IPM Decisions

D4.13 DSS evaluated for economic and environmental benefits: septoria tritici blight and grapevine downy mildew

Grant agreement number: 817617

Start date of project: 01/06/2019 **End date of project:** 31/05/2024

Deliverable due date: 28/02/2021 **Date of delivery:** 26/02/2020

Classification: Public

Version History

Version number	Implemented by	Reason
1.0	Joe Helps, Alice Milne & Frank van den Bosch	Deliverable 4.3 - DSS tested for validity: septoria and grape downy mildew

List of Authors

Company	Author(s)	Contribution
RRES	Joe Helps	Writing, analysis.
RRES	Alice Milne	Writing, analysis.
CU	Frank van den Bosch	Comments.
ADAS	Neil Paveley	Comments.

List of Reviewers

Company	Reviewer	Contribution
AU	Niels Holst	Comments.
AU	Lise Nistrup Jorgensen	Comments.

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1 Public Summary

Growers need information about a DSS' performance so that they can weigh up the relative benefits of using it to make decisions about crop protection. We develop a novel method for evaluating DSS using existing trials data about septoria in wheat and downy mildew in vines.

2 Executive Summary

Decision support systems (DSS) are tools that provide growers with advice on how to manage various aspects of agriculture. DSS that aim to support decisions about the control of pests and pathogens can help the grower to reduce the application of unnecessary pesticides by improvements in the targeting of applications; resulting in both economic gain for the grower and benefiting the environment. However, if a DSS is used in a location in which it wasn't calibrated, the advice may be detrimental, potentially compromising pest control, and resulting in economic or environmental losses. It is important for growers to understand how well a DSS is likely to perform in conditions similar to their own and have knowledge of any potential risks associated with following DSS advice. It is therefore essential that "the value" of DSS be calculated.

Testing DSS by experiment is time consuming and costly. Therefore we explore here possible analytical methods for assessing DSS using existing trials data. Although these data were not gathered for the specific purpose of testing DSS they offer a valuable resource for DSS analysis. In this report we describe a novel method for calculating the value of a DSS from existing field trial data and then apply it to two DSS; one that advises growers when to apply fungicides to wheat to control septoria tritici blotch, and another that guides when to apply fungicides to prevent downy mildew on grapevines. Lack of information about the timing of true risk periods in the data for these two diseases mean that the method can only assess whether the number of sprays predicted is likely to lead to increase value compared with standard practice. Any improvements in timing could not be robustly assessed. The analysis therefore determines the lower limit of potential value; the expected value is likely to be higher. Our analysis shows that on average the septoria DSS offers both economic and environmental value. In a small number of cases the value is negative. This relates to occasions where the DSS predicts less disease risk that observed in the data. However, allowing the user access to this information would allow them to make informed decisions that account for risk. The analysis of the downy mildew DSS proved less optimistic. The DSS over predicted risk in several instances. This contradicts the literature and is likely to be because our analysis used regional met station data rather than field-scale met-data, which are known to be important for accurate prediction.

Horizon 2020

3 Introduction

The aim of this deliverable is to continue to develop analytical tools for analysing the usefulness of decision support systems (DSS). The value of a DSS can be economic (increased profit margin compared with a standard control programme) or environmental (reduced number of pesticide applications without serious loss of yield or quality).

Ideally, we would estimate the value of DSS by conducting field trials over a large number of sites and seasons to compare DSS based pest control practice with standard practice. However, this is often not practical as it is resource intensive, and so instead we turn to analytical methods that make use of existing trials data. In our previous report we considered the case where the trials data consisted of relatively detailed disease progress curves, and so allowed us to assess the timing of risk periods. This enabled us to develop methods to assess whether DSS could improve the timing of applications. Here we develop a new methodology to tackle the cases where the data do not inform on the timing of risk, and so only allow us to assess whether the number of sprays predicted is more or less appropriate than standard practice. To that end, in this report we present a novel method to estimate the economic value of any DSS that predicts the number of pesticide applications. The method uses standard field trial data without needing to experimentally test the DSS itself in the field, and in this way could allow the estimation of value in areas where the DSS has not itself been tested.

To demonstrate the method, one DSS was chosen on each of the two pathosystems required for this deliverable; *Zymoseptoria tritici*, causal agent of Septoria tritici blotch on wheat, and *Plasmopara viticola*, causal agent of downy mildew on grapevine. For septoria, the Crop Protection Online DSS was chosen, which predicts the number of fungicide applications required based on the number of rainy days. For downy mildew, a DSS called Rule 3-10 was chosen, which predicts the number of fungicide applications from a combination of environmental variables and their effect on the rate of development of the disease.

The report is divided up into three main sections. Section 4 summarises experimental literature that analyses the value of different DSS in each pathosystem; Section 5 describes the method in theoretical detail; while Section 6 applies the method to each pathosystem.

4 Value of DSS from the literature

In this section we summarise studies in the literature that have estimated the value of decision support systems for both pathosystems.

4.1 Septoria tritici blotch on wheat

4.1.1 Wheat Disease Control Advisory

The Wheat Disease Control Advisory DSS (WDCA), developed in Israel, considers whether to spray fungicide based on the crop growth stage, climatic conditions, and the consideration of cost/benefit ratios. Field experiments in Israel showed that use of WDCA resulted in a significant increase of 0.78 t/ha in yield, the equivalent of $92.70 USD in net profit compared with standard practice (Shtienberg, Dinoor and Marani, 1990).

4.1.2 Crop Protection Online

Crop protection online is a DSS developed and validated in Denmark, which uses the cumulative number of days with rain to estimate the development of epidemics of *Septoria tritici*. In 2018 and 2019 forty-seven field trials were carried out to validate the risk model. The DSS produced equivalent disease control to a reference treatment, but using 85% and 31% fewer treatments in 2018 and 2019 respectively (Jørgensen, Matzen, Ficke, *et al.*, 2020). In testing during 9 seasons the CPO model has provided similar control and net yield responses compared to a two- spray strategy, but reduced the input of fungicide by 37% (Jørgensen, Matzen, Heick, *et al.*, 2020).

4.1.3 Humidity model

The humidity model is also a DSS developed in Denmark. It uses hourly relative humidity, leaf wetness or rain events to estimate the development of leaf blotch diseases. The same field experiments as for the CPO also evaluated the humidity model. Similarly, the humidity model produced equivalent disease control as a reference treatment, but using 98% and 31% fewer treatments in 2018 and 2019 than the reference treatment (Jørgensen, Matzen, Ficke, *et al.*, 2020).

4.2 Downy mildew on grape

The value of several DSS for downy mildew have been assessed experimentally and we summarise these here.

4.2.1 Vite.net®

The downy mildew model developed by Rossi et al., (2008) was integrated into the DSS Vite.net®. This model was evaluated in more than 100 vineyards across Italy as well as Eastern Canada (see Pertot et al., (2017) and references therein). In particular, the Rossi model was evaluated by Caffi et al., (2017) across six site-seasons between 2006 and 2008. They showed that if growers spray according to the model, they would reduce the number of sprays applied by an average of 50-60% with little to no impact on yield and quality. They estimated average savings between 174 and 224 Euro/ha. The Vite.net downy mildew DSS was further evaluated by Rossi et al., (2014) at 21 locations across Italy during the seasons of 2011 (a year with low disease pressure) and 2012 (a year with high disease pressure). In both years, disease control obtained using Vite.net was not statistically different from that obtained through standard practice, yet fungicide application was reduced by an average of 37% when the DSS was used, representing a saving of 195 €/ha/year for growers.

4.2.2 Rimpro

The downy mildew DSS that forms part of Rimpro was developed as part of the CO-FREE EU project (*CO-FREE (Innovative strategies for copper-free low input and organic farming systems)*, 2017). Between 2008 and 2014 observations of the development of the downy mildew epidemic were made by the CO-FREE partners as well as on untreated vineyards in Bulgaria, Austria, North Italy, on Sicily, Spain, Switzerland, Greece, England, Belgium, The Netherlands and Quebec. In 97% of the cases the first infection was observed on the day it was predicted, or later, meaning that that fungicide treatments can safely be omitted until the DSS signals the first infection event. In many locations, this is reported to result in a considerable reduction in number of fungicide applications.

4.2.3 Mildium

Delière et al. (2015) report on a four-year assessment of the Mildium DSS that targets both downy mildew and powdery mildew. The assessment was conducted on a network of 83 plots across French vineyards. In all four years the average number of sprays was reduced by approximately 30%. In two of the four years this resulted in significantly more disease symptoms across the study sites. However, grower assessments of the impact of the Mildium strategies on yield and quality suggest that in over 93% of cases yield was not negatively impacted and in over and 95% of cases quality was not negatively impacted.

4.2.4 VineSens

VineSens, developed in Spain, consists of both the hardware and software for combining weather-based rule-making together with microclimate measurements to estimate the development of downy mildew. Pérez-Expósito et al., (2017) estimated that the system coupled with the Rule 3-10 could produce savings of up to 14.5 €/ha.

5 Methods

In this section we present a method to estimate the value of a DSS from field trial data. The method is potentially suited to any DSS that predicts how many fungicide applications should be applied in a cropping season, based on a combination of meteorological and crop data.

As previously discussed, the economic value of a DSS is the difference in net income between applying pathogen control using guidance from the DSS versus applying pest control following a standard application program. That is, $V = C_{DSS} - C_S$, where V denotes the value and C_{DSS} and C_S the cost of following the DSS or a standard spray program respectively. The cost to a grower of applying n sprays is made up of the cost of the fungicide treatments, the cost of application and the amount of yield lost due to remaining disease (Equation 1).

$$C(n) = n(F + A) + PL(n, x) \qquad \text{Eqn. 1}$$

where F is the price of a standard dose of fungicide, A is the cost of applying a fungicide treatment to a field, and $L(n, x)$ is the amount of yield lost when n sprays are applied in a situation with disease pressure x, and P is the price of a unit of yield.

The most direct method of determining the value of a DSS would be to experimentally test the DSS against a standard spray program in field trials. However dedicated field trials are time-consuming and expensive. Therefore, the method presented here aims to estimate the value of a DSS from existing field trial data which comprise both untreated trials, and trials treated with one or more fungicides sprayed according to a standard spray program.

First, a disease metric, d, is chosen that gives a strong relationship between that disease and yield, for example the severity at a given crop growth stage or the area under the disease progress curve. We denote this relationship $L = g(d)$. Then we need a relationship between the disease (d), disease pressure (x) and the number of sprays (n). We define this relationship $d = h(x, n)$. Using trials with a single spray, the two pathosystems we consider here have a linear relationship between the treated and untreated sererities, such that with a single spray $d_1 = \theta x$, and with n sprays, $d_n = \theta^n x$. The amount of yield lost can then be calculated from the number of sprays applied and the disease pressure, $L(x, n) = g(\theta^n x)$.

In any given site and year, the disease pressure may be high or low. The distribution of this metric x can therefore be estimated from the untreated trials. Additionally, in a given site and year the number of sprays predicted by a DSS can be calculated from the local weather data. Together we therefore have a joint distribution for disease pressure and predicted number of sprays, we denote this $f(d, n)$.

Finally, the expected value is determined by calculating the costs with the number of sprays according to a DSS and according to a standard spray program, s, for each value of $f(x, n)$, by integrating over x, the untreated severity, and over the predicted spray number, n.

$$V = \sum_{n} \int_{0}^{100} \{n(F+A) + PL(x,n) - s(F+A) - PL(x,s)\} f(x,n) dx \qquad \text{Eqn. 2}$$

To estimate the uncertainty in the value, N random samples were drawn from $f(x,n)$, and the value of the DSS was calculated for each sample.

6 Application of the method to septoria and downy mildew

6.1 Septoria tritici blotch on wheat

6.1.1 DSS

Crop protection online (CPO) is a DSS developed in Denmark, that includes models for several pests and pathogens, among them *Zymoseptoria tritici* on wheat (Hagelskjær and Nistrup Jørgensen, 2003). The DSS aims to predict when different pesticide products should be sprayed, and at what doses, in order to achieve the best control with the lowest inputs. The spray timings and doses are derived from knowledge of the pest-specific weather characteristics, the resistance status of the cultivar being grown, the effectiveness of the product and control thresholds for the pest in question.

For septoria tritici blotch, CPO tracks the cumulative number of days that have greater than 1mm of rain between growth stage (GS) 32 and GS 71. In susceptible cultivars the model suggests that fungicide is applied when four days with more than 1mm of rain have passed, whereas on resistant cultivars five days are required before a fungicide application is suggested and the model first starts counting at GS 37. Once sprayed, the model assumes protection for ten days, after which a spray is recommended after a further four or five days of rain (Jørgensen, Matzen, Ficke, *et al.*, 2020).

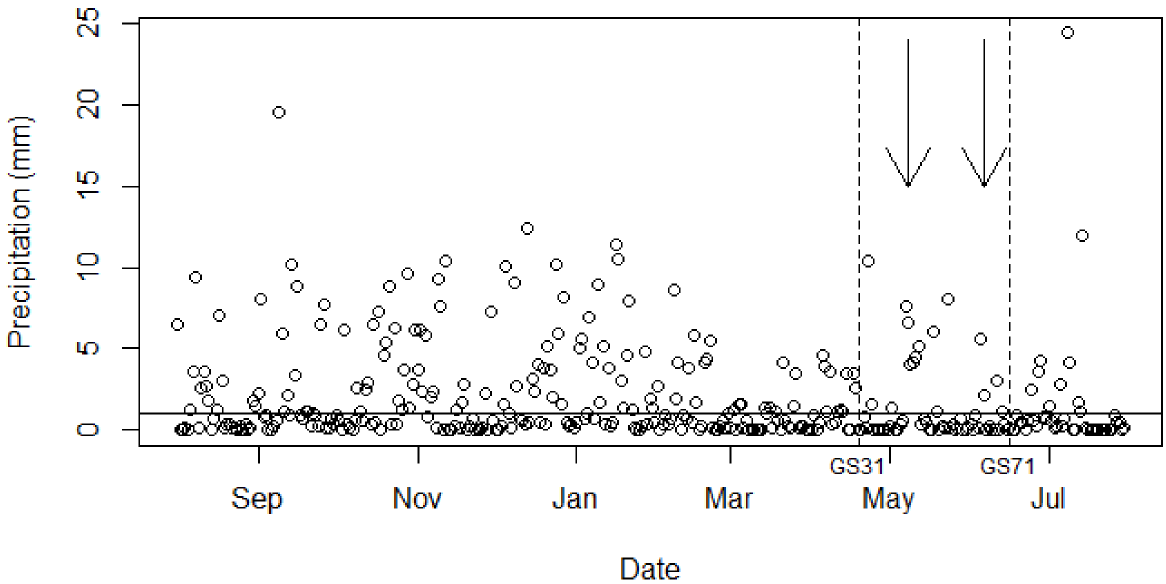

Figure 1. A figure illustrating the functioning of the CPO DSS at one trial. Sprays (shown by arrows) are applied from GS31 to GS71, after four days of more than 1mm of rain (horizontal line).

6.1.2 Data

Data on the disease progress of *Zymoseptoria tritici* was provided by Corteva and BASF to WP 4.2. The data used consisted of 186 trials carried out between 2014 to 2018 in 8 different countries. Trials were excluded if a disease apart from *Zymoseptoria tritici* was recorded at greater than 5%. Table 1 provides a breakdown of the number of trials per country.

Table 1. The number of trials per country in the analysed dataset.

Country	**Number of trials**
Denmark	17
France	47
Germany	45
Ireland	10
Poland	8
Sweden	4
United Kingdom	54

Each trial consists of two or more treatment programmes, including a control where no fungicide was applied (untreated). Usually there are four replicates per treatment. For each replicate, the severity on the top six leaves of wheat was recorded at various times (Figure 2). In many of the trials the growth stage of the wheat was also recorded using the Zadoks decimal code, and the yield was also recorded in many of the trials. The cultivars used in the DSS were assumed to be susceptible or moderately susceptible.

Treated trials included one or more applications of fungicide from a total of 75 different products, although 34 of these were only used in a single trial. Of all the fungicides, six were used in more than five trials applied as a single application, and so these six were used in the following analysis

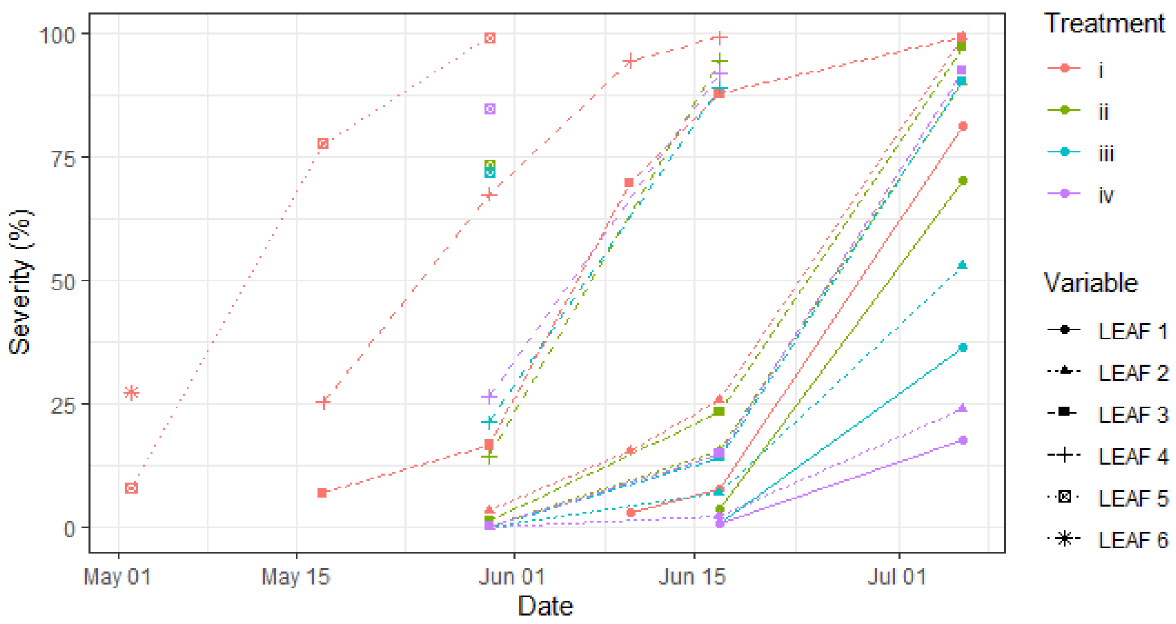

Figure 2. Examples of recorded disease progress in a single trial with four treatments. Treatment i is untreated, while treatments ii, iii, and iv have a single fungicide application applied on May 02, May 02, and May 17 respectively.

Hourly precipitation data was collected from the nearest location to each trial from the ERA5 reanalysis (Copernicus Climate Change Service Climate Data Store, 2020), which has a 30-km grid.

6.1.3 Disease-yield relationship

The severity of septoria at GS75 has previously been found to be a strong predictor of yield (te Beest *et al.*, 2009). The relationship between the yield and the severity on GS75 on each leaf was explored from all trials (untreated and treated) and was found to be strongest on leaf 2. Where necessary the date of GS75 was interpolated linearly from the nearest recorded growth stages, and the severity on leaf two similarly estimated at that date. For trials in which the severity could not be estimated, either because there wasn't suitable growth stages or severity to allow interpolation, the trial was omitted from the analysis.

A linear model was fitted to the remaining data (Figure 3), resulting in therelationship $Y(d) = 10.85 - 0.046\ d$, giving the yield lost as $L(d) = 0.046\ d$, where d is the severity on leaf 2 at GS75.

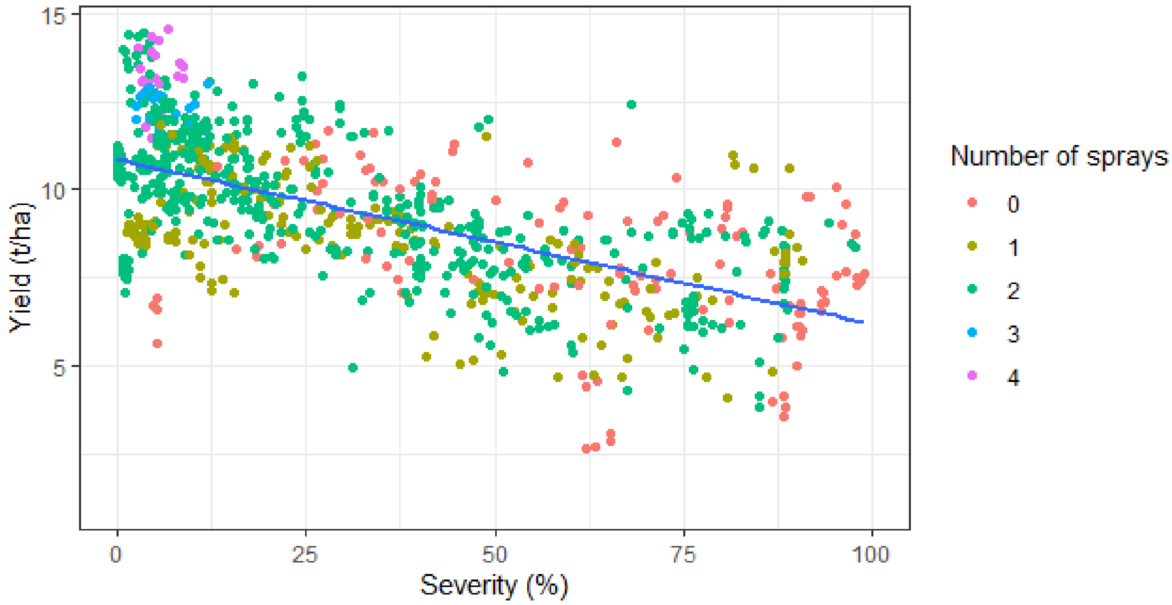

Figure 3. The relationship between the severity on leaf 2 at GS75 on yield in all treatments. The colour represents the number of fungicide applications that were applied to each treatment. The adjusted R2 is 0.43.

6.1.4 Distribution of untreated disease

For each trial for which severity data was available (58 of the 186 trials), the number of sprays predicted by the CPO DSS was calculated from the weather data (see below). Between 1 and 4 sprays were predicted for each trial, with 6, 26, 21, and 3 trials having 1 to 4 sprays respectively.

As severity is bounded between 0 and 100%, the beta distribution is an appropriate distribution to model the severity (scaled between 0 and 1), and was fitted to the untreated severity for each number of predicted sprays using the `fitdist` function from the `fitdistrplus` package in R (Delignette-Muller and Dutang, 2015). Figure 4 shows the resulting fits, while Table 2 gives the shape parameter for each distribution. Together these distributions make up the distribution $f(x,n)$ and, to ensure that its integral is one, each is scaled by the proportion of observations where n sprays were observed (we denote this γ_n).

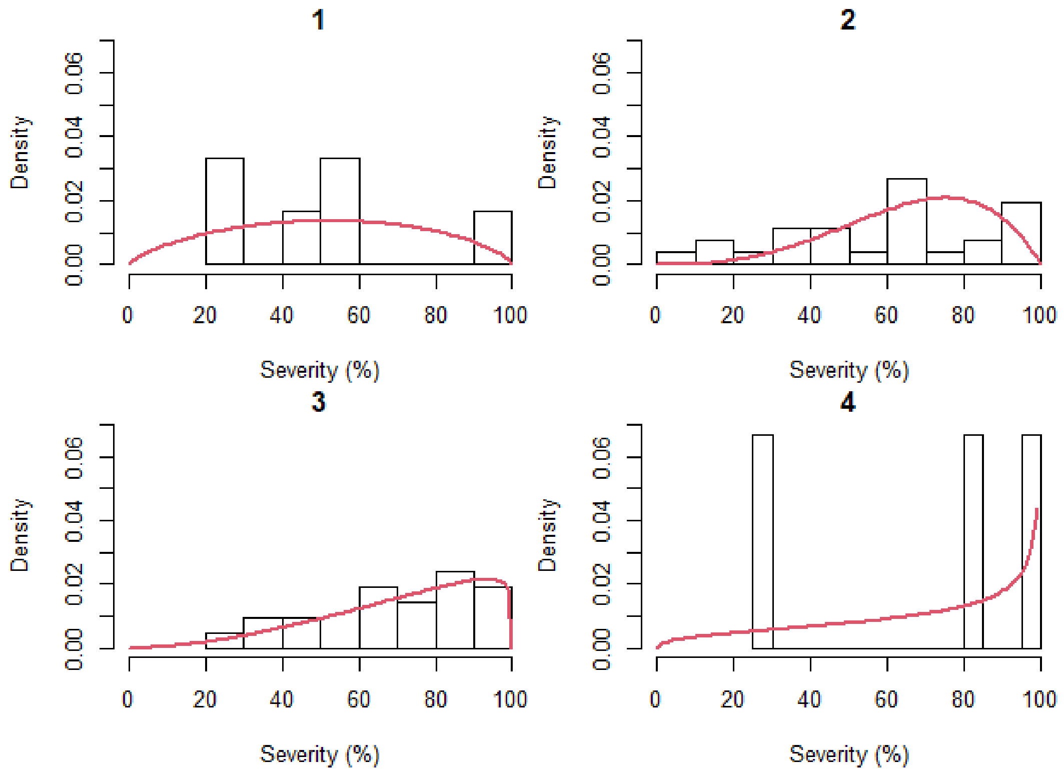

Figure 4. Fitted beta distributions of the severity of septoria on leaf 2 of wheat at GS75 from untreated trials, when 1, 2, 3, or 4 sprays are predicted by the CPO DSS.

Table 2. The shape parameters of the Beta distribution, describing the severity of septoria on leaf 2 of wheat at GS75, depending on whether the CPO DSS predicted 1, 2, 3, or 4 sprays for each trial, and the scaling parameter applied to each distribution.

Number of sprays predicted by CPO	**Shape 1**	**Shape 2**	**Scaling parameter (γ_n)**
1	1.73	1.66	0.106
2	3.90	1.96	0.426
3	2.75	1.12	0.404
4	1.38	0.63	0.064

6.1.5 Effect of a fungicide application

The effect of a fungicide was estimated by regressing the severity from trials treated with a single fungicide against the severity from untreated trials. Linear regression, quadratic regression and exponential fits were all carried out, and the severity given two sprays was predicted for each model, where $d_2 = \theta^2 x$. When each model was validated on data from trials with two sprays, the linear model provided the smallest root mean square error (RMSE). Figure 5 shows the relationship between the untreated severity and the severity with a single spray for each of the 6 products.

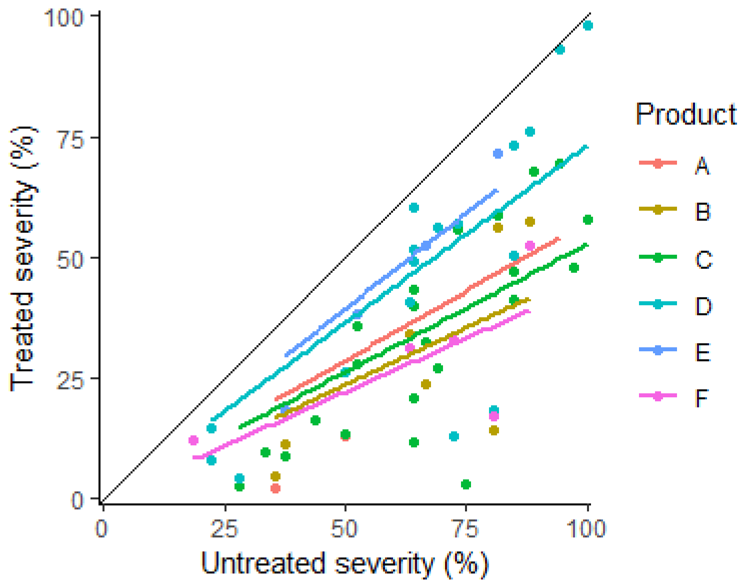

Figure 5. The relationship between untreated and treated severity (%) when trials are treated with a single application of each fungicide.

6.1.6 Value

The expected value for the CPO DSS is calculated using Equation 2, for three values of wheat (100, 150, and 200 €/t). The value of the CPO DSS was greater than or equal to zero €/ha in 58%, 78% and 84% of simulations respectively. Table 3 gives the mean, lower and upper quartiles associated with each price. Figure 6 shows the distribution of the simulated value. This gives us greater insight into the risk of a poor decision based on the DSS.

Table 3. The mean value of the CPO DSS, when the price of wheat is varied between 100 and 200 €/t.

Wheat price (€/t)	**Mean value of DSS (€/ha)**	**Lower quartile (25%)**	**Upper quartile (75%)**
100	-7.05	-13.75	0.0
150	1.81	0.0	10.39
200	10.66	0.0	29.73

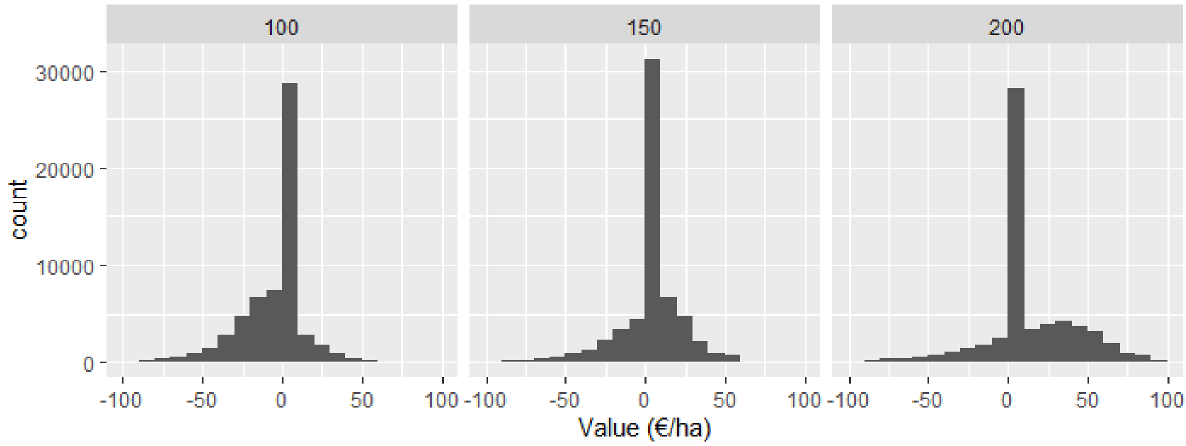

Figure 6. The distribution of the value of the CPO DSS, with a wheat price of €100/t (left), €150/t (centre), or €200/t (right). The large bin in each graph includes the value of €0/ha, when the number of sprays is the same with a standard spray program and with the DSS.

6.2 Downy mildew on grape

6.2.1 DSS

Rule 3-10, described in Pérez-Expósito *et al.,* (2017) is a DSS that tracks the initiation and development of downy mildew epidemics. When suitable thresholds have been passed, an alert is sent to the grower. Once a fungicide treatment has been applied, the system is reset and tracking of the downy mildew development index restarts.

Primary infection, and thus the initiation of the DSS model that tracks the subsequent development of a potential epidemic, is assumed to start when the 3-10 rule is fulfilled, being when the air temperature is greater than 10°C, vine shoots are at least 10cm long, and at least 10mm of continuous rain has fallen during the previous 48 hours (Baldacci, 1947).

Once primary infection is assumed to have happened the model tracks weather conditions thought to be conducive to disease development, following the Goidanich model of disease development based on temperature and relative humidity. Specifically, if the temperature is greater than 12°C, and humidity is greater than 60% or rainfall is >10mm, then an index is incremented by the amount specified in the Goidanich model. When this index exceeds 90 an alert is sent to the grower and a spray recommended (Pérez-Expósito *et al.*, 2017). Once a spray has been applied the calculation restarts.

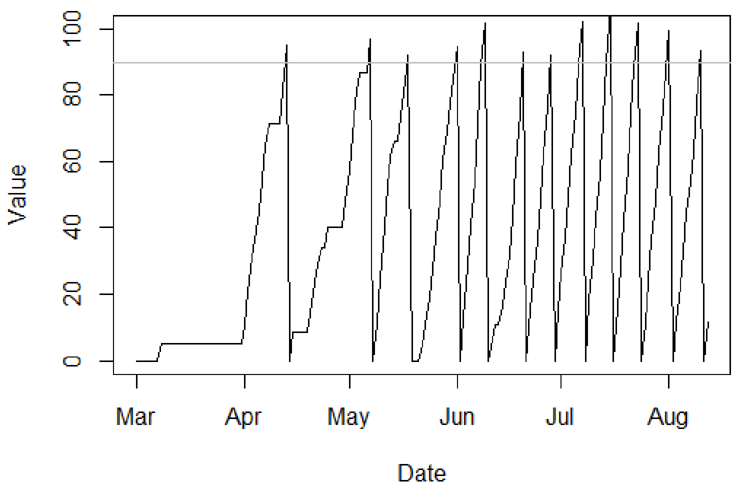

Figure 7. Illustration of Rule 3-10 alert predictions at a given site in Spain. When value exceeds 90 an alert is triggered, and a spray is recommended. Once applied the spray resets the value.

6.2.2 Data

The data used in this report was provided by BASF, and consist of 55 trials from 2012 to 2019, from several countries (Table 5). The data consists of the severity of *Plasmopara viticola* on leaves and/or racemes, in both untreated and treated trials. Between 5 and 11 fungicide applications are applied in the treated trials, although the product names and rates are not given.

Table 5. The number of trials per country in the provided dataset.

Country	**Number of trials**
France	20
Germany	9
Greece	6
Hungary	1
Italy	7
Portugal	6
Slovakia	4
Spain	2

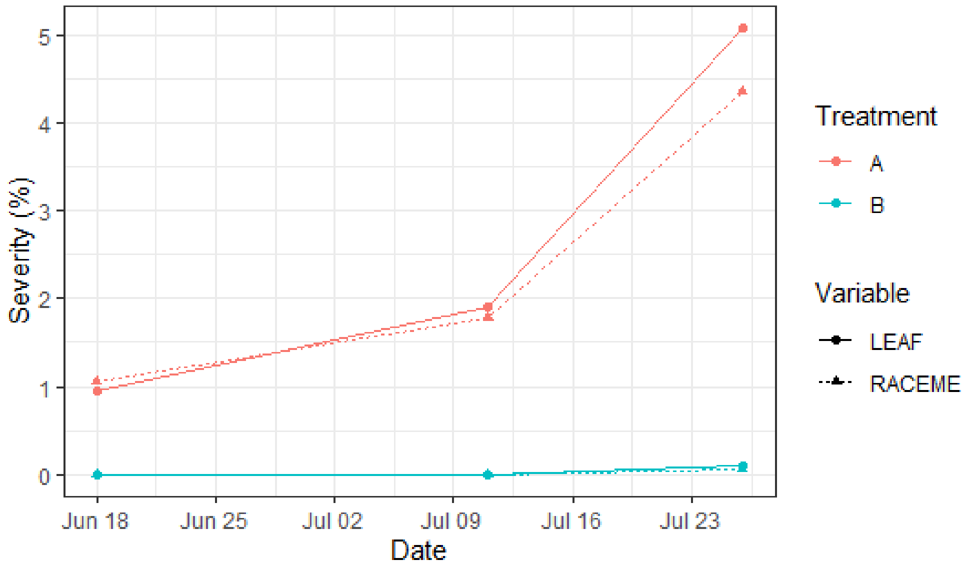

Figure 8. Disease progress of *Plasmopara viticola* in a single trial in which the severity on both the leaf and raceme is reported in both an untreated (A) and a treated trial (B).

Hourly weather data (comprising the precipitation, surface pressure at 2m, and temperature) was collected from the ERA5 reanalysis (Copernicus Climate Change Service Climate Data Store, 2020) for each site and year for which we had disease data.

The relative humidity was calculated using the August-Roche-Magnus approximation (Alduchov and Eskridge, 1996).

6.2.3 Disease-yield relationship

As the data do not include yield information, a disease-yield relationship was derived from the literature. Specifically, Jermini, Blaise & Gessler (2010) carried out field experiments to quantify the relationship between disease severity on leaves and yield quality losses. They found that while there was not a significant drop in the quantity of yield until around 50% severity, increased leaf severity did cause a reduction in soluble solids, as much as a 2°Brix reduction.

We therefore modified a general yield-loss relationship (Equation 3) described in Madden, Hughes, & van den Bosch (2007) based on the data reported in Jermini, Blaise & Gessler (2010). The relationship is shown in Figure 9.

$$L(d) = \frac{\mu d}{1 + \sigma d} \qquad \text{Eqn. 3}$$

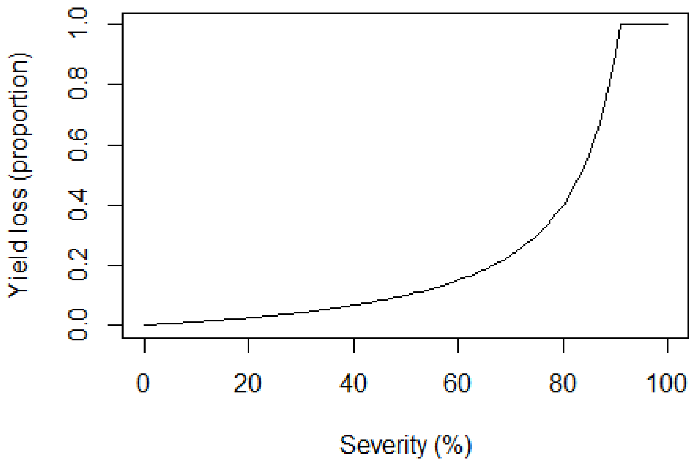

Figure 9. The proportional yield loss as a function of severity ($L(d)$), with parameters $\mu = 0.1$, and $\sigma = -1$.

6.2.4 Distribution of untreated disease

The frequency distribution of untreated disease and number of predicted sprays, $f(x, n)$ is shown in Figure 10. Visual inspection suggests that the distribution does not conform to our expectation that increasing disease pressure should lead to more sprays predicted. Additionally, there were too few trials per predicted number of sprays to reliably fit a Beta distribution to the data.

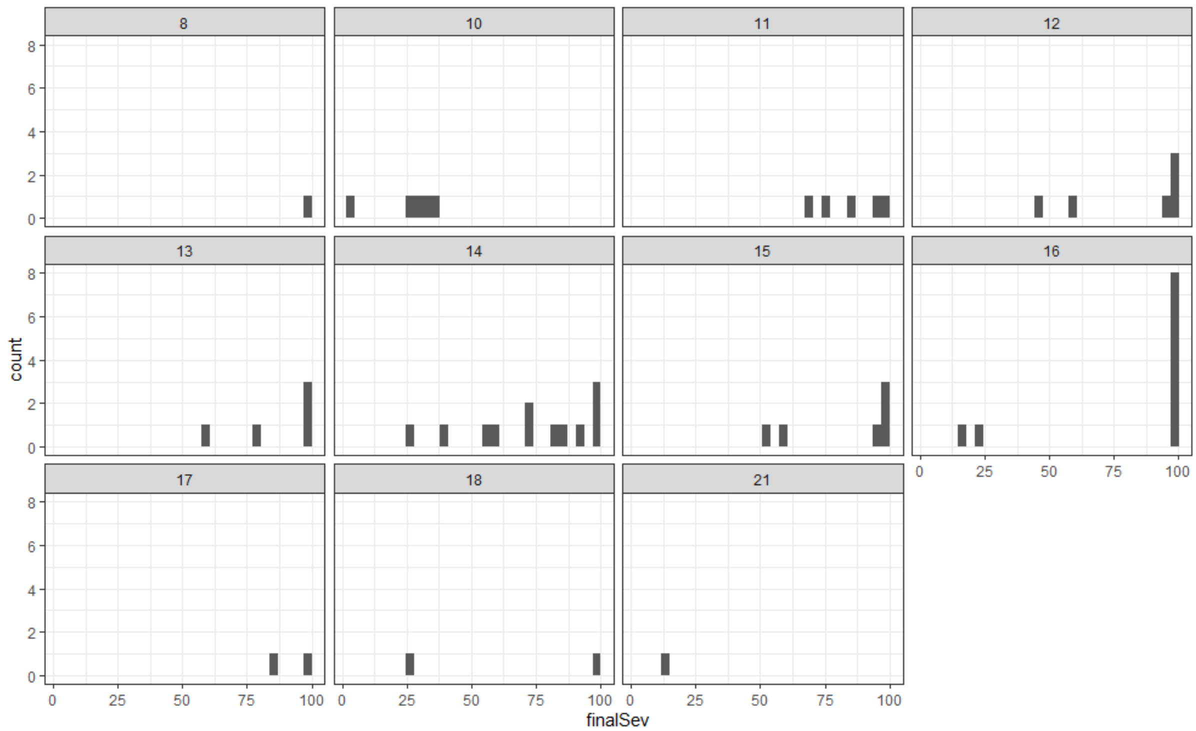

Figure 10. Frequency distribution of the untreated severity in trials with different numbers of predicted fungicide applications.

6.2.5 Effect of fungicide

The data contains no trials with only a single fungicide application. Therefore the effect of a single fungicide application was calculated by assuming the severity with n sprays, d_n, was related to the severity with 0 sprays, x as: $d_n = \theta^n x$, so that $\theta = \sqrt[n]{\frac{d_n}{x}}$. Figure 10 gives the distribution of $(1 - \theta)$, with greater values indicating that the fungicide reduces severity more. The median value of θ is 0.75, indicating a reduction in the severity of 25% from a single fungicide treatment. Four trials had a final severity of 0%, and so a fungicide efficacy of 100%.

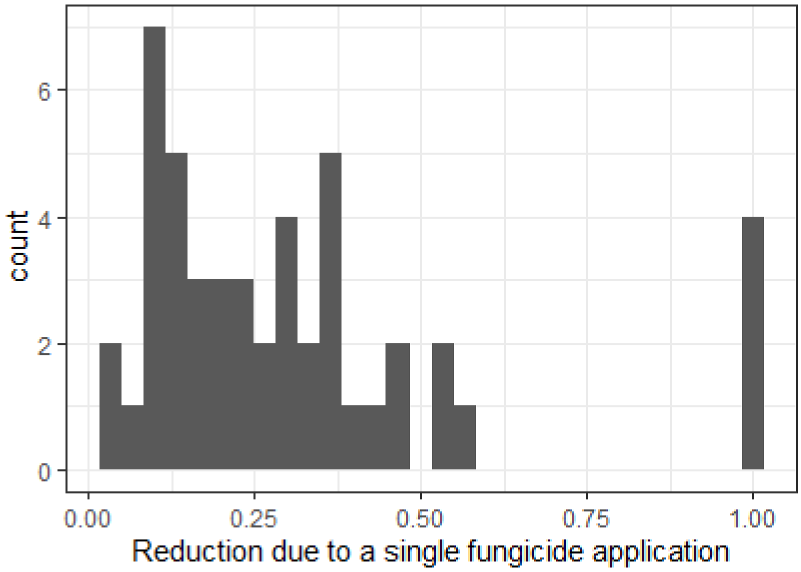

Figure 10. The distribution of the reduction due to a single fungicide application, θ.

6.2.6 Value

We were unable to calculate the value of the DSS described here, as we could not fit the joint distribution of the untreated severity and the predicted number of sprays by the DSS.

7 Discussion

In this report we build on the toolbox of methods for evaluating the value of DSS. Previously we developed methods to calculate the value of a DSS by estimating the degree to which fungicide treatments coincided with risk periods predicted by the DSS. However this required a high number of disease observations within each year. Here we have presented a method for estimating the economic value of any DSS that predicts the number of fungicide sprays to be applied in a given year (rather than the exact timings) from pre-existing field trials. The method presented could be applied to individual regions, by defining $f(x, n)$ for any given region, thereby establishing the value, as well as the variability of the value, of DSSs in different regions, given enough field trial data. However, the method does have limitations. As we have shown it can require a large amount of data, particularly when the DSS predicts a large number of possible sprays, such as with the Rule 3-10 DSS for grapes. While the method presented is less accurate than dedicated field experiments, it allows an indication of how DSS could perform in different regions from standard trials.

By Applying the method to the Crop Protection Online DSS, which estimates the number of sprays needed to prevent septoria leaf blotch epidemics, we found that in 58%–84% of simulations the DSS resulted in a greater than or equal net income compared to a standard spray program. While over half of simulations resulted in a positive or zero value for Crop Protection Online DSS, the mean value was negative when the wheat price was low, due to the decrease in relative value of the yield compared with the cost of spraying. Positive value from a DSS occurs either when the DSS predicts more sprays than a standard regime and a large epidemic occurs, or when the DSS predicts fewer sprays than the standard regime and a small epidemic occurs. Large negative values occur mostly when the DSS predicts fewer sprays than needed, and there is a large epidemic which results in a large yield loss. The presence of such risks is thought to also be a factor in DSS (Gent, De Wolf and Pethybridge, 2011). Therefore, it is important to be able to identify DSS that minimise the potential of large risks to growers and present potential risks to the end user.

For the Rule 3-10 DSS, which estimates the number of sprays for downy mildew on grape, the large number of discrete categorical sprays resulted in the data being too dilute to accurately estimate the distribution of disease pressure and the predicted number of sprays.

Additionally, by using satellite-based weather data rather than data from local met stations we are disadvantaging the DSS. It is likely that with local microclimate data the DSS would perform better than they can using the large resolution weather that we have available. Finally, many DSS, including both tested here, specify the day on which to spray, whereas we have only compared the number of fungicide applications in the field, which may provide more effective control than a uninform standard spray program.

8 References

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