant Pathol.* 43:651-662.
- Loyce, C., Meynard, J. M., Bouchard, C., Rolland, B., Lonnet, P., Bataillon, P., Bernicot, M. H., Bonnefoy, M., Charrier, X., Debote, B., Demarquet, T., Duperrier, B., Félix, I., Heddadj, D., Leblanc, O., Leleu, M., Mangin, P., Meausoone, M., and Doussinault, G. 2008. Interaction between cultivar and crop management effects on winter wheat diseases, lodging, and yield. *Crop Prot.* 27:1131-1142.
- Loyce, C., Meynard, J. M., Bouchard, C., Rolland, B., Lonnet, P., Bataillon, P., Bernicot, M. H., Bonnefoy, M., Charrier, X., Debote, B., Demarquet, T., Duperrier, B., Félix, I., Heddadj, D., Leblanc, O., Leleu, M., Mangin, P., Méausoone, M., and Doussinault, G. 2012. Growing winter wheat cultivars under different management intensities in France: A multicriteria assessment based on economic, energetic and environmental indicators. *Field Crops Res.* 125:167-178.
- Magnard, A. 2012. Analyse et modélisation des effets des pratiques culturales et de la situation de production sur la rouille brune du blé. Mémoire d'Ingénieur INP Toulouse-ENSAT, Toulouse, France.
- Mahmood, T., Marshall, D., and McDaniel, M. E. 1991. Effect of winter cultivar mixtures on leaf rust severity and grain yield. *Phytopathology* 81: 470-474.
- Mascagni, H. J., Jr., Harrison, S. A., Russin, J. S., Desta, H. M., Colyer, P. D., Habetz, R. J., Hallmark, W. B., Moore, S. H., Rabb, J. L., Hutchinson, R. L., and Boquet, D. J. 1997. Nitrogen and fungicide effects on winter wheat produced in the Louisiana Gulf Coast region. *J. Plant Nutr.* 20:1375-1390.
- McIntosh, R. A. 2015. Catalogue of gene symbols for wheat. Online publication. <https://shigen.nig.ac.jp/wheat/komugi/genes/macgene/supplement2015.pdf>
- Mille, B., and de Vallavieille-Pope, C. 2001. Associations varietales et interventions fongicides contre les septorioses et la rouille brune du blé d'hiver [Cultivar mixtures and fungicide sprays against leaf and glume blotch and brown rust in winter wheat]. *Cah. Agric.* 10:125-129.
- Mishra, A. N., Varma, P. K., and Ruwali, K. N. 1994. rust incidence in late-sown wheat (*Triticum aestivum*). *Indian J. Agric. Sci.* 64:266-267.
- Moschini, R. C., and Perez, B. A. 1999. Predicting wheat leaf rust severity using planting date, genetic resistance, and weather variables. *Plant Dis.* 83:381-384.
- Nolot, J. M., and Debaeke, P. 2003. Principes et outils de conception, conduite et évaluation de systèmes de culture [Principles and tools for the design, management and evaluation of cropping systems]. *Cah. Agric.* 12:387-400.
- Ogg, A. G., Jr., and Parker, R. 1989. Control of volunteer crop plants. *Ext. Bull. EB 1523*. Cooperative Extension, College of Agriculture, Washington State University, Pullman, WA.
- Ordoñez, M. E., and Kolmer, J. A. 2007. Virulence phenotypes of a worldwide collection of *Puccinia triticina* from durum wheat. *Phytopathology* 97: 344-351.
- Papaix, J., Goyeau, H., Cheyron, P. D., Monod, H., and Lannou, C. 2011. Influence of cultivated landscape composition on variety resistance: An assessment based on wheat leaf rust epidemics. *New Phytol.* 191:1095-1107.
- Pelzer, E., Fortino, G., Bockstaller, C., Angevin, F., Lamine, C., Moonen, C., Vasileiadis, V., Guerin, D., Guichard, L., Reau, R., and Messean, A. 2012. Assessing innovative cropping systems with DEXiPM, a qualitative multicriteria assessment tool derived from DEXi. *Ecol. Indic.* 18:171-182.
- Pfleger, T. G., and Mundt, C. C. 1998. Wheat leaf rust severity as affected by plant density and species proportion in simple communities of wheat and wild oats. *Phytopathology* 88:708-714.
- Pickett, A. A. 1993. Cereals: Seed shedding, dormancy and longevity. Pages 17-28 in: Aspects of Applied Biology. Association of Applied Biologists, Wellesbourne, Warwick, U.K.

- Räder, T., Racca, P., Jörg, E., and Hau, B. 2007. PUCREC/PUCTRI—A decision support system for the control of leaf rust of winter wheat and winter rye. *Bull. OEPP/EPPO Bull.* 37:378-382.
- Robert, C., Bancal, M. O., and Lannou, C. 2002. Wheat leaf rust uredospore production and carbon and nitrogen export in relation to lesion size and density. *Phytopathology* 92:762-768.
- Robert, C., Bancal, M. O., and Lannou, C. 2004a. Wheat leaf rust uredospore production on adult plants: Influence of leaf nitrogen content and *Septoria tritici* blotch. *Phytopathology* 94:712-721.
- Robert, C., Bancal, M. O., Nicolas, P., Lannou, C., and Ney, B. 2004b. Analysis and modeling of effects of leaf rust and *Septoria tritici* blotch on wheat growth. *J. Exp. Bot.* 55:1079-1094.
- Robin, M. H., Colbach, N. L. P., Monfort, F., Cholez, C., Debaeke, P., and Aubertot, J. N. 2013. Injury Profile SIMulator, a hierarchical aggregative modeling framework to predict an injury profile as a function of cropping practices, and abiotic and biotic environment. II. Proof of concept: Design and evaluation of IPSIM-Wheat-Eyespot, a model that predicts eyespot injuries on winter wheat. *PLoS One* 8:e75829.
- Rocque, B. I. 1991. Rouille brune du ble: Prevision des risques et des dates de traitement. Presentation de deux modeles operationnels [Two operational models for forecasting the risk of wheat brown rust and dates for treatment]. *Bull. OEPP* 21:469-476.
- Roelfs, A. P. 1989. Epidemiology of the cereal Rusts in North America. *Can. J. Plant Pathol.* 11:86-90.
- Roelfs, A. P., Singh, R. P., and Saari, E. E. 1992. Rust Diseases of Wheat: Concepts and Methods of Disease Management. CIMMYT, El Batán, Mexico.
- Rossi, V., Racca, P., Giosue, S., Pancaldi, D., and Alberti, I. 1997. A simulation model for the development of brown rust epidemics in winter wheat. *Eur. J. Plant Pathol.* 103:453-465.
- Sache, I. 2000. Short-distance dispersal of wheat rust spores by wind and rain. *Agronomie* 20:757-767.
- Samborski, D. J. 1985. Part I. Wheat leaf rust. Pages 39-59 in: *The Cereal Rusts, Volume II. Diseases, Distribution, Epidemiology, and Control*. Academic Press, Inc., London.
- Savary, S., Willocquet, L., Elazegui, F. A., Teng, P. S., Pham Van, D., Zhu, D., Tang, Q., Huang, S., Lin, X., Singh, H. M., and Srivastava, R. K. 2000. Rice pest constraints in tropical Asia: Characterization of injury profiles in relation to production situations. *Plant Dis.* 84:341-356.
- Seck, M., Roelfs, A. P., and Teng, P. S. 1988. Effect of leaf rust (*Puccinia recondita tritici*) on yield of four isogenic wheat lines. *Crop Prot.* 7:39-42.
- Shtienberg, D. 2013. Will decision-support systems be widely used for the management of plant diseases? *Annu. Rev. Phytopathol.* 51:1-16.
- Spearman, C. 1904. General intelligence, objectively determined and measured. *Am. J. Psychol.* 15:201-293.
- Thepot, S., and Gouache, D. 2009. Etude d'un modele climatique de prevision de la nuisibilite de la rouille brune sur ble dur en France [Evaluation of a climate model for predicting the severity of brown rust on durum wheat in France]. Pages 505-514 in: *Association Francaise de Protection des Plantes, 9eme conference international sur les maladies des plantes*, Tours, France.
- van der Werf, H. M. G., and Zimmer, C. 1998. An indicator of pesticide environmental impact based on a fuzzy expert system. *Chemosphere* 36: 2225-2249.
- Vilich-Meller, V. 1992. Mixed cropping of cereals to suppress plant-diseases and omit pesticide applications. *Biol. Agric. Hortic.* 8:299-308.
- Wolfram Research, Inc. 2015. Mathematica, version 10.1.0.0 (Mac OS X x86 platform). Wolfram Research, Inc., Champaign, IL.
- Zadoks, J. C., and Bouwman, J. J. 1985. Epidemiology in Europe. Chapter 11 in: *The Cereal Rusts, Vol. II. Diseases, Distribution, Epidemiology, and Control*. A. P. Roelfs and W. R. Bushnell, eds. Academic Press, Orlando, FL. <https://globalrust.org/sites/default/files/cereal-rusts/volume2.pdf>