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## OPTIPAON, A DECISION SUPPORT SYSTEM TO PREDICT THE RISK OF PEACOCK EYE OF OLIVE IN SOUTHERN FRANCE

C. Roubal<sup>a</sup>, S. Regis<sup>a</sup> and P.C. Nicot<sup>b</sup>

<sup>a</sup>ONPV. Quartier Cantarel, BP 70095, F-84143 Montfavet CEDEX. France <sup>b</sup>INRA, UR407 Pathologie végétale, F-84140 Montfavet, France. philippe.nicot@avignon.inra.fr

#### **ABSTRACT**

Peacock eye, caused by *Fusicladium oleagineum*, is a major disease in most olive production regions, including southern France. Its control relies on up to 6 treatments per season. A more accurate evaluation of disease risk would allow to reduce the frequency of treatments.

Work was conducted to develop a field-operational model for disease prediction based on climatic conditions, using data form a 10-year survey. As disease outbreaks are known to be linked to rain, models were evaluated for their ability to predict if infection would occur following a rain event, depending on air temperature and duration of relative humidity above 85%. We examined a total of 134 rain events followed by confirmed leaf infection and 191 rain events not followed by detectable infection. The field data were adequately fitted with two regression models describing high boundary values of high humidity duration, above which no infection occurred over the temperature range, and low boundary values below which no infection occurred. One problem associated with risk prediction of peacock eye is the long latent period (time between infection and the first detection of leaf spots) of this disease. We thus developed a second model to relate the duration of the latent period as a function of air temperature after the beginning of rain. Used together, these two models allowed to predict the numbers of ongoing latent infections. They were included in a decision support system (DSS), referred to as "OPTIPAON", to help farmers optimize the number and timing of their treatments. In addition to estimating the ongoing latent infections, this DSS takes into account six other risk factors related to the location of the orchard and its recent history. This system is currently being evaluated by a group of farmers in Provence.

**Keywords:** Expert system, *Spilocaea oleagina*, IPM, infection, incubation

#### INTRODUCTION

Olive production covered over 10 million ha worldwide in 2013 (FAOSTAT – freely accessible at http://faostat.fao. org/). Peacock eye, caused by *Fusicladium oleagineum*, is a major disease in most olive production regions, including France, where production is located in the South and covers 40,000 ha. In this region, the fungus essentially causes leaf spots and may result in substantial defoliation in severely attacked orchards. The fungus does not produce sexual spores but numerous cycles of conidial production can occur year round. Disease results from leaf infection by airborne conidia and is dependent on the concomitant

occurrence of rain and mild temperatures (Miller, 1949). The risk periods in southern France are thus mostly restricted to spring and autumn. Disease control relies mostly on fungicides, requiring up to 6 sprays per season. One possibility to reduce the use of fungicides (usually copper) would be to limit treatments according to the actual risk of disease development. Relationships between climate parameters (temperature and duration of leaf wetness) and leaf infection or symptom development have been reported in previous studies (Obanor et al. 2008; Viruega et al., 2002, 2011). However, these data may be difficult to use directly for field prediction purposes, as they have been produced in stable, controlled conditions. Field conditions

can fluctuate widely and are usually heterogeneous within an orchard. Furthermore the reliability of wetness sensors for field use is often considered as questionable (Magarey et al, 2006; Sentelhas et al., 2005).

The purpose of the present study was thus to develop field-based disease prediction models, based on easily measured climatic conditions, and to integrate them into an expert system.

#### MATERIALS AND METHODS

Over a 10-year period, climatic parameters and the incidence of peacock eye were monitored weekly in an untreated orchard of southern France (Mas-de-la-Dame, in the Baux-de-Provence Valley). Air temperature, relative humidity (RH) and rain intensity (mm per hour) were recorded continuously with the help of climate sensors linked to a weather station. Disease incidence was assessed one to three times a week on samples of 100 leaves randomly collected in the orchard. The number of leaves with visible spots was recorded and leaves without symptoms were processed as described before to reveal latent infections (Roubal et al. 2013). These data were used to develop two types of models.

An initial step prior to model construction was dedicated to linking rain events and leaf infection events. Rain is known to be necessary for leaf infection, but infection will occur only if conditions during and after the rain are favourable. Each rain event between 1999 and 2009 was thus examined to determine if it resulted in an increase in the percentage of infected leaves in the orchard. This assessment was carried out according to two iterative steps described elsewhere (Roubal et al. 2013). These steps were based on known effects of temperature on (i) leaf infection by *F.oleagineum* and (ii) the duration of symptom development. This allowed to identify "high boundary values", representing

data points with the longest duration of high humidity (RH>85%) below which infection never occurred after a rain. Similarly, "low boundary values" were identified, defining the shortest duration of high humidity above which infection always occurred after a rain (Figure 1).

The first modelling step consisted in performing regression analysis on the boundary values to establish the relationship between the occurrence of infection and two key climate parameters: (i) the average temperature during the rain and (ii) the duration of high humidity after the beginning of the rain. Six non-linear models were assessed and compared based on the standard error of their estimates and the correlation coefficients.

The second modelling step consisted in estimating the duration of the incubation period (the time needed for symptoms to appear after infection has occurred) as a function of air temperature after the beginning of an "infectious" rain. To this end, polynomial regression analysis was performed.

The two predictive models were then combined to build a software allowing the characterization of the successive cycles of disease and the prediction of symptom outbreaks based on observed and forecasted weather. However, actual risk could vary widely depending on other factors related to the specific location of the orchard and its recent history. For example, the microclimate at orchard level could be somewhat different from that at the reference weather station. To take these additional factors into account, a decision support system (DSS) was developed. The additional risk factors include the susceptibility of the cultivar, the mode of irrigation, the number of previously applied copper treatments, a global climatic risk linked to average rainfall in the production region, the type relief of the orchard and an estimation of disease incidence. This latter information must be provided online by the grower at every use of the DSS. Three risk levels are considered for each criterion (Table 1).

**Table 1.** Criteria used in the OPTIPAON decision support system to modulate risk assessment based on the specific conditions of an olive orchard.

| Input criteria                                | Choice 1                                  | Choice 2                      | Choice 3  |
|---|---|-------------------------------|---|
| Current disease incidence (% infected leaves) | < 10 %                                    | >10 % &<20 %                  | > 20 %  |
| Cultivar susceptibility                       | Low<br>(Picholine)                        | Medium<br>(Aglandau, Verdale) | High<br>(Grossane, Tanche,<br>Lucque, Bouteillan) |
| Water management                              | no irrigation                             | occasional irrigation         | regular irrigation, humid soil                    |
| Climatic risk zone                            | Low risk<br>(few disease cycles per year) | Medium risk                   | High risk<br>(many disease cycles per year)       |
| Environmental situation of the orchard        | Open space,<br>well ventilated            | Flat land,<br>few wind breaks | Confined,<br>lowland, river,<br>many windbreaks   |
| Last year's treatments                        | None                                      | 1                             | 2 or more   |

#### **RESULTS**

Among 376 rain events that occurred in the orchard between 1999 and 2009, 134 were identified as leading to confirmed leaf infection and 191 were clearly not followed by detectable infection by *F. oleagineum* (Figure 1). In addition, 51 rain events could not be clearly assigned and were not used for model construction.

The best models describing the low and high boundary values were the Logistic and the Vapor Pressure models, respectively. The equations and parameters of these models are presented in Table 2.

The best regression line for the prediction of the incubation period was obtained with a four-degree function. Its equation was:

$$D = 364.76 - 89.57 * T + 9.12 * T^{2} - 0.43 * T^{3} + 0.0078 * T^{4}$$

Where *D* and *T* represent the duration of incubation and the average daily temperature during incubation, respectively.

The software combining the two predictive models allows the user to assess the risk of disease development following a rain event. An example of output from this software for the whole 2013 growing season is shown on Fig. 2. Based on the temperature and RH during the day after rain onset, the first model provides an answer to the question "Is this rain going to lead to leaf infection"? If the model estimates that infection will occur, a red circle is shown on the graph, and a yellow

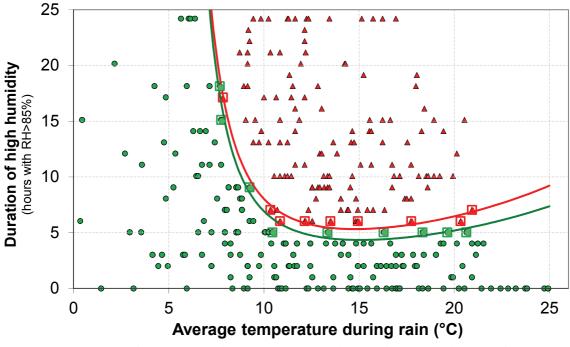


Figure 1. Characterization of rain events according to temperature and duration of high relative humidity after rain onset.

Green circles (♠) indicate rains that did not lead to infection while red triangles (♠) indicate those that did not lead to leaf infection. Green and red squares represent the "high" and "low boundary values" described in the Materials and Methods. The curves represent the regression lines.

Table 2. Regression models fitted to the boundary values described in Figure 1

| Model          | Equation                       | Parameters                                | Standard<br>error | Correlationcoefficient |
|----------------|--------------------------------|---|-------------------|------------------------|
| Vapor Pressure | $y = \exp(a+b/x+c*ln(x))$      | a = -16.4927<br>b = 72.8655<br>c = 4.8386 | 0.960             | 0.986                  |
| Logistic       | $y = a / (1 + \exp(b - c^*x))$ | a = 6.1582<br>b = -1069.84<br>c = 0.9398  | 0.418             | 0.996                  |

horizontal bar indicates the incubation period, when symptoms remain invisible. Based on the average daily temperature after rain onset, the second model provides an answer to the question: "When will the symptoms become visible?" The estimated date is shown on the graph as a red triangle, which indicates the end of the incubation period. Overall, the user can easily visualize the different ongoing incubation periods and forecast periods when substantial outbreak of leaf spots will occur. Examples of such dangerous periods are shown as wide red bars on Fig. 2. Based on this knowledge, an Alert Bulletin is sent to growers and posted online to indicate the occurrence of a general risk.

Farmers can adapt the risk assessment to the specific situations of their own orchards by logging on OPTIPAON and entering the information needed for each of the 6 additional risk factors. The output of the DSS provides an orchard-specific risk index on a scale from 0 to 5. This information can then be used by the farmer to make a rational decision on the pertinence of spraying the orchard.

#### **DISCUSSION**

The analysis of weather and disease incidence data over a 10-year period has allowed the development of two complementary field-based biological models describing the relationship between easy-to-measure climate parameters and the infection of olive leaves by *F.oleagineum* and the appearance of symptoms in the orchard. These two predictive models have been validated with additional observations since 2010. They also have been used as a basis to evaluate the risk of disease outbreak, using data provided by more than 20 weather stations distributed throughout the olive production region, and to produceAlert Bulletins widely disseminated to French olive growers.

The development of the OPTIPAON DSS has provided each farmer the ability to adapt the risk assessment to the specific condition of their own orchards. Several elements constitute a favourable context for the wide adoption of OPTIPAON by farmers to devise rational strategies for the protection of their olive orchard and thus reduce the use of fungicides. The epidemic development of the disease is overall slow in southern France and practical damage thresholds are relatively high, with no significant leaf drop if the incidence of diseased leaves remains below 20% and an absence of yield loss if it remains below 10%. As a consequence, a possible occasional underestimation of disease risk by OPTIPAON could efficiently be corrected by the farmer at the occasion of the next Alert Bulletin.

This system is hosted on the website of CIRAME (Centre d'Information Régional Agrométéorologique) and is currently being tested by a group of farmers. Further improvements in the parameterization of the

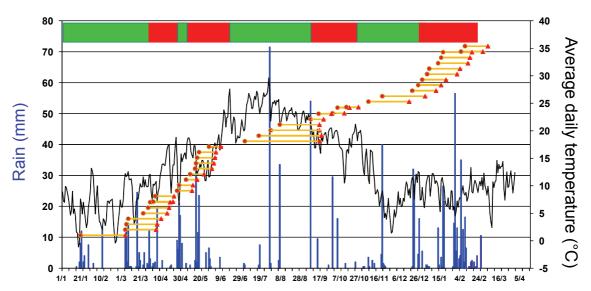


Figure 2. Example of output from the software developed to characterize the successive cycles of disease based on weather data for 2013. Red circles show the estimated dates of leaf infection. Yellow bars show the duration of the incubation period and red triangles the estimated dates of symptom appearance. Blue bars indicate daily rain amounts and the black line shows the average daily temperature. The wide bar above the graphs show the periods of estimated low (green) or high (red) risk based on the occurrence of ongoing disease cycles.

system are envisioned, using the data collected by the testers. In addition, the susceptibility level of a larger number of olive cultivars may be taken into account in the future, on the basis of an ongoing survey.

#### **ACKNOWLEDGEMENTS**

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