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Decision Support Systems for Downy Mildew (*Plasmopara viticola*) Control in Grapevine: Short Comparison Review

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

Plasmopara viticola, the aetiological agent of grapevine downy mildew (DM), is the most important pathology afflicting viticulture and requires a great number of fungicide treatments to avoid severe yield losses and quality decreasing. To date, great efforts have been made to reduce the use of plant defensive products. Resistant cultivars, new agrochemicals and, finally, epidemiological models have been elaborated to better manage plant phytoiatric treatments. Nowadays, models are widely used because they allow the cultivation of traditional varieties, limiting agrochemicals. Using such models, implemented in a DSS (Decision Support System), results in a lower risk of grapevine damage by diseases and pests and, in many cases, in a lower input of active substances. Thanks to the information reported in a DSS, users could become more conscious of the relations between weather conditions, pathogen's cycle, and infections risk, which is an issue not yet well understood by lots of winegrowers. For this instance, DSSs have been established as important tools for the achievement of more sustainable agricultural practices. Hence, understanding their working

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principles might be really important. In fact, in this way, technicians and farmers can adopt the suitable system to fit their own agricultural reality, aiming at a better vineyard management under a sustainable point of view.

Keywords: Predicting models; viticulture; disease control; PV-sensing.

1. INTRODUCTION

Vitis vinifera has been cultivated for over 7000 years. Mildews are among the most important problems that afflict this culture. In fact, to date, about 67% of all fungicides used in the agriculture sector are sprayed in viticulture to defend grapevine against mildews, in particular downy mildew (DM). This fact is even more relevant considering that viticulture occupies only 3.3 % of the entire agricultural area worldwide [1].

Plasmopara viticola (Berk et Curt.), the aetiological agent of grapevine DM (Fig. 1 and Fig. 2), is one of the most important diseases afflicting grapevines in all temperate areas, characterized by a medium-high rainfall frequency and a medium-warm climate [2]. *P. viticola* (an oomycete) is a biotrophic pathogen, obligate parasite of *Vitis vinifera*, heterothallic and dimorphic (sexual and asexual spores and linked cycles, which overlap for a great part of the growing season). Oospores, which represent the sexual stage of *P. viticola*, are generated by the fusion of an oogonium and an antheridium [3] in host leaves [4]. These latter overwinter in the soil and are the main culprit for enhancing the primary infections in the following season [5]. In the next spring, under proper conditions of temperature and humidity, they germinate in a macrosporangium releasing zoospores. These reach all plant tissues by splashes and are equipped with a flagellum, which is capable of making zoospores swim on the leaf surface toward the stomata [6], and lead to the first infections, followed by asexual cycles during the vegetative season [7]. This disease is potentially destructive and, if not controlled, quickly brings to a complete loss of production, with severe damages to the plant and its productivity not only in the ongoing year, but also compromising the productivity of the oncoming growing season. For this reason, grapevine requires protection through the use of fungicides, with the well-known problems directly linked to the use of these substances (environmental and human health impact, impact on soil microbiome, accumulation in soil; must). Several relationships between environmental factors, host susceptibility and the pathogen have been observed and studied so far. Historically, to predict DM infection, the first model was the so called “3–10 rule” created by Baldacci (1947) [8]. Many farmers still identify the beginning of treatments according to this directive. After applying this rule at the beginning of the season, farmers tend to continue the phytochemical treatments "on schedule" or according to the cadence of rainfalls, without a proper awareness if the weather conditions are being favourable or not for the development of the disease. Consequently, this might result in the use of more agrochemicals than what it is needed to contain the infections or, however, in an improper use of agrochemicals.

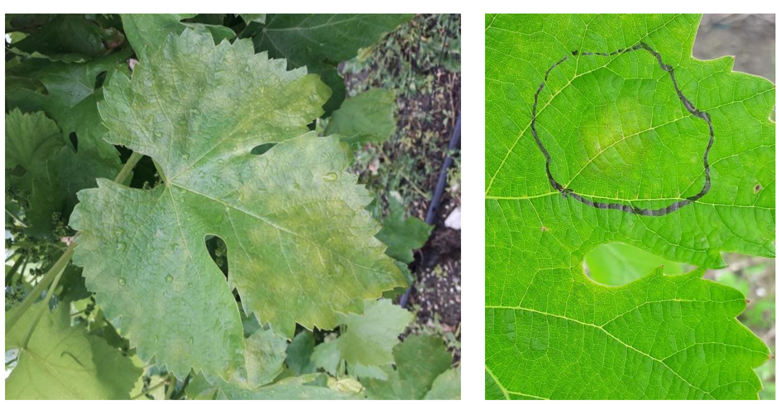

Fig. 1. Downy mildew on grapevine leaves: heavy (right) and slight (left) symptoms (photo taken by authors, 2019)

Fig. 2. Downy mildew attack on grapes: Mild (right) and heavy symptoms (left)

2. MODELS AND DECISION SUPPORT SYSTEMS

In order to reduce the negative impacts on human health, soil, and the environment, as well as the management costs for farmers, the European legislation [9] indicated he need to use plant protection products in a more sustainable way to all Member States. Thus, every State transposed this indication into Laws. For this instance, many a efforts have been made. One of these efforts is the developing of epidemiological models, elaborated to optimize the management of fungicides, especially in the viticulture sector [10]. By adopting such models, the fungicides amount can be reduced and the yield quality enhanced, resulting in a more sustainable and effective defence strategy that meets the EU requirements [11]. Since the middle of the 1980s, software programs to support farmers in the decision process regarding timings, dosages and optimal types of plant protection products were developed [12,13]. After the simplified “3 – 10” rule, the creation of more structured grapevine DM models steadily begun. In the beginning, studies conducted by Goidànich et al. [14] (1957), developed provisional models and then the availability of new computers allowed the development of a larger range of different simulation models.

Some of these models calculated the risk of infection only on the secondary cycle (MILVIT) [15], some simulated only particular phases of the epidemic cycle [16] and some the first date of primary infection followed by the secondary cycle with quantitative outputs [17,18,19]. Exploratory simulation models were constructed as well by using the newly available computing power [20]. DSS have been established as important tools for the achievement of more sustainable agricultural practices [13]. In fact, they have just been validated with field trials in many countries. Results consist in a correlation of the forecasts made by DSSs and the data collected on the field about the infection outbreak, establishing that DSSs can provide good advice on applications of plant protection products and help to reduce the input of active substances, thanks to a lower dependency on agrochemicals. Furthermore, farmers are not usually fully aware of the DM cycle development and infection process, representing a limit in the efficacy and/or sustainability of the management of their plant health. Using DSSs, farmers will become more conscious of the relations between weather conditions, pathogen’s cycle and efficacy of plant protection products.

A short description of the general components and functioning of a DSS is given as it follows. A DSS is a software which collects, organizes and integrates site-specific information (static and dynamic, e.g. climate, etc.), namely the inputs. Indeed, as outputs, it gives an interpretation of the inputs for operative suggestions. As components we firstly have a hardware system for acquiring climate data from multiple sources: for agricultural applications, data are generally taken from public weather stations, while in the most advanced DSS, they are taken from sensors located in the cultural environment of interest. Secondly, such data flow from the hardware to the DSS, which stores and elaborates these data by using mathematical models implemented in software algorithms. Finally, DSSs interpret data through a comparison with previously defined rules (e.g., algorithms). DSSs should also have automatic procedures for interpretation, that allow the transition from data processed to agronomic advice [21].

To develop models there are two kind of approaches:

2.1 Empirical Models (or Data Models)

They are numerical constructs that mathematically represent a set of observed data, such as weather data concomitant with the appearance of a disease, adapting constructed equations to the real observations made in field. For these models, a lot of data is required to be collected in different years in an agronomic environment, in order to fully represent the specificity of this analysed site. For this instance, these models are often not applicable to other environments.

2.2 Mechanistic Models

They use fundamental knowledge of the interaction between variables involved in the system to be modelled in order to define the model structure. Hence, they require precise definition of functional relationships between these variables [22]. Mechanistic models could offer the possibilities to increase the understanding of the behaviour of a pathogen and can lead to the prediction of the disease under a wide range of circumstances [23]. These models are more related to the development of a biological knowledge.

3. AIM OF THE REVIEW

The aim of this work is to carry out a review on the main DM models used in viticulture in order to make their functioning mechanism clear, allowing users to choose the best DSS for their own situation. The most commonly used models simulating occurrence of primary *P. viticola* infections are then reviewed in this work and, at least, the specifics of a now one released in 2020 is also reported (PV-sensing).

4. MODELS

These following models are different for: the approach used in modelling the infection process (from empirical to mechanistic), the level of complexity in considering the different stages of the infection chain, the time steps, the input data and the accuracy level and approach in field validation.

4.1 Empirical Models

4.1.1 3–10 Rule

Baldacci (1947) elaborated this first rule concerning DM infections in Northern Italy (Oltrepò Pavese, Pavia Province). On the basis of this model, the following conditions are required for the beginning of the infection process: air temperature equal or higher than 10°C; at least 10 cm length of grapevine shoots and 10 mm of rainfall in the last 24 – 48 h. This rule is quite easily applied by farmers because only few input parameters are considered, but it is too simplified to describe the whole infection process of Downy mildew, since there are lots of different variables [10]. For this, 3-10 rule might be unreliable and it is not appropriate to represent the complexity of the phenomenon in an environment, where more factors should be taken into consideration.

4.1.2 EPI model (Ètat Potentiel d’Infection)

EPI is an empirical model that was developed in the Bordeaux region (France) by Strizyk (1983) [24]. It is based on the hypothesis that *P. viticola* could be adapted in a specific area with specific climatic conditions and its development is also influenced by annual climatic variations of that area. EPI works estimating the maturation of the oospores and their ability to cause infection by *P. viticola* inoculums [10,25]. Unlike other models, EPI does not include rainfalls as an influential factor in the kinetic equation. Thus, it is mostly used to estimate the risk when winter ends. However, being based and calibrated on the climate conditions present in a specific area, this model needs to be calibrated every time it is used out of that area.

4.2 Mechanistic Models

4.2.1 UCSC model

The UCSC (Università Cattolica del Sacro Cuore) model is a mechanistic one [26]. Regarding its functioning, this model works simulating the entire DM infection’s process in one hour, from the beginning stage (oospores) to the last one of the process (symptoms appearing). Yet, all fungal biological stages are considered and, in this model, their growth is thought to be mainly regulated by weather conditions [27]. The UCSC model is quite complex but it has the advantage of working well in a wide range of environments. This is because it has been tested in several environments with good results. Moreover, its functioning takes the most important variables of the DM infection process into consideration.

4.2.2 DM cast model

DM Cast (i.e., Downy Mildew foreCast) is a model designed in Geneva, New York (USA), that is mostly based on the weather data, in order to forecast both the primary and secondary infection. Shortly, when weather conditions favour oospore germination and their dispersal in the environment, the primary infection starts [28]. It is an easy model to set up and works quite well in different environments, since it takes general and just well-known parameters into consideration (e.g. temperature, rainfall). Perhaps, as a limit, we may report that the parameters implied in the infection prediction are too simples to define DM infections and their occurrence in a biological environment.

4.2.3 Vitimeteo – Plasmopara

VitiMeteo-Plasmopara is a biological model developed by Agroscope Changins-Wädenswil (ACW), in collaboration with the Weinbauinstitut of Freiburg in Breisgau (WBI, Germany) and programmed by the Geosens company. It integrates every stage of the development cycle of *P. viticola* with the aid of specific algorithms. After the first infection occurred from oospores splashing from soil, it calculates the infection risk during following vegetative-growing season. Here, three different outputs are considered by this model, which are easily available for users. Firstly, a general risk summary of the daily infection, secondly a meteorological data, thirdly a phenological development and, finally, the degree of maturation of oospores and primary infections [29]. Nevertheless, being a non-dynamic model, it does not consider the inoculation decreasing of oospores in the soil during the season. Therefore, there might be too high of an infection risk threshold within the season and for the next season.

4.2.4 RimPro

RIMpro-Plasmopara is a DSS that derives from the Apple scab management (*Venturia inaequalis*). It finds basis on a dynamic simulation model, that quantifies the seasonal epidemiology of *P. viticola*, as well as the primary and secondary infections, taking weather and data provided by a local agrometeorological station into consideration. Thus, outputs given are: 1) the likelihood of infection, 2) the quantity of sporulation and 3) the increasing of infected leaves in the controlled vineyard. This DSS has the great advantage of being a simple based model, which might be adapted in different situations and environments. In fact, it could be associated with a meteorological station. As a disadvantage, it might be indicated that the DSS has not got its own weather data collecting [30].

4.2.5 Further minor models

POM model [31] is used especially in the Bordeaux area. It estimates the severity of DM infections in the spring and subsequently calculates the optimal period of oospore maturation, on the basis that rain is the most important factor in influencing oospores maturation. Another one is the SIMPO model [32], which simulates the germination times of the oospores, indicating the periods during which these germinate in less than two days. At the end, other models have been developed to simulate secondary infection but are still not widely used [19].

4.2.6 VineSens

This model has a platform composed by different hardwires. Moreover, a wireless sensor network system is present. In this, some sensors that allow to obtain detailed knowledge on different viticulture processes are included. Thus, concerning the functioning, VineSens generates alerts that warn farmers about infection risks, whilst at the same time it also stores the historical weather data collected from the vineyard. Such data can then be accessed through a web-interface through internte, that is user-friendly. Yet, it could be accessed both by using desktop or mobile devices [33]. Hence, it could be reported how it is easy to be used, both from a computer station or on field using mobile devices. Nevertheless, not too many variables are considered despite the output seems to be quite accurate and then helpful.

4.2.7 The "PV-sensing" model

The PV-sensing model, where PV stands for "*Plasmopara viticola*", is a new model developed in Italy in 2017 by the private company (CET Electronics) with the collaboration of CREA-VE (council for agriculture research and economy analyses - viticulture and oenology section) and the University of Padova. At a first glance, the model structure resembles the one of other mechanistic models (e.g., RimPro or UCSC), where the main stages of the pathogen life cycle are identified and their evolution is modulated by various formulas extrapolated from empirical observations described in the literature. In comparison to the previous models (all reported and described previously), in PV-sensing what is used are new inputs, which are obtained by using specific sensors/devices located in the cultural environment (inside the canopy), entering the simulation of the pathogen life cycle.

The distinct features characterizing the model are the following:

1. dependence on new input variables (water covering level on leaves and water percolation from upper leaves to lower ones, humidity and temperature on the soil surface and, finally, the canopy volume)
2. a stochastic approach.
3. specific new sub models based on empirical data.

A set of free parameters which has been tuned from field observations in the Veneto region for the model calibration.

In details:

A) ACTUAL LEAF SURFACE

A measurement of this variable is carried out indirectly by the daily images from a particular stereo camera, suitable for permanent installation in the field, framing some sample plants during the whole season. A specific software for automatic image analysis provides a foliage segmentation and its 3-dimensional reconstruction, obtaining a measurement of the canopy volume and estimating the actual leaf surface enclosed in it, which is assumed to be representative, on average, of the whole vineyard (or specific vine variety). Such information constitutes a new input considered in the *P. viticola* life cycle, normally absent in other models or replaced by sub models which simulate the vegetative development, mainly according to climate data. The advantage is a higher accuracy obtained by the direct observation with a camera in the field, taking into account all the variability of the environment, which can influence the vine canopy development by specific factors beyond the climatical ones, such as: fertilization, soil composition, rootstock, training/pruning system, etc., whose effects can be well simulated in a model. Such an input enters the PV-sensing model at various levels:

- the total leaf area adjusts the overall level of forecasted infection (the larger the vegetation is, more the disease can spread).
- detecting the new-born vegetation daily allows to quantify the leaf area of a given age, and thus model the susceptibility to the infection according to such a distribution.
- In an advanced version of the PV-sensing model (to be released in 2021) the actual leaf area - and its history - enter in the simulation of degradation/dilution.

B) TEMPERATURE AND MOISTURE OF THE SOIL AT THE SURFACE LEVEL

The superficial soil moisture and temperature are fundamental variables for assessing a good model of maturation and germination of the *P. viticola* oospores, wintering on the soil surface. In other models, such variables are not normally measured but simulated by temperature and RH data collected at 2 m above the soil from a weather station, with the inconvenience that such data may not be representative of the real climate at the soil level (depending on factors as soil composition, structure, covering). Direct measurements of superficial soil moisture and temperature are obtained through a set of newly developed sensors, which differ from the common soil moisture probes, as the (patented) electronic mechanism only involves the first millimetres of the soil surface, i.e., where the oospores actually overwinter and germinate. Soil surface is a critical point for moisture measurements, as many transitional factors compete in fast variations of the water content at this level: evaporation, percolation, absorption. The correlation of primary infections with measurements of the soil surface moisture is also investigated in this project with specific (and still ongoing) oospores germination experiments, that may eventually provide a new design on the maturation and germination models.

C) LEAF WETNESS AND CLIMATE (T, RH) INSIDE THE CANOPY AND WATER DRIPPING

With respect to other models, PV sensing considers the air temperature, air humidity and leaf wetness measured not only at the station level (at a height of 2 meters, outside of the vegetation) but also by sensors placed inside the canopy as inputs. A weighted average of the two quantities is modulated during the season according to the canopy development. The system considers the variability between the climate quantities inside and outside of the canopy, which can be significantly high in some stages, thus providing a more detailed description of the possible conditions for infection development. Also, the PV sensing model uses the measurement of "dripping" of water from the leaves, taken by a specific (patented) leaf wetness sensor. Dripping is related not only to rainfall, but also to important overnight accumulations of dew on leaves, parameters that not are detected by all types of weather stations, or, at least, not really spread in among all winegrowers In the presence of infections, the dripping water holds the pathogen spores and drags them from leaf to leaf and on clusters, causing possible new infections. Dripping also affects the wash off of plant protection products, even in the absence of rain. Such measurements thus affect the overall cycle of secondary infection simulation.

5. CONCLUSION

Grapevine is one of the most important cultivated plants worldwide, as well as one of the most remunerative crops. As for every crop, the cultivation and plant protection are always a tough tasks [34]. In this scenario, phytoiatric control is essential to guaranteeing a good production in terms of both quality and yielding. Among the great number of pathologies affecting *V. vinifera*, DM may be indicated as the more dangerous. In fact, its control requires a great amount of plant protection products [35,36]. In spite of this, annual grape losses range from 20% to 40% [37]. Yet, probably due to the reckless use of agrochemicals occurred in the last century, several breeds of DM became resistant to lots of chemical active substances. This made the control of this pathogen even more complex, with a greater use of agrochemicals and more costs for the whole agricultural management of vineyards. In this contest, DSSs have been proven as good systems, in order to reduce agrochemicals in viticulture and make vineyard management more sustainable. Various DM models have been elaborated and then implemented into a DSS to be used in viticulture. Such models are developed by different approaches and have been tested in different areas on different grape variety. Specifically, farmers and technicians can rely on different DSSs. Everyone is made by a different approach (mechanistic and/or empirical), based on algorithms and/or data collection extrapolated from the literature or from own experience. This allowed the creation of a good number of models, each of them having pros and cons. Hence, the choice of using one or another might only be about the type of approach, the geographical area of interest and, perhaps, the grape varieties. For this, we can state how successful DSSs are those in which the users (winegrowers) were involved in the design of the model, from the conception to the final release on the market. Furthermore, it is very important to use models developed and tested in the same geographical area. Nevertheless, the systems were not designed to make an absolute decision; indeed, they collect and process relevant information, interpret them and communicate a range of suitable options to be considered in the decision-making process by winegrowers. For instance, fungicide usage should be avoided when models do not predict an infection. Indeed, they have to be applied when the models report an infection risk, [2,38] to avoid the environmental and human impact and for the management costs as well. For this, the DSS can help a lot, in order to get a reduction of costs involved in the plant protection process, since the correct positioning of the chemical treatments can make a difference in the agronomic and economic management of a winery or a general farm. The common forecasting models usually consider inputs such as rain, temperature and air humidity, leaf wetness and wind speed. Indeed, the PV-sensing has an innovative forecasting model for downy mildew infections, in which some new variables are measured on field and considered as an input, with the aim of making the simulation of the entire life cycle of the pathogen (DM) - and thus the forecast of infections- more accurate. After two testing years, we can report how PV sensing seemed to work well, predicting DM infections as they were effectively recorded on field, with good correlations indices, despite its perfectioning is still ongoing. Last but not least, using DSSs along with an optimal agronomic strategy may be the right way for the innovation in viticulture, towards a more sustainable cultivation process.

DISCLAIMER

The products used for this research are commonly and predominantly products used in our area of research and country. There is absolutely no conflict of interest between the authors and producers of the products because we do not intend to use these products as an avenue for any litigation but for the advancement of knowledge. Also, the research was not funded by the producing company, but rather it was funded by personal efforts of the authors.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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