A Weather-Based Simulation Model for the Development of Wheat Stem Rust Epidemics

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***Abstract*—Wheat stem rust, a highly destructive wheat disease caused by the fungal pathogen *Puccinia graminis f. sp. tritici*, has been considered for years to be almost eradicated in Western Europe. However, changes in climatic conditions and appearance of new races, overcoming the previously developed wheat resistances, are fostering its re-emergence. Several outbreaks have already been documented in Europe. The consequences on upcoming wheat productions, due to wind-borne spore dispersal, may be destructive. In this work we present a weather-based infection model for wheat stem rust, developed using laboratory and field data from literature. A warning system, based on the simulation of stem rust infectivity, was also developed to improve field monitoring and help farmers maximize crop protection strategy efficiency. A preliminary validation was performed on actual data not used in model building and pertaining to a wide range of conditions (wheat crops in northern Italy between 2016 and 2020). Satisfactory agreements between simulated and actual data were found.**

I. INTRODUCTION

Wheat stem rust also known as black rust (*Puccinia graminis f. sp. tritici* Erikss. & Henn.) is a devastating fungal disease afflicting wheat leaves and stems [1]. In most serious cases this fungus, causing the presence of black pustules, may even penetrate in the plant upper side, on the ears [2]. This disease has been considered widely eradicated, until an alarm was raised in 2016 [3]. In Sicily there was a heavy outbreak of black rust, causing an extensive damage to production and marking the biggest European outbreak since the 1950s [4]. The relatively small size of stem rust uredospore makes the propagation through atmospheric condition the major vector of disease spread, even crossing oceans [5]. This has suggested a stem rust re-emergence in Europe, the world's biggest wheat producer, with severe impact for production [6] and, consequently, for food sustainability [5].

The new spread of this disease, caused by extremely virulent strains [6], [7], and the warmer climate favoring it [8] have led to a renewed interest for the development of strategies to prevent it. Despite calendar spraying still represents an effective strategy, from an economic point of view only a necessary and prompt fungicide application, at most one, is feasible to protect wheat from foliar diseases [9]. Therefore, for a more effective and sustainable agricultural management, it is crucial to access timely and detailed information useful to support the decision-making process.

In the era of precision agriculture, the so-called decision support systems (DSS) are emerging to face agricultural challenges, contributing to the development of more efficient and environmentally sustainable strategies [10]. In this context, information and communication technology (ICT) can contribute significantly [10]. Systems usually based on weather and disease-inducing conditions, empirical relationships and regression equations have already been developed for other common wheat diseases [11], [12], [13], [14]. For instance, authors in [14] developed a model to assess the development of Septoria leaf blotch, a foliar disease caused by *Zymoseptoria tritici*. According to this model, an infection can occur when precipitation of at least a couple of consecutive hours (> 0.1 mm for the first hour, > 0.5 mm for the second one) is followed by 16 hours with relative humidity higher than 60% and 24 hours characterized by temperatures above 4°C. The relationship between pathogen development and meteorological conditions (as precipitation, temperature, relative humidity, leaf wetness and solar radiation) usually represents the basis for forecast model building. Pathogen inoculum spread is considered less frequently [15].

In this work, we present a dynamic simulation model for stem rust infection on wheat, founded on the effect of weather condition on rust uredospore cycles (spore germination, appressoria formation, host entry by penetration). A warning system, based on the simulation of the infection risk, was also developed to guide field monitoring and support producers in the decision of the best pest management. A preliminary validation was performed on actual data including a wide range of conditions. Data not used in model building and pertaining to wheat crops in Ravenna, northern Italy, between 2016 and 2020 were considered. Experimental results proved a strong correlation between simulated and actual data, this suggesting a promising application in sustainable agriculture of this DSS.

II. MATERIAL AND METHODS

A. Model description

Uredospore infection by the fungal pathogen *Puccinia graminis f. sp. tritici* is considered a biphasic process (Fig. 1) [16]. The first phase includes:

- spore germination, involving the growth of germ tubes, perpendicular to leaf veins, until the stomata (the pores present on the epidermis of the leaves) are reached [16], [17];
- formation of the appressorium, the first infection structure produced over the stomatal aperture [18], [19].

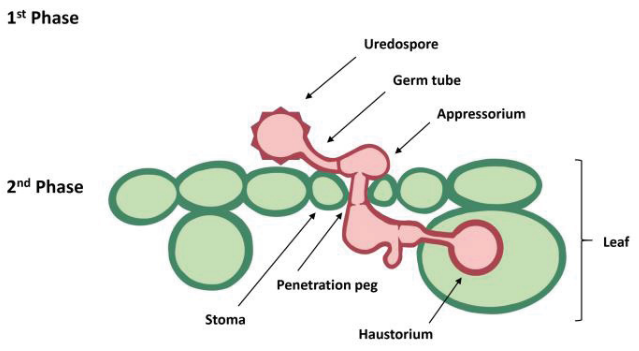

Fig. 1. Biphasic stem rust infection process, outlining the main infection structures formed during its development: germ tube, appressorium, penetration peg passing through the stomata, and haustorium, finally infecting the host cell.

Both processes require the presence of free water on the leaves and darkness [1], [20], since light causes the inhibition of uredospores germination and appressoria formation [21].

The second phase regards the penetration of the fungal pathogen into the leaf tissue, performed through a short peg pushing into the stomal opening [20]. To result in a successful fungal penetration causing latent infections, this mechanism requires the presence of light and wet on leaf surface [18], directly stimulating the fungus [22] and the leaf stomata opening [16]. Therefore, the first phase usually occurs during the night, after sunset, while the second phase, needing the light, generally occurs in the early morning, after sunrise.

The effect of temperatures and dew periods in the development of the stem rust disease has been widely studied in literature, usually performing laboratory tests. For the first phase, evidence shows that uredospores reached at least 98% of germination within 2 hours at all temperature ranging from 6 to 28 °C [23]. Author in [1] found that spore germination occurs at 4 – 29 °C, with an optimum close to 15 – 23 °C. A similar result for germination was also found in [18], reporting a range of 2 – 30 °C with optimum temperatures of 15 - 24 °C. While as regards appressorium formation, slightly higher temperatures are needed with an optimum reached at 16 - 27°C, still in dark condition [18].

As for the second phase, appressoria produce penetration structures if temperatures are higher than the first phase [1]. The range is from 15 to 35 °C [18], with optimum temperatures varying from 29 to 30 °C [1], [18], [20]. Contrary to the first phase, the second phase occurs in the presence of light [1], [18], [20]. Author in [20] reported that the formation of fungal infectious structures occurs within 1.5 hours of light exposure.

For the success of the whole infectious process including the two phases, the duration of surface wetness is decisive. Indeed, under laboratory conditions, maximum infections are obtained with a leaf wetness lasting 8 – 12 hours at a temperature of 18 °C [18]. Instead, in field conditions, a dew period or free moisture from rains of 6 – 8 hours resulted adequate for the completion of an infection process [18], [24].

The model devised is built on the correlations between infection processes and weather data previously reported (Table I). It is based on temperature, precipitation and leaf wetness, with the following rationale: in order to establish an infection, fungal mechanisms require the presence of leaf wetness at defined temperatures and light exposures.

TABLE I. LIST OF INPUT PARAMETERS USED IN THE MODEL

Acronym	Parameter	Unit/Description
TMP	Hourly temperature	°C
P	Hourly precipitation	mm
LW	Hourly leaf wetness	0 (dry) or 1 (wet)
DATE	Date of the current day	dd-mmm-yyyy
UTCoff	Time zone, local time offset to UTC (Coordinated Universal Time)	h
LAT	Latitude	DD (decimal degrees)
LONG	Longitude	DD (decimal degrees)

As reported in [1], the success of an infection (number of pustules) increases linearly with the duration (hours) of leaf wetness at optimum temperatures. In order to consider the effect of suboptimal temperatures on the two fungal infection phases, two different temperature response functions, $Rate_1$ and $Rate_2$, were devised. As regards the first phase, the relation between spore germination with appressorium formation and temperatures has been approximated by a 3-segment function, as reported in solid blue line in Fig. 2, using the cardinal temperatures reported in [18]. Analogously, the relation between peg penetration and temperatures has been modelled by a 3-segment function, as reported in dash-dot red line in Fig. 2, using the cardinal temperatures taken from [18], [20].

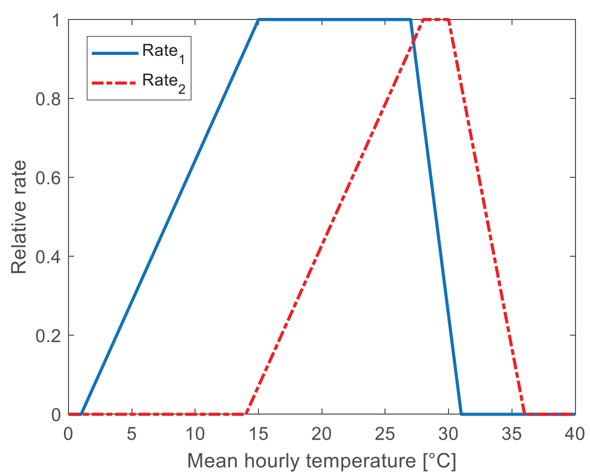

Fig. 2. Effect of mean hourly temperature on first ($Rate_1$) and second ($Rate_2$) phase fungal process. Cardinal temperatures for the two phases are from [18, 20].

As predictive variables we considered the temperature-weighted wet periods pertaining to the first (LWT_{1st_phase}) and second phase (LWT_{2nd_phase}), being both essential to cause latent infections. More specifically, for the first phase only overnight wet periods characterized by consecutive moisture hours were considered. That is, LWT_{1st_phase} is computed only if, after sunset and just before sunrise, a wet period without interruption in wetness occurred. In the absence of consecutive wet hours LWT_{1st_phase} is assigned to 0. Formally, on current day i, $LWT_{1st\_phase}(i)$ is calculated on the hours h composing the first phase wet period, as in (1):

$$LWT_{1st\_phase}(i) = \sum_h LW(h) \cdot TMP(h) \cdot Rate_1(TMP(h)) \qquad (1)$$

where $LW(h)$ and $TMP(h)$ are the leaf wetness and temperature detected in the hour h. $LW(h) = 1$ stands for presence of wetness, while $LW(h) = 0$ for its absence. $Rate_1(TMP(h))$ represents the adjusting factors taking into account the effect of suboptimal temperatures on the first phase.

Regarding the second phase, only 2 hours after sunrise have been considered, resulting adequate for plants to become infected [1]. The great correlation between infection and period of 2 hours after sunrise was also confirmed in [25], where 2 hours resulted equally or more highly correlated with infections than shorter or longer periods after sunrise. Therefore, on day i, $LWT_{2nd\_phase}(i)$ is calculated on the 2 hours h after sunrise, as in (2):

$$LWT_{2nd\_phase}(i) = \sum_h LW(h) \cdot TMP(h) \cdot Rate_2(TMP(h)) \qquad (2)$$

where $LW(h)$ and $TMP(h)$ are the leaf wetness and temperature detected in the hour h. $Rate_2(TMP(h))$ represents the adjusting factors considering the effect of suboptimal temperatures on the second phase. Therefore, in the absence of leaf wetness ($LW = 0$), during both the hours considered for the second period, $LWT_{2nd\_phase}(i)$ results to be equal to 0.

Sunset and sunrise times were calculated through the equations in [26], using as input the date of the current day, the local time offset, the latitude and longitude of the field under monitoring (Table I). The algorithm was implemented in Matlab (MathWorks, Natick, MA, USA).

B. Infection efficiency

As already stated, both fungal processes are required for the success of an infection. Therefore, as performed in [25] for the stem rust model of perennial ryegrass, the infection likelihood, $INF\_prod(i)$, was modelled as the product of the first and second phase favorability. Therefore, for each day i, $INF\_prod(i)$ is calculated as in (3):

$$INF\_prod(i) = LWT_{1st\_phase}(i) \cdot LWT_{2nd\_phase}(i) \qquad (3)$$

$INF\_prod(i)$ results to be different from 0 only in the presence of the two morning/night wet periods at appropriate temperatures, necessary to trigger a stem rust infection.

In order to provide a more intelligible index for end-users, the relative infection index INF (%) was also devised. INF represents the INF_prod variable normalized by the minimum value (INF_norm) that, based on literature data, is proved to cause successful infection events. As already stated, the greater the number of wet hours at optimum temperatures, the greater will be the likelihood of infection [1] and also the infection efficiency [23]. It is worth noting that a greater infectious efficiency corresponds to a greater number of spores that complete the infectious process and, consequently, cause high disease pressure (epidemic). Therefore, we assume that INF_prod values greater than INF_norm are associated with effective infection events (INF = 100%), while lower values point out less probable infection events. INF_norm was calculated using Equation (3), by considering 7 wet hours (4 for spore germination, 2 for appressorium formation and 1 for peg penetration) at each minimum optimum temperature [18], [24]: $INF\_norm = (15 \cdot 4 + 16 \cdot 2) \cdot (29 \cdot 1) = 2668$. Thus, for each day i, the relative infection index INF (%) is calculated as in (4):

$$INF(i) = (INF\_prod(i) / INF\_norm) \cdot 100 \qquad (4)$$

Therefore, in a precautionary way, INF values greater than 75% can be reasonably associated with highly probable and efficient infection events. Instead, values between 50 and 75% report less probable infections. However, still in a precautionary perspective, they also indicate a situation to be monitored. Indeed, as previously discussed, even few wet hours, at least two, could be able to trigger successful infections albeit with a lower infectious efficiency [1]. Finally, INF values below 50% represent unlikely infections.

This information will be accessible by users in different ways, always enclosing a representative color:

- red for highly probable infection ($INF \geq 75\%$)
- yellow for less likely infections ($50\% < INF < 75\%$)
- green for unlikely infections ($INF \leq 50\%$)

This should help farmers in the interpretation of system outputs. Indeed, the devised system provides an easily interpretable graphical widget, a plot representing INF data, and a table reporting this value along with the date of infection. In particular, as regards the widget, this information is displayed through a thermometer divided into three parts and enhancing the correct color, as one can see in Fig. 3, where a highly probable infection is suggested.

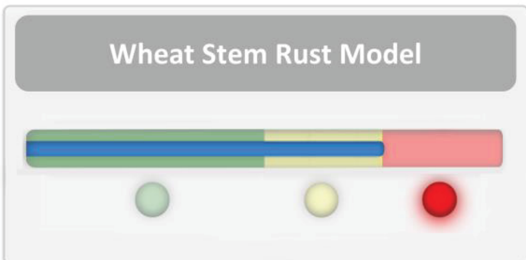

Fig. 3. Stem rust model output, enhancing high (red), medium (yellow) and low infection risk. In this example, a high-risk infection is suggested.

C. Latent period

The latent period is the time elapsed between the beginning of the infectious process, caused by a unit of inoculum, and the start of production of infectious units, that is the eruption of sporulating pustules [27].

The three-parameter logistic model developed by authors in [28] to predict latent period duration of wheat stem rust has been implemented. The model is based on hourly temperatures, considering a minimum temperature of 1.8 °C and a maximum temperature of 30.9 °C. Optimum temperatures for latent period, fostering short intervals, range from 24°C to 29°C. Indeed, at 29 °C latency duration was 128 hours [28].

Generally, at the end of the latent period the infection become visible on leaves and stems as rusted areas, as reported in Fig. 4. For infections occurring when plants are already in senescence the symptoms could not appear. For instance, infections occurring late close to wheat harvesting, carried out on totally dry senescent plants (i.e., dead and collapsing plants), may be visually undetectable. This because stem rust pathogen needs living green tissue for its life cycle and to cause visible infections.

Fig. 4. Stem rust symptoms on wheat.

The latency period is computed only when *INF* ≥ 50%, thus in the presence of probable and potentially effective infectious events. As a result, the date of probable symptoms appearance is provided in a table along with the *INF* value and the date of infection.

D. Model validation

The model was preliminary tested on four independent datasets, different from the data used for model development. As reported in Table II, the datasets pertain to two different locations in Ravenna (RA), northern Italy, over four years, from 2016 to 2020.

Field weather conditions were monitored every year with a wireless weather station (Vantage Pro2 plus 6162; Davis Instruments Corporation, California, USA). Air temperature and humidity at 1m above canopy height were measured with temperature and humidity sensors contained in a passive solar radiation shield (Temperature/Humidity Sensors 6830, Davis Instruments Corporation). Precipitations were measured at 1.5 m above the ground with a pluviometer (rain collector with flat base 07852, Davis Instruments Corporation).

Leaf wetness duration was measured with an electrical-resistance sensor working as an artificial-leaf (Leaf Wetness Sensor 6420, Davis Instruments Corporation). This sensor is composed of a sensing grid, a low-voltage bi-polar excitation circuit, and a conductivity-sensing circuit allowing the detection of surface moisture. Leaf wetness sensor is mounted at an angle of 45° to simulate a typical leaf position and to permit runoff of excessive moisture. It is maintained approximately 5 cm below the top of the canopy. When moisture is present, the sensor detects an electrical resistance change, then reported as a value between 0, completely dry, and 15, totally wet.

Meteorological data were recorded every 10 minutes and averaged over the hour. For each time interval (1 hour), leaf wetness duration was transformed into binary data (0 - 1) reflecting wet and not wet conditions. In details, an interval was assumed to be wet if any of the following was true: leaf wetness sensor output >= 4 or precipitation value > 0.

TABLE II. DATASETS USED FOR MODEL VALIDATION

ID	Location	Sowing date	Harvesting date
1	San Romualdo (RA)	28/10/2019	31/06/2020
2	San Romualdo (RA)	13/11/2018	03/07/2019
3	San Romualdo (RA)	31/10/2017	29/06/2018
4	Sant'Alberto (RA)	04/11/2016	23/06/2017

As for the wheat cultivars, only varieties susceptible to the stem rust disease were considered for field experiments: the bread wheats *Arkeos* and *Gioconda*, and the durum wheat *Farah*. Each year these varieties were sown in an experimental field with plots of 10.5 m^2, using an experimental design in randomized blocks, with 2 replications. For all the plots considered, no fungicides were performed in order not to affect the normal course of the disease.

At present, evaluation of stem rust disease is left to the subjectivity of experts' assessment. For this study, 100 plants per plot chosen at random were considered and the number of plants affected by stem rust symptoms was counted, this representing the incidence of the disease as a percentage. In order to perform a comparison with simulation data, a proper taxonomy based on a three-point scale was devised:

- Type 1, no epidemics, no plants show symptoms;

- Type 2, moderate epidemics, less than 50% of the plants presents symptoms;
- Type 3, severe epidemics, characterized by the presence of diffuse symptoms on more than 50% of the plants.

These data were previously collected by an expert agronomist, who performed weekly evaluation of disease presence, by also annotating the dates of first disease comparison and new symptoms. Field surveys were carried out until before the senescence phase, taking into account for each variety the trend of the two replications. Then, the mean value computed on the two replications was considered.

Simulations of the devised model were performed in Matlab (MathWorks, Natick, MA, USA) using weather data starting from the 1st October, which represents the most compatible date in northern Italy for the start of sowing operations. A comparison between the actual symptom dates and those obtained through model simulation was performed. Moreover, in order to evaluate the capability of the devised index *INF* to represent the epidemic risk, also a comparison with the epidemic type identified by the expert was performed.

III. Results

The datasets considered for the preliminary validation (Table III) covered a wide range of epidemics from absent (Type 1), as occurred in Sant'Alberto and San Romualdo fields sowed in 2016 (ID4) and 2017 (ID3), to moderate (Type 2) and severe (Type 3), as for the San Romualdo fields sowed in 2019 (ID1) and in 2018 (ID2).

TABLE III. Field surveys for model validation

ID	Date of symptom detection	Epidemics type
1	16/06/2020	Type 2
2	14/06/2019	Type 2
	21/06/2019	Type 3
3	None	Type 1
4	None	Type 1

The comparison between actual and simulated data shows a very good agreement. Indeed, although a perfect match of the dates was not possible as field data had already been collected weekly, the simulated infections resulted always compatible with the field surveys and the disease pressure evaluations.

As one can see in Table IV and in Fig. 5 (red diamonds), showing the results of the simulation for the experimental field in San Romualdo sowed in 2019 (ID1), two infection events of medium risk were reported. Onsets of symptoms identified by the simulation were 12/06/2020 and 15/06/2020, respectively. The presence of these infections was confirmed by the field assessment carried out on 16/06/2020, where the three wheat cultivars (*Arkeos*, *Gioconda* and *Farah* considered for the analysis) showed to be homogeneously but not severely affected by stem rust disease, with no changes until before wheat harvesting on 31/06/2020. Only about 15% of plants resulted affected (17.5±0.7% of *Arkeos*, 15±1.4% of *Gioconda* and 12±1.4% of *Farah*, values obtained considering two plot replications), this is why ID1 was assigned a Type 2 epidemic. This was correctly simulated by the model, showing medium risks highlighted by yellow circles in Fig. 5. In the previous field assessment performed on 09/06/2020, no symptoms were detected. Accordingly, simulation for this period reported low risk of epidemics, pointed out by the green circles in Fig. 5.

TABLE IV. Data extrapolated from model output related to ID1

ID	Date of infection	Date of symptom appearance	INF [%]
1	05/06/2020	12/06/2020	65 ●
1	08/06/2020	15/06/2020	61 ●

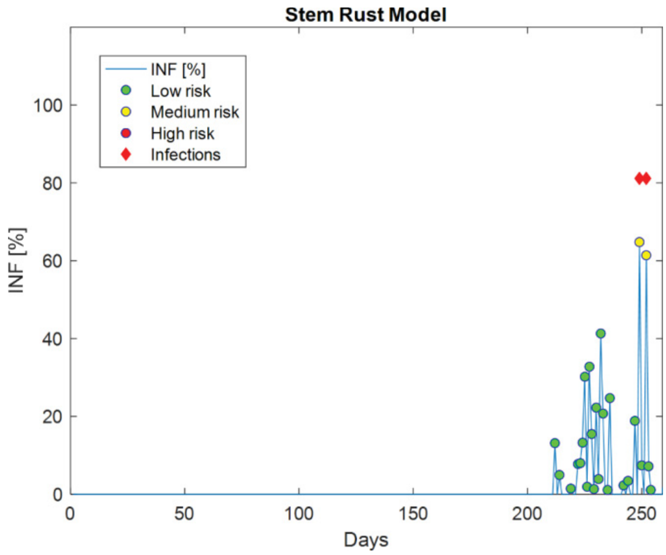

Fig. 5. Result of the simulation for ID1 using San Romualdo weather data, starting from 1st October 2019 until the last field survey (16/06/2020). Green, yellow and red circles stand for low, medium and high risk, respectively. Red diamonds evidence the presence of successful infection events. Here, two infection events of medium risk (highlighted with the yellow circles) are reported.

As one can see in Table V and in Fig. 6, showing the results of the simulation for the experimental field at San Romualdo sowed in 2018 (ID2), two infection events of medium and high risk were reported. Onsets of symptoms identified by the simulation were 13/06/2019 and 16/06/2019. These infections were confirmed by the field assessments performed on 14/06/2019 and 21/06/2019 (Fig. 7), where bread wheat cultivar (*Arkeos* and *Gioconda*) proved to be more susceptible than the durum wheat cultivar (*Farah*) observed. In fact, during the field survey, when first symptoms appeared, about 14% of *Arkeos* and *Gioconda* plants were affected by stem rust (14±2.8% for *Arkeos* and 13.5±0.7% for *Gioconda*, values obtained considering two plot replications) while only 7±1.4% of *Farah* plants revealed symptoms. This is the reason why at first ID2 was assigned a Type 2 epidemic. During the following field survey performed on 21/06/2019 more than 60% of *Arkeos* and *Gioconda* plants resulted infected by stem rust (67±2.8% for *Arkeos* and 63±1.4% for *Gioconda*), while only 32.5±0.7% of *Farah* plants showed symptoms. This is the reason why ID2 was globally assigned a Type 3 epidemic. In agreement with these findings, stem rust model simulated a medium-risk infection event followed by a high-risk event, evidenced in Fig. 6 with a yellow and red circle, respectively.

TABLE V. DATA EXTRAPOLATED FROM MODEL OUTPUT RELATED TO ID2

ID	Date of infection	Date of symptom appearance	INF [%]
2	08/06/2019	13/06/2019	61
2	10/06/2019	16/06/2019	100

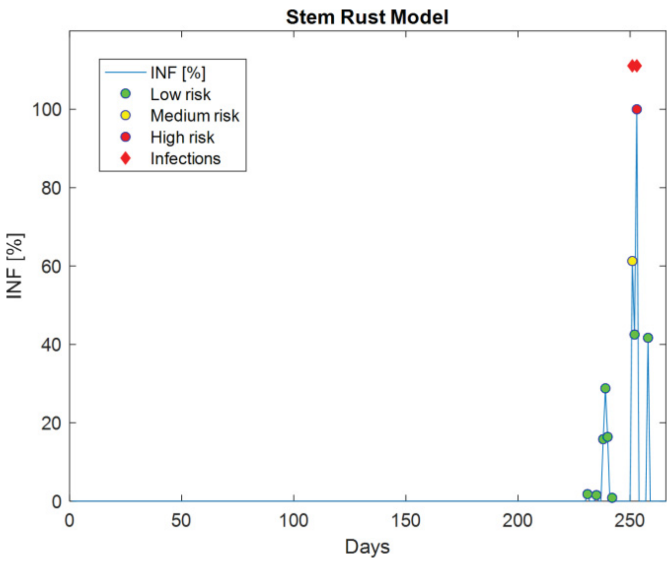

Fig. 6. Result of the simulation for ID2 using San Romualdo weather data, starting from 1st October 2018 until the last field survey (21/06/2019). Green, yellow and red circles stand for low, medium and high risk, respectively. Red diamonds evidence the presence of successful infection events. Here, two infection events of medium and high risk (pointed out by the yellow and red circle, respectively) are reported.

Fig. 7. Black rust on wheat (21 June 2019, Ravenna, Italy).

As one can see in Table VI and in Fig. 8, showing the results of the simulation for the field at San Romualdo sowed in 2017 (ID3), no infection events occurred. The absence of infections was confirmed by field assessments weekly performed, reporting no symptoms detected. For this reason, ID3 was assigned a Type 1 epidemic. In agreement with these findings the simulation showed a low-risk epidemic (Fig. 8), i.e., no likely infections were triggered by climatic conditions.

TABLE VI. DATA EXTRAPOLATED FROM MODEL OUTPUT RELATED TO ID3

ID		Date of infection	Date of symptom appearance	INF [%]
3		None	None	-

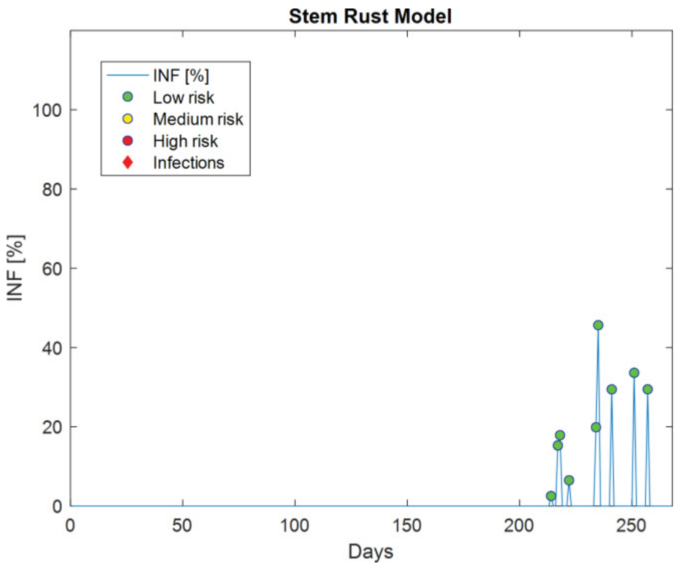

Fig. 8. Result of the simulation for ID3 using San Romualdo weather data, starting from 1st October 2017 until the last field survey (23/06/2018). Green, yellow and red circles stand for low, medium and high risk, respectively. Red diamonds evidence the presence of successful infection events. Here, no infection events are reported.

Analogously to ID3, as one can see in Table VII and in Fig. 9, showing the results of the simulation for the experimental field at Sant'Alberto sowed in 2016 (ID4), no infection events occurred. The absence of infections was confirmed by field assessments weekly performed, reporting no symptoms detected and, therefore, a Type 1 epidemic was assigned to ID4. In agreement with field assessments, the output of the simulation shows only the presence of low-risk events, highlighted with green circles (Fig. 9).

TABLE VII. DATA EXTRAPOLATED FROM MODEL OUTPUT RELATED TO ID4

ID	Date of infection	Date of symptom appearance	INF [%]
4	None	None	-

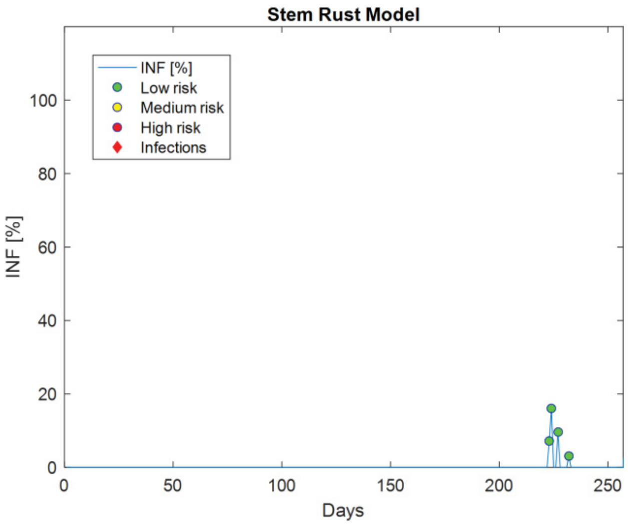

Fig. 9. Result of the simulation for ID4 using Sant'Alberto weather data, starting from 1st October 2016 until the last field survey (14/06/2017). Green, yellow and red circles stand for low, medium and high risk, respectively. Red diamonds evidence the presence of successful infection events. Here, no infection events are reported.

IV. CONCLUSION

Wheat stem rust is a destructive disease, usually appearing late in the wheat growing period, when temperatures are high [18]. A crop that looks healthy three weeks before harvest can be rapidly devastated by stem rust [19], if sufficient inoculum arrives and meteorological conditions are adequate [24].

The aim of this study was to develop a model to determine the effect of weather data on infection of wheat by *Puccinia graminis f. sp. tritici*. The model allows to distinguish the two main fungal mechanisms triggering an infection, by considering the effect of weather data on each phase. The general assumption is that, in presence of inoculum, an infection can be triggered with sub-optimal temperatures and a large number of wet hours or, on the contrary, with a lower number of wet hours characterized by temperatures closer to optimal.

Preliminary results show that this system is able to identify the successful infection events causing symptoms on wheat, also providing symptoms appearance dates. In all the cases considered, the infections simulated by the model corresponded with the actual infections detected during the weekly field assessments. Moreover, the index devised, *INF*, enclosing the information of infection likelihood and, indirectly, also of its efficiency, showed to properly represent the actual epidemic levels detected. More in detail, the risk levels simulated perfectly matched the epidemic types detected for the bread wheat varieties *Arkeos* and *Gioconda*, overestimating the risk level for the durum *Farah* cultivar only once in 2019, when the simulation reported a high-risk infection event but the epidemic detected for *Farah* variety was of Type 2.

As already stated, for this study only wheat cultivars susceptible to stem rust disease (*Arkeos*, *Gioconda* and *Farah*) were used. Slightly differences between the two bread and the durum varieties have already been observed and other varieties may show further tolerance differences. Thus, other experiments are needed to set up a varietal susceptibility coefficient to adapt and improve model outputs. Therefore, at present the system is calibrated for the worse case, thus permitting the use of this tool in the most precautionary way. Further limitation of this study regards the size of the dataset. A greater number of monitored fields and climatic datasets are needed to continue testing the model. At the moment, being the disease reappeared in Southern Italy in 2016 and this study based on the work performed on our experimental field, no further data could have been considered. It is worth noting that for more robust field data, cultivar plot replications were taken into account.

This DSS represents a useful tool to guide field monitoring in the detection of wheat stem rust disease, activity that usually takes long time and several attempts. Furthermore, the alerts provided by the model could support decision making in the choice of the most suitable rust control strategy, allowing to respond with timely fungicide applications. Moreover, this system could allow to better understand the relations between pathogen biology and weather conditions, enhancing our knowledge of stem rust epidemiology and helping in monitoring the effect of climatic changes on this disease. The ultimate use of this model could be in conjunction with other wheat disease models to combine technical information and facilitate environmental impact evaluations, economic analyses and risk assessments.

In conclusion, this system represents a promising support tool to enhance wheat stem rust control, especially under warmer climate. Preliminary results show a strong correlation between simulated and field data, this suggesting a promising application in sustainable agriculture of this DSS.

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