A fuzzy control system for decision-making about fungicide applications against grape downy mildew

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A fuzzy control system for decision-making about fungicide applications against grape downy mildew

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Abstract A fuzzy control system (FCS) was developed to determine whether a fungicide application is needed to control *Plasmopara viticola*, the causal agent of downy mildew, in a vineyard. The FCS was conceived as an expert system to be used in connection with vite.net, which is a decision support system (DSS) for sustainable vineyard management. Using the information provided by the DSS, the FCS was able to reproduce the expert reasoning regarding the decision to apply a fungicide against *P. viticola* in a vineyard. The FCS uses the following information provided by the DSS as input variables: i) grapevine phenology; ii) risk of primary infection; iii) abundance of secondary sporangia; iv) risk of secondary infection; and v) residual protection provided by the last fungicide application. All possible combinations of these inputs are expressed as IF-THEN rules; fuzzification interface, inference engine, and defuzzification interface provide the FCS output as a label: 'treatment' or 'no-treatment'. The FCS was tested by comparing the scheduling of copper fungicides against *P. viticola* in 18 organic vineyards of Italy as determined by a panel of five experts vs. the FCS. The FCS was able to reproduce the expert reasoning with an overall accuracy of 0.992. The probability that the FCS recommended a treatment given that the expert panel did was 0.878, and the probability that the FCS did not recommend a treatment given that the expert panel did not was 1. Once the FCS is incorporated into the DSS, it will help inexpert viticulturists in taking right decisions about downy mildew control.

Keywords *Plasmopara viticola* · Decision support system · Expert system · Grapevine

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Introduction

Modern agriculture has long relied on artificial inputs such as fungicides for crop protection (Ekström and Ekbom 2011). In recent decades, however, new and more restrictive regulations regarding fungicide use have been formulated in some parts of the world to reduce the negative effects of pesticides on human health and the environment (Alavanja et al. 2004; Epstein 2014; Shtienberg 2013). In the EU, Directive 128/2009/EC encourages the development and introduction of integrated pest management (IPM). Article 13 of the Directive states that professional users should have ready access to information and tools for pest monitoring and decision making, and also to IPM advisory systems.

The purpose of an advisory system is to reduce the rates and frequency of pesticide applications while providing effective crop protection. Farmers expect specialised guidance from plant protection experts (i.e., plant pathologists) regarding decision about treatments. During on-farm consultations, these experts use their knowledge about the biology and epidemiology of pathogens and also information concerning the past occurrence of the disease and the crop's development, health status, and nutritional condition (Rossi et al. 2014). The plant protection expert also assesses the current level of disease in the crop because the diseased tissue currently present will potentially provide the inoculum for further disease development. The expert will consider the possible lasting effects of plant protection measures already implemented. Finally, the plant protection expert may recommend a treatment if it is likely that a disease outbreak will occur that will irreparably damage the crop and cause yield losses and if the target pathogen is in a controllable developmental stage (Visser et al. 1994).

It follows that decision-making for the sustainable use of pesticides is a complex task that is based on multiple criteria and up-to-date information. To support decision-making in plant disease control, researchers have developed various tools, including warning services, on-site devices, and decision support systems (DSSs) (Rossi et al. 2012). DSSs became practical in the 1970s with the development of minicomputers, timeshare operating systems, and distributed computing (Power 2007). DSSs are applied management tools that can be used to interpret complex information and help the farmer make informed decisions (Shtienberg 2013). DSSs are designed to provide all the information that is needed to make decisions (e.g., vine growth, diseases, insect pest phenology, or soil water content) but are not designed to replace the decision makers (e.g., by indicating the necessity of a treatment or an irrigation). To provide advice to farmers—as an advisory system does—a DSS should be able to provide an on-site plant protection consultation and specialised recommendations on a level equal to that of an expert. To behave like an expert, a DSS should incorporate an expert system (Liao 2005).

An expert system can be defined as a collection of software that is developed for a particular purpose (i.e., that uses encoded knowledge to suggest solutions to specific problems) and that provides solutions similar to those that would be provided by human experts (Patterson 2004). Unlike DSSs, expert systems can act as a decision makers and problem solvers. The core of an expert system is the inference engine. An inference engine applies rules to the available knowledge in order to arrive at a conclusion or recommendation (Roseline et al. 2012).

A basic principle of expert systems is that the expert's knowledge is available even in the absence of a human expert, i.e., the knowledge can be available at all times and at all places as needed (Joy and Sreekumar 2014). Expert systems have been designed in many different ways. Some are rule-based or knowledge-based; others use case-based reasoning, neural networks, object-oriented methodology, ontology, or fuzzy logic (Liao 2005). Fuzzy logic is able to handle the uncertainty in our knowledge. In a broad sense, fuzzy logic refers to fuzzy sets, which are sets with blurred boundaries; in a narrow sense, fuzzy logic aims to formalize approximate reasoning (Bih 2006). Fuzzy logic is especially useful when evaluation of a system requires human experience that is expressed by 'linguistic' terms (e.g., a *high* risk of infection or *low* residual fungicide protection) (Chen and Pham 2000).

In this paper, a fuzzy control system (FCS) was developed to estimate the need for a fungicide application in a vineyard to control *Plasmopara viticola*, the causal agent of downy mildew. The FCS was conceived as an expert system to be used in connection with a specific DSS for sustainable management of vineyards (Rossi et al. 2014). This DSS, which is named vite.net, collects multiple data in the vineyard, analyzes them by means of mathematical models, and finally provides up-to-date information to the farmer for supporting the decision making process (Rossi et al. 2014). The FCS developed here considers some of the information currently provided by the DSS (specifically, grapevine phenology, risk of primary and secondary infection, abundance of secondary sporangia, and residual fungicide protection) to estimate the need for a fungicide application against *P. viticola* in the vineyard.

Materials and methods

Development of the FCS

Fuzzy control is based on a set of linguistic rules that capture the available knowledge about how to control a process or how to make a decision. Linguistic variables, e.g., 'risk of infection', describe the time-varying controller inputs and outputs. Linguistic variables assume linguistic values, such as 'low', 'moderate', or 'high'. Linguistic variables and values provide a language for the expert to express her/his ideas about the decision-making process. These linguistic quantifications are used to specify the set of linguistic rules in the general IF-THEN form (IF premise, THEN consequence).

In addition to containing a set of linguistic rules, an FCS for decision making is composed of three other components: i) a fuzzification interface, ii) an inference engine; and iii) a defuzzification interface (Passino and Yurkovich 1998) (see Fig. 1). Fuzzification transforms 'crisp' data, i.e., the measured, well-defined data that are the inputs into the FCS, into fuzzy sets. To perform this transformation, 'membership functions' are created for each linguistic variable and linguistic level; membership functions are chosen based on the user's experience (Chen and Pham 2000). The inference engine evaluates which control rules are relevant. It simulates human decision making by performing approximate reasoning to achieve the desired output; the combination of inputs then produces a new logical variable as a function of the existing one. Finally, defuzzification is used to produce a non-fuzzy decision (i.e., a 'crisp' output) from the inferred fuzzy decision produced by the inference engine.

Identification of input variables To determine whether a fungicide application against *P. viticola* is necessary, the following information provided by the DSS vite.net was considered as crisp input to the FCS: i) grapevine phenology; ii) risk of primary infection; iii) abundance of secondary sporangia; iv) risk of secondary infection; and v) residual protection by the last fungicide application. Grapevine phenology is predicted by a dynamic crop growth model that is based on weather data and that predicts the formation and unfolding of the leaves (Cola et al. 2014); because stomata are not functional in leaves before unfolding (Allègre et al. 2007), the presence of unfolded leaves was considered as a proxy of vine susceptibility to *P. viticola* infection through stomata (Gessler et al. 2011). Risk of primary infection is predicted by a mechanistic, weather-driven model that predicts oospore germination, release of the zoospores from sporangia, splash dispersal of the zoospores to leaves, and finally infection by zoospores as influenced by wetness duration and temperature (Rossi et al. 2008). Abundance of secondary sporangia and risk of secondary infection are predicted by another mechanistic model that accounts for production of sporangia on downy mildew lesions, the dispersal and survival of sporangia, and finally infection (Caffi et al. 2013). Residual fungicide protection is predicted by a specific model that simulates the decline in the fungicide efficacy after application based on weather conditions (influencing drying-out, rain-fastedness and rainfall tenacity of the fungicide) and plant growth and development (Caffi et al. 2012).

Fuzzification The above crisp input variables were transformed into linguistic variables in a heuristic manner based on experience and published results (Table 1). For susceptibility of grapevine phenology, the linguistic value low refers to the absence of leaves, medium to the 1st and 2nd unfolded leaves, and high to the 3rd (and beyond) unfolded leaves (i.e., values from <100 to ≥103 on the BBCH phenology scale for grape according to Lorenz et al. 1995). For the risk of primary and secondary infections of *P. viticola*, the linguistic values low, medium, and high refer to different combinations of wetness duration and temperature during the wet period (Blaeser and Weltzien 1979).

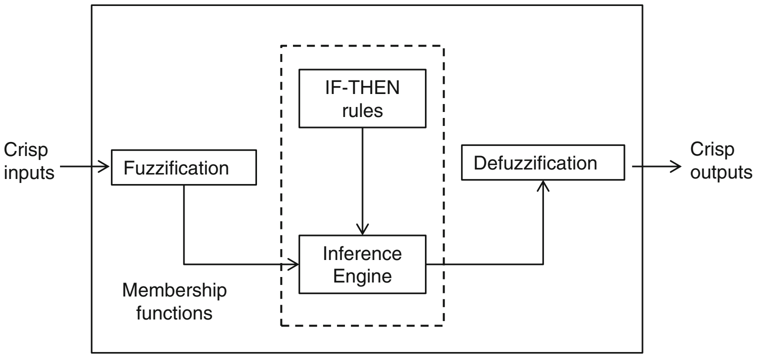

Fig. 1 Diagram of the fuzzy control system

Table 1 Input variables, crisp values, and linguistic values used in the fuzzy control system for deciding whether to apply a treatment to control *Plasmopara viticola*

Input variable	Crisp value	Linguistic value
Grapevine receptivity: growth stage according to Lorenz et al. (1995)	< 101	Low
	100–103	Medium
	>102	High
Risk of *P. viticola* infection for both primary and secondary infections: product of wetness duration (hours) and average temperature (°C) during the wet period	< 45	Low
	35–65	Medium
	> 55	High
Secondary inoculum of *P. viticola*: number of hours with favourable conditions for sporulation	< 6	Low
	> 4	High
Fungicide protection: residual efficacy of the fungicide (%)	< 85	Low
	> 75	High

For the level of secondary inoculum of *P. viticola*, the linguistic values low and high refer to the number of hours in the dark with environmental conditions suitable for sporulation (Caffi et al. 2013). For fungicide protection, the linguistic values low and high refer to the percentage of residual activity of the previously applied fungicide, with protection =100 % at the time of application (Caffi et al. 2012).

Fuzzification of the inputs is then carried out by trapezoidal/triangular membership functions (Fig. 2) (Yen and Langari 1999; Ying 2000) based on experience and published results (Klir and Yuan 1995). Starting from the crisp values of *n* input linguistic variables X_1, X_2, … X_n (x-axis in the functions of Fig. 2), the membership functions generate the $x_1, x_2, \ldots, x_n$ (y-axis in the functions of Fig. 2) values to be used in the inference engine.

Definition of the IF-THEN rules and inference In fuzzy logic, relationships between the fuzzy controller inputs and the fuzzy controller outputs are expressed through IF-THEN rules in the following form: 'IF premise THEN consequence', where premises are associated with the inputs and the consequeces are associated with the outputs. If multiple inputs are considered, rules could be composed as in the following example: 'IF premise 1 AND premise 2 THEN consequence'. With more than two premises, the combination of inputs produces a new logical variable (Y) as a function of the existing ones. The combination rule would be, for instance: 'IF X_1 is high AND X_2 is moderate AND… X_n is low THEN Y is low'; the logical operation AND is defined as $\min\{x_1, x_2 \ldots xn\}$ as usual (Mamdani and Assilian 1975). Because a binary output is considered here (treatment vs. no-treatment), the value $\min\{x_1, x_2, \ldots, x_n\}$ also represents the degree of applicability of this rule to the situation described by the input (x_1, x_2, …, x_n).

IF-THEN rules based on the five variables involved in primary and secondary infections of *P. viticola* are defined as in Tables 2 and 3, respectively, based on experience. For instance, the following rules were constructed: 'IF grapevine susceptibility is low AND risk of primary infection is low AND fungicide protection is high THEN no-treatment' (Table 2); 'IF secondary inoculum is high AND risk of secondary infection is high AND fungicide protection is low, THEN treatment' (Table 3).

Defuzzification The conclusion derived from the combination of inputs, output membership functions, and fuzzy rules is still a vague element. This needs to be converted to a crisp variable via the defuzzification process.

In the present case, this linguistic output is the label 'treatment'/'no-treatment'; this output is obtained by selecting the highest activation level of all the possible combinations for primary and secondary infections (Tables 2 and 3). For instance, consider the following DSS information for the risk of a primary *P. viticola* infection: i) grapevine susceptibility =108 (i.e., the 8th leaf is unfolded); ii) risk of primary infection is T × WD = 62; and iii) residual fungicide protection =84 %. The above values are fuzzified by the membership functions of Fig. 2. For instance: the premise 'IF susceptibility is high' leads to a degree of membership of 1; the premise 'IF primary infection risk is high' leads to a degree of membership of 0.7; and the premise 'IF fungicide protection is low' leads to a degree of membership of 0.11 (Table 4). The combination of these premises would form: 'IF susceptibility is high AND primary infection risk is high AND fungicide protection is low'. Thus, the degree of applicability of this combination will be $\min\{1, 0.7, 0.11\} = 0.11$ (Table 4). Taking into account the different linguistic terms that the three

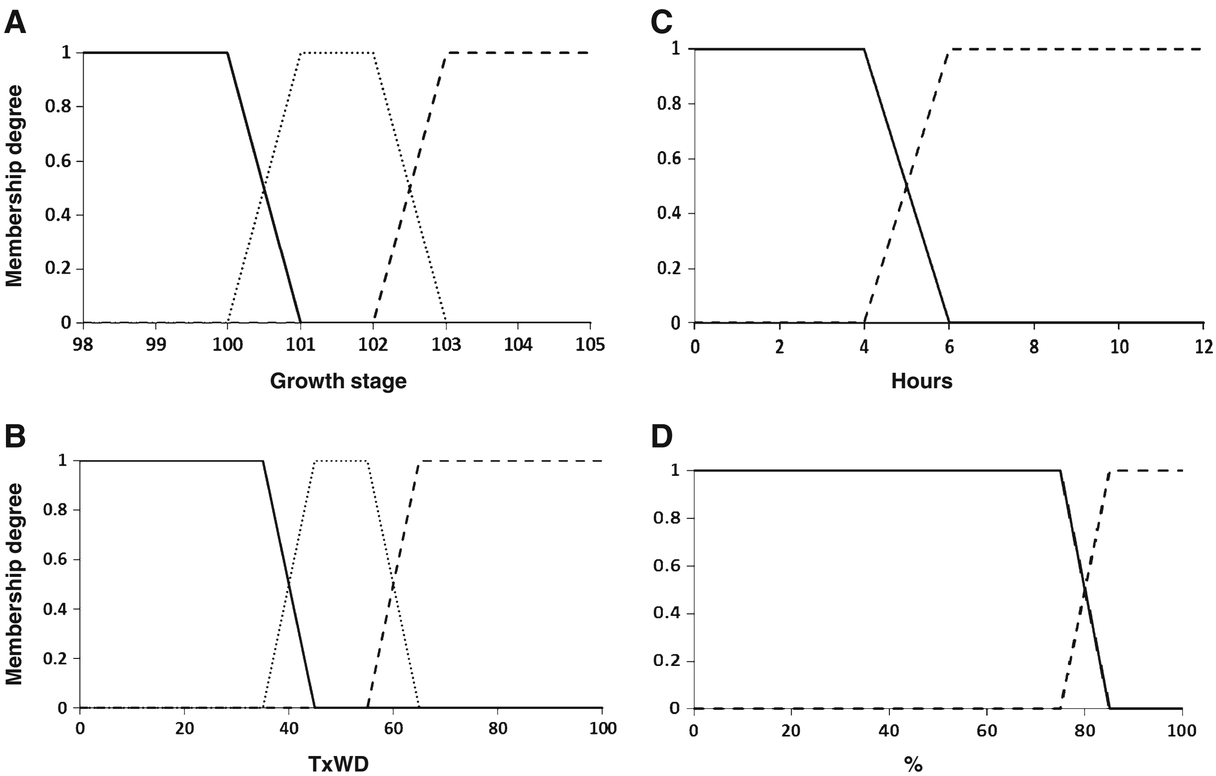

Fig. 2 Membership functions of the linguistic variables included in the fuzzy control system for deciding whether to apply a treatment to control *Plamopara viticola*. **a** grapevine suceptibility: growth stage according to Lorenz et al. (1995). **b** risk of *P. viticola* infection for both primary and secondary infections: product of wetness duration (hours) and average temperature (°C) during the wet period. **c** secondary inoculum of *P. viticola*: number of hours with favourable conditions for sporulation. d fungicide protection: residual efficacy of the fungicide (%). Solid lines, dotted lines, and dashed lines indicate that the linguistic value is 'low', 'medium', and 'high', respectively

premises can adopt, 18 combinations are possible (Table 5). In the defuzzification step, the highest activation level (i.e., the highest value) of the set of rules is selected. In the example presented here, the highest activation level for all the labels 'no-treatment' (i.e., the combinations marked with "-" in Table 2) is 0.7. In the case of the label 'treatment', the highest activation level (i.e., the combinations marked with "+" in Table 2) is 0.11 (Table 5). So, because the activation level is

Table 2 IF-THEN rules for the three variables used in the fuzzy control for deciding whether to apply a treatment to control primary infection by *Plasmopara viticola*. A minus sign indicates 'no-treatment' and a plus sign indicates 'treatment'

Grapevine receptivity	Fungicide protection	Primary infection risk		
		Low	Medium	High
Low	Low	–	–	–
	High	–	–	–
Medium	Low	–	–	+
	High	–	–	–
High	Low	–	+	+
	High	–	–	–

Table 3 IF-THEN rules for the three variables used in the fuzzy control for deciding whether to apply a treatment to control secondary infection by *Plasmopara viticola*. A minus sign indicates 'no-treatment' and a plus sign indicates 'treatment'

Secondary inoculum	Fungicide Protection	Secondary infection risk		
		Low	Medium	High
Low	Low	−	−	+
	High	−	−	−
High	Low	−	+	+
	High	−	−	−

higher for 'no-treatment' than for 'treatment', the FCS recommends no-treatment.

Evaluation of the FCS

To evaluate the ability of the FCS to make expert decisions, i.e., to make the same decision that an expert would make about the need for a fungicide treatment against *P. viticola*, the FCS output (i.e., treatment vs. no-treatment) was compared with the decisions made by a panel of experts.

For this comparison, the DSS vite.net was operated in five vineyards during different grape-growing seasons (Table 6). A panel of five plant pathologists, expert in using the DSS, decided the scheduling of treatments that were needed to control downy mildew between bud break and harvesting. To make these decisions, the experts used the same DSS information that were used as inputs in the FCS, i.e., grapevine phenology, risk of primary infection, level of secondary inoculum, risk of secondary infection, and residual fungicide protection from the last treatment. On each day between bud break and harvest, the FCS was operated and the output ('treatment recommended' or 'no-treatment recommended') was recorded.

To evaluate the ability of the FCS to reproduce the schedule of treatments decided by the expert panel (which is considered as the 'true value'), all the possible combinations of experts (E) treatments vs. FCS treatments were organized in a 2 × 2 contingency table. In this table, the two groups E− FCS− (treatment not recommended by the expert panel or the FCS) and E+ FCS+ (treatment recommended by the expert panel and the FCS) were correct estimates, while the two groups E − FCS+ and E+ FCS− were incorrect estimates; cases in which the difference between a day marked by experts and that marked by the FCS was ±1 day were considered as E+ FCS+. With this contingency table, the true positive proportion (TPP), true negative proportion (TNP), false positive proportion (FPP), and false negative proportion (FNP) were calculated and used to estimate the conditional probabilities (Yuen and Hughes 2002). In this case, the conditional probabilities were: the probability that the FCS recommended a treatment given that the expert panel did, Pr(FCS + |E+); the probability that the FCS recommended a treatment given that the expert panel did not, Pr(FCS + |E-); the probability that the FCS do not recommend a treatment given that the expert panel did, Pr(FCS-|E+); and the probability that the FCS do not recommend a treatment given that the expert panel did not, Pr(FCS-|E-).

Results

The overall data set considered for the FCS evaluation consisted of 2754 days over the 18 combinations of vineyard and year. The expert panel marked 151 days (5.5 % of the days) (Table 6) as suitable for applying a treatment against *P. viticola*. The number of treatments recommended by experts in one vineyard and in 1 year ranged between 20 and 3 (Table 6). The average number of treatments per vineyard per year was 8.3.

Table 4 Fuzzified values of the three input variables used in the fuzzy control system for deciding whether to apply a treatment to control primary infection by *Plasmopara viticola* when grapevine receptivity =108 (i.e., the 8th leaf is unfolded), risk of primary infection (T × WD) = 62, and residual fungicide protection =84 %. Values were obtained by the membership functions of Fig. 2

Linguistic value	Grapevine receptivity	Primary infection risk	Fungicide protection
Low	0	0	0.11
Medium	0	0.3	-
High	1	0.7	0.89

Table 5 Fuzzified values corresponding to all of the IF-THEN combinations for the three input variables used in the fuzzy control system for deciding whether to apply a treatment to control primary infection by *Plasmopara viticola* (the combinations are shown in Table 2, with the corresponding recommendation) when grapevine receptivity =108 (i.e., the 8th leaf is unfolded), risk of primary infection (T × WD) = 62, and residual fungicide protection =84 %

Grapevine receptivity	Fungicide Protection	Primary infection risk		
		Low	Medium	High
Low	Low	0	0	0
	High	0	0	0
Medium	Low	0	0	0
	High	0	0	0
High	Low	0	0.11	0.11
	High	0	0.30	0.70

In the same data set, the FCS indicated 172 days as suitable for sprays (6.2 % of the days), i.e., 21 days more than the expert panel (0.7 % of days) (Table 6). In 10 of the 18 combinations of vineyard and year, a higher number of treatments was recommended by the FCS than by the expert panel; in eight combinations, the recommendations of the FCS matched those of the expert panel. The expert panel never recommended a higher number of treatments than the FCS (Table 6).

Table 6 Comparison of the number of fungicide treatments recommended by the fuzzy control system (FCS) vs. a panel of five experts with respect to control of *Plasmopara viticola* in 18 combinations of vineyard and year in Italy

Vineyard	Geographical coordinates	Year	Number of treatments recommended	
			FCS	Experts
Cormons	45°57′05″N	2014	23	20
(Friuli Venezia Giulia)	13°27′19″E	2013	12	12
		2012	10	10
		2011	9	7
Butera	37°11′00″N	2013	3	3
(Sicily)	14°11′00″E	2012	4	4
		2011	6	6
Canneto Pavese	45°02′44″N	2014	11	10
(Lombardy)	09°16′60″E	2013	14	13
		2012	5	5
		2011	13	10
Montefalco	42°55′32″N	2014	18	12
(Umbria)	12°38′27″E	2013	14	12
		2012	3	3
		2011	8	7
Massafra	40°35′06″N	2014	11	10
(Apulia)	17°10′41″E	2013	5	4
		2012	3	3
Total			**172**	**151**

All treatments recommended by the expert panel were also recommended by the FCS, giving TPP = 1 and FNP = 0. Because the FCS recommended a treatment that was not recommended by the expert panel in 21 cases, FPP = 0.008. In 2582 cases, no treatment was recommended by either the expert panel or the FCS, giving TNP = 0.992. The probability that the FCS recommended a treatment given that the expert panel did was Pr(FCS + |E+) = 0.878, and the probability that the FCS recommended a treatment given that the expert panel did not was Pr(FCS + |E-) = 0.122. The probability that the FCS did not recommend a treatment given that the expert panel did not was Pr(FCS-|E-) = 1. Finally, the probability that the FCS did not recommend a treatment given that the expert panel did was Pr(FCS-|E+) = 0.

The overall accuracy of the FCS relative to the expert panel was 0.992 based on accurate vs. total recommendations, and 0.985 based on the Youden's index (J = TPP-FPP). The discrepancies occurred when FCS recommended treatments that were not recommended by the experts. This occurred mainly for two reasons. The first resulted from the subjective evaluation by the experts when the residual fungicide protection provided by a copper application dropped to 75–60 % within 1–2 days after application because of washing by rain. In Cormons vineyard in 2013, for example, a treatment was recommended by both the expert panel and the

FCS on 10 May because of 'high' susceptibility, a 'high' risk of primary infection, and 'low' fungicide protection. On the following day, the FCS recommended another treatment because the susceptibility and infection risk were still 'high', and the fungicide protection had dropped to 'low' because of a 30-mm rain. In this situation, however, the experts decided not to apply the second treatment. This discrepancy between the FCS and the expert panel occurred in a total of 11 cases.

The second reason for the FCS to recommend treatments when the experts did not concerns treatments recommended by the FCS in the late stages of berry maturity. In these periods, experts decided not to recommend a treatment in spite of favorable conditions for infection because the possible infections would not cause damage and because of the required pre-harvest interval without fungicide application. The FCS, in contrast, recommended a treatment because the FCS lacks rules concerning infections late in berry maturation. This discrepancy between the FCS and the expert panel occurred in a total of five cases.

Discussion

The decision to apply a fungicide to control downy mildew in a vineyard is based on multiple criteria. These criteria include the presence of susceptible vegetation, the abundance of *P. viticola* inoculum, the risk of primary and secondary infection, and the residual level of protection provided by the last fungicide applied. The DSS vite.net was recently developed to help viticulturists in decision making (Rossi et al. 2014). This DSS has two main components: (i) an integrated system for real-time monitoring of vineyard data, and (ii) a web-based tool that analyses these data by using mechanistic, dynamic models that are able to predict grapevine growth, risk of primary infection, abundance of secondary sporangia, risk of secondary infection, and residual protection by the last fungicide application. Each of these models has been published and their accuracy validated (Cola et al. 2014; Rossi et al. 2008; Caffi et al. 2013; Caffi et al. 2012).

Based on model outputs, the DSS produces supports/alerts, but the final decision about fungicide application is the responsibility of the user (Rossi et al. 2014). When the DSS was used by expert viticulturists, the number of copper treatments against downy mildew was reduced by 24 % and the total amount of copper applied was reduced by 37 % compared to a calendar-scheduling of copper application that provided the same level of protection in organic vineyards (Rossi et al. 2014). However, the ability to make the correct decision based on the multiple criteria provided by the DSS largely depends on user expertise.

An expert system would be very useful for inexpert viticulturists, assuming that the expert system provides the same advice as an expert. The fuzzy control system (FCS) developed in this work was able to reproduce the expert reasoning regarding the decision to apply a fungicide against *P. viticola* in a vineyard. The current study compared the scheduling of copper fungicides applications in 18 organic vineyards located in different parts of Italy as recommended by a panel of five experts and as recommended by the FCS. The comparison showed that the FCS was able to reproduce the expert reasoning with an overall accuracy of 0.992 (with 1 indicating perfect agreement). The probability that the FCS recommended a treatment given that the expert panel did was 0.878, and the probability that the FCS did not recommend a treatment given that the expert panel did not was 1.

From the total of 2754 days evaluated, the FCS recommended a treatment when the experts did not on only 21 days. The reasons why the experts did not recommend a treatment on these 21 days were: (i) the level of fungicide protection was 75–60 % and a treatment had been applied 1 or 2 days before; and (ii) the harvest time was near. To prevent the FCS from recommending fungicide treatment under the latter condition, the FCS should be modified to include a pre-harvest interval during which fungicides are not used. This interval ranges between 20 days for copper compounds to 28 days for mancozeb and metalaxil (http://www.salute.gov.it/fitosanitariwsWeb_new/FitosanitariServlet). A further improvement would involve the recognition that the ontogenic resistance of bunches changes with grapevine phenology. Kennelly et al. (2005) found that berries acquire a certain level of ontogenic resistance to *P. viticola* two weeks after grapevine bloom; stomata become inactive, preventing the fungus from penetrating the berry and also preventing sporulation. Travis and Hed (2001) also found that when fungicide protection was maintained until approximately three weeks post-bloom, subsequent fungicide application did not provide additional control of downy mildew on berries.

The FCS was developed based on the principles of fuzzy logic (Zadeh 1965) and the fuzzy theory set

(Passino and Yurkovich 1998). Fuzzy logic is currently being applied in many scientific areas including engineering, mathematics, computer software development, natural science (mainly biology and ecology), medical research, and social science (mainly psychology) (Singh et al. 2013). Fuzzy logic is also being used in plant science (Divya and Sreekumar 2014; Sannakki and Rajpurohit 2011).

In plant pathology, fuzzy logic has been mainly used in: (i) expert systems that help researchers, advisors, and farmers identify the pathogen associated with observed symptoms (Chathuranga and Anthonys 2011; Kolhe et al. 2011; Suhartono et al. 2013); (ii) image processing methodology to automatically grade the disease on a plant or plant organ (Deshpande et al. 2014; Ghaiwat and Arora 2014; Naik et al. 2014); and (iii) weather-based models for predicting the development of rust infection in soybean (Alves et al. 2011; Kim et al. 2005), infection caused by *Phytophthora* spp. on chestnut (Dal Maso and Montecchio 2015), *Neonectria galligenea* on apple (Kim and Beresford 2012), and *P. viticola* on grapes (Orlandini et al. 2003). In a few cases, fuzzy logic has been applied to assist decision making for crop protection (Visser et al. 1994; Roseline et al. 2012).

The FCS developed in this work could be incorporated into the DSS, in order to help the viticulturist in the process of decision making. In addition to helping inexpert viticulturists make 'expert' decisions, the FCS described here is likely to increase the expertise of users with respect to disease control (Zadoks 1989). Gent et al. (2011) suggested that after a period of using an expert system, growers may learn how the system arrives at its recommendations so that they no longer need the system to make correct decisions. In other words, a repeated use of the FCS may help growers understand how the system arrives at correct decisions. An expert system may also help users, regardless of their levels of expertise, make objective decisions. This is important because disease risk perception associated with a predictive system varies among individuals (Gent et al. 2013; McRoberts et al. 2011), and given the same disease prediction, a risk-averse grower may be tempted to apply more treatments than a risk-tolerant grower (Bar-Shira et al. 1997). By calibrating their decision to an objective level of risk, the FCS developed in this work may benefit both kinds of decision makers.

References

Alavanja, M. C. R., Hoppin, J., & Kamel, F. (2004). Health effects of chronic pesticide exposure: cancer and neurotoxicity. *Annual Review of Public Health*, *25*, 155–197.

Allègre, M., Daire, X., Héloir, M., Trouvelot, S., Mercier, L., Adrian, M., & Pugin, A. (2007). Stomatal deregulation in *Plasmopara viticola*-infected grapevine leaves. *New Phytologist*, *173*, 832–840.

Alves, M., Pozza, E. A., Sanches, L., & de Carvalho, L. G. (2011). Fuzzy logic system modeling soybean rust monocyclic process. Resource document. http://www.intechopen.com/books/soybean-physiology-and-biochemistry/fuzzy-logic-system-modeling-soybean-rust-monocyclic-process.

Bar-Shira, Z., Just, R. E., & Zilberman, D. (1997). Estimation of farmers' risk attitude: an econometric approach. *Agricultural Economics*, *17*, 211–222.

Bih, J. (2006). Paradigm shift-an introduction to fuzzy logic. *IEEE Potentials*, *25*, 6–11.

Blaeser, M., & Weltzien, H. C. (1979). Epidemiologische studien an *Plasmopara viticola* zur verbesserung der spritzterminbestimmung. *Zeitschrift fur Pflanzenkrankheiten und Pflanzenschutz (Journal of Plant Diseases and Protection)*, *86*, 489–498.

Caffi, T., Legler, S. E., Carini, M., & Rossi, V. (2012). Mode of action and rainfastness of copperbased products against grapevine downy mildew. *Journal of Plant Pathology*, *94*(4S), S4.59.

Caffi, T., Gilardi, G., Monchiero, M., & Rossi, V. (2013). Production and release of asexual sporangia in *Plasmopara viticola*. *Phytopathology*, *103*, 64–73.

Chathuranga, T. D. N., & Anthonys, G. (2011). Disease diagnose of rice plants using fuzzy-expert hybrid system. *In Proceeding of the Eight Annual Sessions. Sri Lanka Association for Artificial Inteligence*, *14–20*.

Chen, G., & Pham, T. T. (2000). *Introduction to fuzzy sets, fuzzy logic, and fuzzy control systems*. Boca Raton: CRC press.

Cola, G., Mariani, L., Salinari, F., Civardi, S., Bernizzoni, F., Gatti, M., & Poni, S. (2014). Description and testing of a weather-based model for predicting phenology, canopy development and source-sink balance in *Vitis vinifera* L. cv. Barbera. *Agricultural and Forest Meteorology*, *184*, 117–136.

Dal Maso, E., & Montecchio, L. (2015). Large-scale fuzzy rule-based prediction for suitable chestnut ink disease sites: a case study in north-east Italy. *Forest Pathology.* doi:10.1111/efp.12172.

Deshpande, T., Sengupta, S., & Raghuvanshi, K. S. (2014). Grading and identification of disease in pomegranate leaf and fruit. *International Journal of Computer Science and Information Technologies*, *5*, 4638–4645.

Divya, J., & Sreekumar, K. (2014). A survey on expert system in agriculture. *International Journal of Computer Science and Information Technologies*, *5*, 7861–7864.

Ekström, G., & Ekbom, B. (2011). Pest control in agro-ecosystems: an ecological approach. *Critical Reviews in Plant Sciences*, *30*, 74–94.

Epstein, L. (2014). Fifty years since silent spring. *Annual Review of Phytopathology*, *52*, 377–402.

Gent, D. H., De Wolf, E., & Pethybridge, S. J. (2011). Perceptions of risk, risk aversion, and barriers to adoption of decision support systems and integrated pest management: an introduction. *Phytopathology*, *101*, 640–643.

Gent, D. H., Mahaffee, W. F., McRoberts, N., & Pfender, W. F. (2013). The use and role of predictive systems in disease management. *Annual Review of Phytopathology*, *51*, 267–289.

Gessler, C., Pertot, I., & Perazzolli, M. (2011). Plasmopara viticola: a review of knowledge on downy mildew of grapevine and effective disease management. *Phytopathologia Mediterranea*, *50*, 3–44.

Ghaiwat, S. N., & Arora, P. (2014). Detection and classification of plant leaf diseases using image processing techniques: a review. *International Journal of Recent Advances in Engineering & Technology*, *2*, 1–7.

Joy, J., & Sreekumar, K. (2014). A survey on expert system in agriculture. *International journal of computer science and information technologies*, *5*, 7861–7864.

Kennelly, M. M., Gadoury, D. M., Wilcox, W. F., Magarey, P., & Seem, R. C. (2005). Seasonal development of ontogenic resistance to downy mildew in grape berries and rachises. *Phytopathology*, *95*, 1445–1452.

Kim, K. S., & Beresford, R. M. (2012). Use of a climatic rule and fuzzy sets to model geographic distribution of climatic risk for European canker (*Neonectria galligena*) of apple. *Phytopathology*, *102*, 147–157.

Kim, K. S., Wang, T. C., & Yang, X. B. (2005). Simulation of apparent infection rate to predict severity of soybean rust using a fuzzy logic system. *Phytopathology*, *95*, 1122–1231.

Klir, G. J., & Yuan, B. (1995). *Fuzzy sets and fuzzy logic* (p. 574). New Jersey: Prentice Hall PTR.

Kolhe, S., Kamal, R., Saini, H. S., & Gupta, G. K. (2011). A web-based intelligent disease-diagnosis system using a new fuzzy-logic based approach for drawing the inferences in crops. *Computers and Electronics in Agriculture*, *76*, 16–27.

Liao, S. H. (2005). Expert system methodologies and applications-a decade review from 1995 to 2004. *Expert Systems with Applications*, *28*, 93–103.

Lorenz, D. H., Eichhorn, K. W., Bleiholder, H., Klose, R., et al. (1995). Phenological growth stages of the grapevine *Vitis vinifera* L. ssp. vinifera. Codes and descriptions according to the extended BBCH scale. *Australian Journal of Grape and Wine Research*, *1*, 100–103.

Mamdani, E. H., & Assilian, S. (1975). An experiment in linguistic synthesis with a fuzzy logic controller. *International Journal of Man-Machine Studies*, *7*, 1–13.

McRoberts, N., Hall, C., Madden, L. V., & Hughes, G. (2011). Perceptions of disease risk: from social construction of subjective judgments to rational decision making. *Phytopathology*, *101*, 654–665.

Naik, S. I., Kanandreddy, V., & Sannakki, S. (2014). Plant disease diagnosis system for improved crop yield. *International Journal of Innovations in Engineering and Technology*, *4*, 198–204.

Orlandini, S., Dalla Marta, A., D'Angelo, I., & Genesio, R. (2003). Application of fuzzy logic for the simulation of *Plasmopara viticola* using agrometeorological variables. *EPPO Bulletin*, *33*, 415–420.

Passino, K. M., & Yurkovich, S. (1998). *Fuzzy control*. Menlo Park, California: Addison Wesley.

Patterson, D. W. (2004). *Introduction to artificial intelligence and expert systems*. New Delhi: Prentice-Hall.

Power, D.J. (2007). A brief history of decision support system. http://DSSResources.COM/history/dsshistory.html. Accessed 2 May 2015.

Roseline, P., Tauro, C., & Ganesan, N. (2012). Design and development of fuzzy expert system for integrated disease management in finger millets. *International Journal of Computer Applications*, *56*, 31–36.

Rossi, V., Caffi, T., Giosuè, S., & Bugiani, R. (2008). A mechanistic model simulating primary infections of downy mildew in grapevine. *Ecological Modelling*, *212*, 480–491.

Rossi, V., Caffi, T., & Salinari, F. (2012). Helping farmers face the increasing complexity of decision-making for crop protection. *Phytopathologia Mediterranea*, *51*, 457–479.

Rossi, V., Salinari, F., Poni, S., Caffi, T., & Bettati, T. (2014). Addressing the implementation problem in agricultural decision support systems: the example of vite.net®. *Computers and Electronics in Agriculture*, *100*, 88–99.

Sannakki, S. S., & Rajpurohit, V. S. (2011). A survey on applications of fuzzy logic in agriculture. *Journal of ComInternational Journal of Electrical Energyputer Applications*, *4*, 8–11.

Shtienberg, D. (2013). Will decision-support systems be widely used for the management of plant diseases? *Annual Review of Phytopathology*, *51*, 1–16.

Singh, H., Gupta, M. M., Meitzler, T., Hou, Z. G., Garg, K. K., Solo, A. M., & Zadeh, L. A. (2013). Real-life applications of fuzzy logic. *Advances in Fuzzy Systems*. doi:10.1155/2013/581879.

Suhartono, D., Aditya, W., Lestari, M., & Yasin, M. (2013). Expert system in detecting coffee plant diseases. *International Journal of Electrical Energy*, *1*, 156–162.

Travis, J.W., & Hed, B. 2002. Evaluation of fungicides for control of downy mildew, powdery mildew, and Phomopsis cane and leaf spot of grapes, 2001. Fungicide and Nematicide Tests (online) Report 57:SMF17. The American Phytopathological Society, St. Paul, MN.

Visser, U., Voges, U., & Streit, U. (1994). Integration of AI-, database- and telecommunication-techniques for the plant protection expert system PRO_PLANT. *Industrial and Engineering Applications of Artificial Intelligence and Expert Systems*, *7*, 367–374.

Yen, J., & Langari, R. (1999). *Fuzzy logic: intelligence, control and information*. Upper Saddle River: Prentice Hall.

Ying, H. (2000). *Fuzzy control and modelling*. New York: IEEE Press.

Yuen, J. E., & Hughes, G. (2002). Bayesian analysis of plant disease prediction. *Plant Pathology*, *51*, 407–412.

Zadeh, L. A. (1965). Fuzzy sets. *Information and Control*, *8*, 338–353.

Zadoks, J. C. (1989). EPIPRE, a computer-based decision support system for pest and disease control in wheat: Its development and implementation in Europe. In K. J. Leonard, & W. E. Fry (Eds.), *Plant Disease Epidemiology Vol 2: Genetics, Resistance, and Management*. New York: McGraw-Hill.