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D4.12 DSS evaluated for economic and environmental benefits: apple scab and potato late blight

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1.0	Joe Helps, Alice Milne & Frank van den Bosch		Deliverable 4.12 – environmental and economic benefits of DSS.

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1 Contents

2 Summary

The value of a decision support system (DSS) is the value following a DSS compared with the value following standard agronomic practice. That value can be economic (increased yield and/or diminished treatment costs), or environmental (e.g. a reduction in the number of sprays).

In this report we develop a method for calculating the value of a DSS, based on how often fungicide sprays target pathogen infection risk periods, as determined by a DSS. As examples of application of the analysis, we use this method to calculate the value of three DSSs, two that identify risk periods for potato late blight (caused by the oomycete *Phytophthora infestans*), and one that identifies risk periods for apple scab (caused by the fungus *Venturia inaequalis*). The DSS chosen act as examples of DSS which have a binary outcome, i.e. they predict either the presence or absence of infection risk in a given time period. The two pathosystems contrast in the way in which disease affects marketable yield and hence affects the economic outcome.

In each case we show that as fungicide sprays more closely align with infection risk periods (IRPs) disease control is improved. However, the profit over spray cost (income from the crop minus the cost of spraying the fungicides) is not always increased by spraying more fungicides.

Finally, we estimated the economic value of each DSS considered (as compared to a standard spray program). We show that the value of the DSSs could be large.

3 Introduction

The aim of this deliverable is to provide the first outputs from Task 4.3, 'Analyzing the usefulness of decision support systems (DSSs)'. Within this task we aim to develop methods to evaluate DSSs in terms of their value, be that economic (increased profit margin) or environmental (for example by decreasing the number of pesticide sprays). The ambition is to design methods by which the value of any DSS can be evaluated. As different DSS address IPM in agronomic systems with widely differing biological and economic characteristics, the evaluation methods used need to be adapted to the agronomic system. Here we present a method for calculating value, which we then apply two to DSSs in two different systems: potato late blight, and apple scab.

In estimating the value of a DSS, we are essentially asking whether a farmer can expect to realize an economic and/or environmental gain by following a DSS compared with following standard practice. If, for example, a DSS identifies optimal fungicide application timings, the economic value of the DSS may be the difference in profit between applying fungicides when informed by a DSS, compared to applying fungicides following a standard spray program. Alternatively, an environmental value of the DSS could be the reduction in the number of fungicide treatments that have to be applied without compromising yield.

In this deliverable we selected two DSSs that identify infection risk periods for potato late blight, and one DSS that identifies infection risk periods for apple scab. Using historical data on disease progress gathered in WP 4.1, together with associated weather data, we were able to estimate when the DSS would have predicted high infection risk periods (IRPs). Using these predictions, we determined to what extent spraying during these periods of high risk would have resulted in better control of the disease, and hence greater yields, or when sprays could have been reduced.

4 Data

4.1 Field trial data

WP 4.1 received data from project participants Corteva, for potato late blight trials, and BASF, for apple scab trials. In both cases the field trials contained assessments of disease progress in plots treated with a fungicide, and plots not treated with a fungicide, as well as a measure of yield. The timings, products, and rates of the different fungicide applications were also included.

4.1.1 Potato late blight

The dataset on potato late blight consists of disease progress curves from 42 individual trials (each trial being a distinct year/site combination) between 2013 and 2017, from within the UK and Ireland.

Each trial consists of one or more treatments, typically with four replicates per treatment. Disease assessments are recorded as the percentage severity of potato late blight on the leaf, while the yield of tubers is recorded in tonnes per hectare (t/ha). The spray program for each treatment was recorded, with fungicides applied in regular intervals of between 7-10 days.

Figure 1 shows an example disease progress curve, from a single trial in 2013, with four replicates of three treatments (of which treatment 3 – the blue line – is untreated). The treated trials – treatments 1 and 2 – had fungicides applied at each of the times indicated by the arrows. The average yield of each of the three treatments was 24.7, 23.4, and 9.7 t/ha for treatments 1, 2, and 3 respectively.

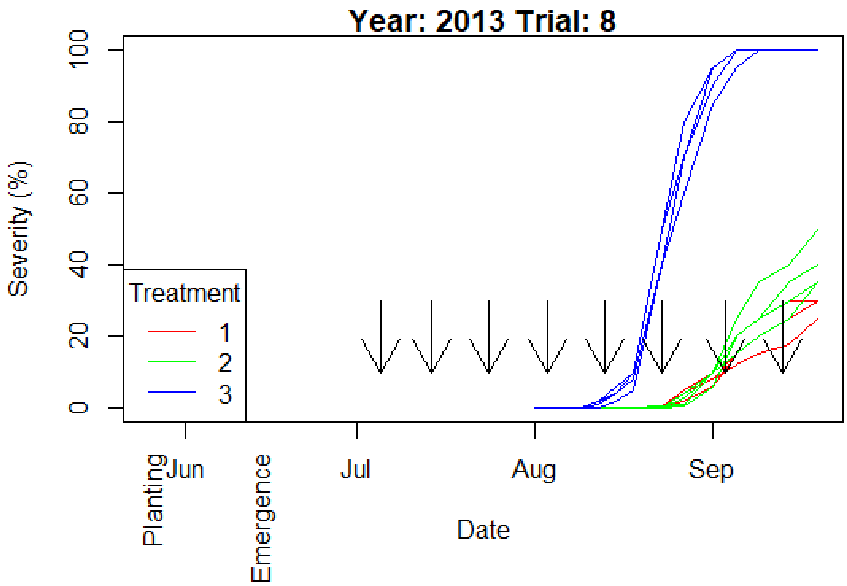

Figure 1. An example of disease progress curves. Disease observations were collected from August onwards, with four replicates of three treatments: untreated (blue), and two treated with different products (red and green). The vertical arrows indicate when fungicide treatments were applied.

4.1.2 Apple scab

The apple scab dataset consists of 122 trials from around Europe. Each trial contains a record of leaf severity at different assessment points, as well as fruit severity. Each trial has between one and five leaf assessments, and between one and three fruit assessments. The fungicide spray times, products used, and rates are also given. In all trials, fungicides were applied at regular intervals following the start of applications.

Figure 2 shows a typical trial, with two treatments – treatment 1 (in red) is the untreated – while treatment 2 has fungicide treatments applied at each of the times indicated by arrows.

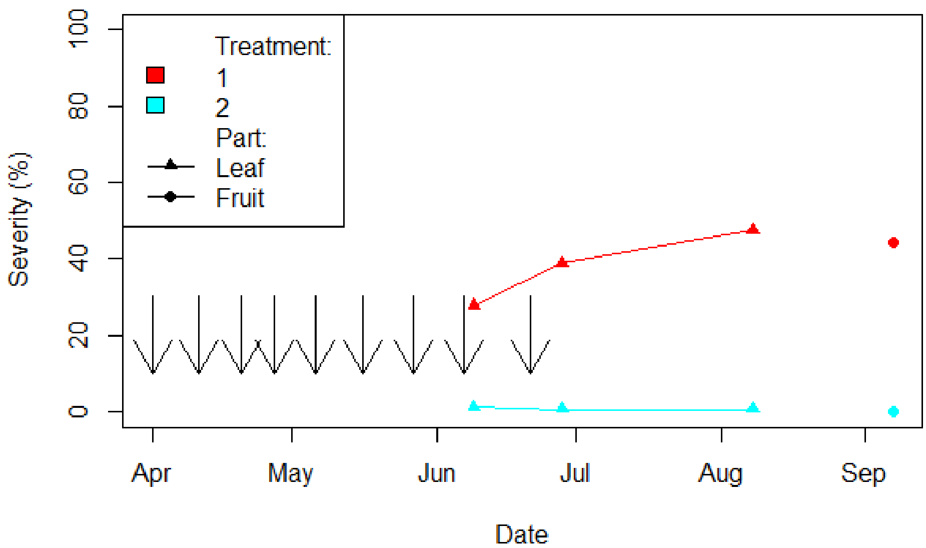

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Figure 2. An example disease progress curve for apple scab. Disease observations on the leaf were collected from June to August (lines with triangles), while observations on the fruit were collected in September (circles). There were two treatments in this trial: untreated (red), and one with fungicide applied at each of the times indicated by arrows.

4.2 Weather data

Hourly weather data (comprising the minimum temperature at 2m, and the dewpoint temperature) was collected from the ERA5 reanalysis (Copernicus Climate Change Service (C3S), 2017) for each site and year for which we had disease data.

Two additional measures were calculated using simple approximations:

- Relative humidity was calculated using the August-Roche-Magnus approximation (Alduchov and Eskridge, 1996).
- Leaf wetness was estimated very simply by assuming a leaf is wet if the relative threshold is above 90% (Rowlandson *et al.*, 2015).

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5 Methods

In both disease systems, we aim to calculate the value of following the guidance of a DSS, whether that value is economic or environmental.

In the following, we first describe the DSSs considered, before showing how we use them in each system, and then how we calculate the value of each DSS from the data described above.

5.1 Decision support systems

To develop our methods, we chose to use DSSs that have relatively simple models, that are widely established and recognized, and which have open implementations. This enabled us to independently code the DSSs and embed them in our methodology. For potato we chose the Smith criterion and the Hutton criterion and for apple scab the Mill's period. It is not critical which DSS are used as example systems for the analysis, provided they have characteristics which are shared by a range of other DSS. In this case, for example, the prediction of the systems are binary, either there is, or there is not, a risk period. The weather data described above was used to determine when each of the DSSs would have predicted areas of high risk for each trial.

5.1.1 Potato late blight

Two DSSs were analysed – the Smith criterion and the Hutton criterion – both of which identify weather periods with high infection risk for potato late blight. The DSSs can therefore be used to optimize the timings of fungicide spray applications. These DSS were chosen because they are well known in the UK / Ireland, where the data came from, with the Hutton criterion being an updated parameterization of the Smith criterion.

1. Smith criterion (Smith, 1956).
    - The first DSS is based on identifying Smith periods. These are defined as periods with two consecutive days with a minimum temperature of 10°C or higher, and a relative humidity >90% for 10 hours of each day. Figure 3 shows predicted Smith periods overlain on the disease progress curves of a single trial data from 2013.
2. Hutton criterion (Dancey, Skelsey and Cooke, 2017)
    - The second DSS is based on identifying Hutton periods. These are defined as periods with two consecutive days with a minimum temperature of 10°C or higher, and a relative humidity >90% for 6 hours of each day. The Hutton period is an updated version of the Smith period and aimed to decrease the number of false negatives (outbreaks that were not predicted by using the Smith period). The criterion for risk is therefore less stringent.

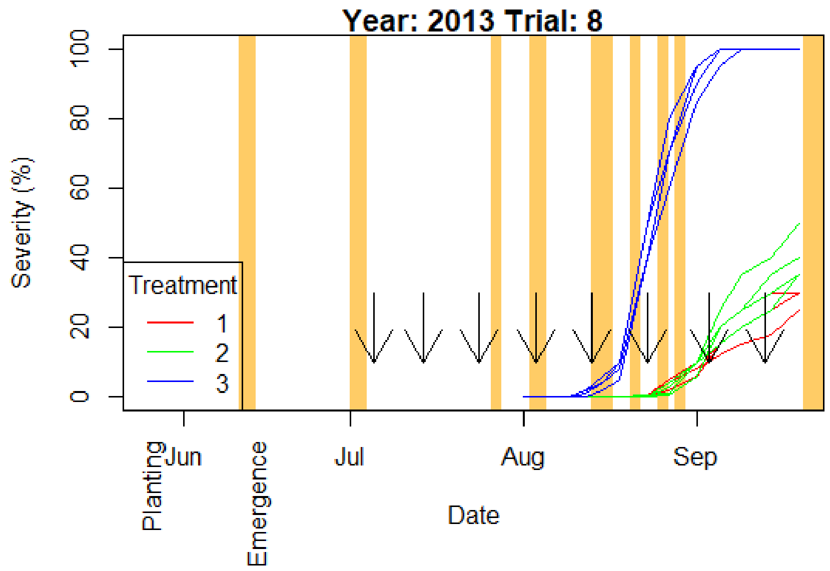

Figure 3. Example of disease progress curve with Smith periods identified by the vertical yellow bars.

5.1.2 Apple scab

One DSS has been considered for apple scab, the Mills criterion (Mills, 1944), which predicts weather periods conducive to the spread of apple scab disease. The Mills criterion underlies the VIPS apple scab model which has been identified on the priority list for WP3 (see deliverable 4.9). The criterion relates temperature and leaf wetness duration (Figure 4). There is a high infection risk if there is sufficient leaf wetness at a given average daily temperature. Figure 5 shows the distribution of high infection risk periods predicted by the Mills criterion within a single trial.

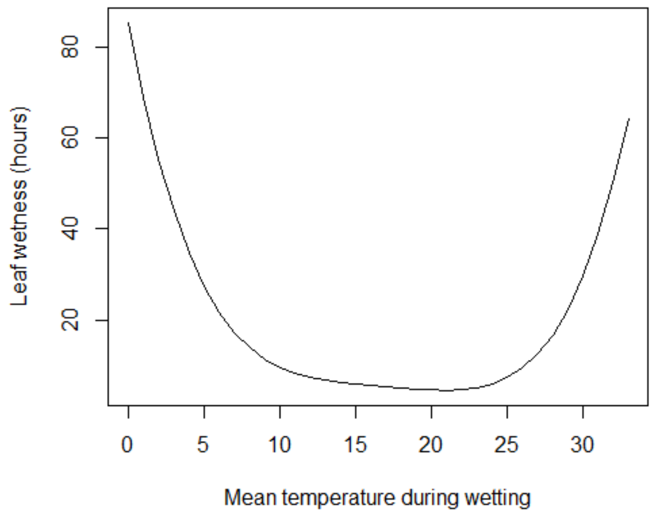

Figure 4. The Mills criterion. For a given mean temperature, if there are more leaf wetness hours than indicated by the line, there is a high chance of infection.

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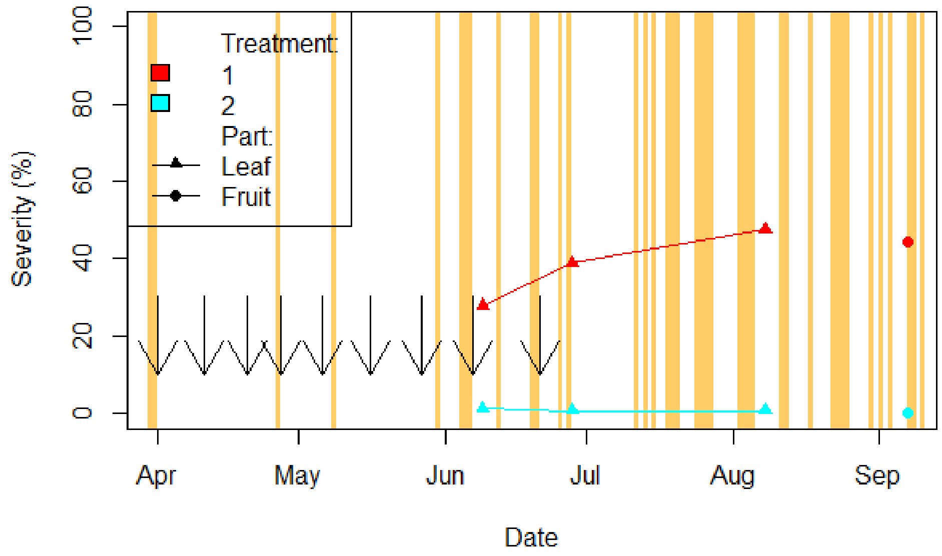

Figure 5. Mills periods overlain on the disease progress graph in Figure 2. The periods of high infection risk have been marked in yellow.

5.2 Counting risk periods

5.2.1 Potato late blight

Fungicide applications against potato late blight are typically applied from rosette stage of the crop canopy onwards. We therefore count the number of risk periods from emergence (or, if no emergence data is given, 30 days after planting) until harvest. We consider an IRP to be strongly protected by a fungicide application if it is applied on the day of the IRP or within 2 days beforehand. This assumption can be modified to account for the particular protectant or eradicant action of particular fungicides.

5.2.2 Apple scab

Treatments against apple scab are typically applied between bud burst and late June. The number of Mills periods was therefore counted between the 1st of April and the end of June. A Mills period was considered strongly protected by a fungicide application if a fungicide had been applied either on the day of the Mills period, or within 2 days beforehand.

Although the dataset includes leaf severity observations outside this critical period, the severity of apple scab on the fruit is primarily due to leaf severity early in the season, while severity later in the season contributes instead to overwinter inoculum. In the following therefore, we measure leaf severity as the highest severity recorded on the leaf within the critical period.

We use fruit severity data, which we convert to fruit incidence, which is used as a proxy for yield (see below). Where treatments included multiple assessments of fruit severity at different time points, we used the maximum fruit severity recorded.

5.3 Theoretical toolkit

The DSSs detailed above specify time periods within which weather conditions are conducive to pathogen infection. If fungicide applications are targeted to align with the infection risk periods (IRPs) then yield loss should be reduced and so economic profit increased. Alternatively, this may mean that fewer sprays (or a lower total dose) could be used.

To calculate the value of DSSs, we therefore need to estimate the yield from two given spray programs, one following the guidance from a DSS, and one following a standard protocol.

We therefore need to establish two relationships:

1. the relationship from a given spray program to the resulting level of disease
2. the relationship between that level of disease and the resultant yield.

In the following sections we describe a mathematical framework that allows us to consider these steps.

5.3.1 Calculating the average growth rate

Disease progress over time in untreated plots can be modelled by a logistic growth curve $s(t) = \frac{K}{1+\frac{K-s_0}{s_0}e^{-rt}}$, where $s(t)$ is the severity at time t, $K = 100$ is the maximum severity, s_0 is the initial severity at the start of a growing season, and r is the growth rate over time of the pathogen population.

We assume that there are two rates of increase, r_0 being the rate of growth of the disease in normal circumstances, and $r_I = \theta r_0$ inside IRPs, where $\theta > 1$.

Early on in a disease progress curve the disease grows exponentially. At this stage, the timing of the IRPs does not affect the amout of population growth within a given period (but the number of IPRs does), so we can instead calculate an average population growth rate simply from the number of days with a high infection risk, T_I (Equation 1).

$$r = \frac{r_0}{T}(T + (\theta - 1)T_I) \qquad (1)$$

The application of a fungicide reduces the growth rate of a pathogen according to a dose-response curve, $r(D) = re^{-\kappa D}$, such that when dose (D) is high r tends to zero, whereas when $D = 0, r(D) = r$.

If a fungicide is applied on T_F days, the growth rate of the pathogen on those days will be $r_0 e^{-\kappa D}$ or $r_I e^{-kD}$ depending on whether that day is also an IRP. In order to work out the average growth rate of a pathogen population with IRPs and fungicide applications, we first must specify how frequently the fungicide applications fall in IRPs. Assuming that there are fewer sprays than IRPs, we specify the proportion, $0 \leq \psi \leq 1$, of fungicide treatments that fall within IRPs. If the treatments were randomly applied, $\psi = \frac{T_I}{T}$, whereas following a DSS we assume $\psi > \frac{T_I}{T}$.

The average growth rate of a population with IRPs and fungicide applications is therefore:

$$r = \frac{r_0}{T}\left(T + (\theta - 1)T_I + \big(\theta\psi(e^{-\kappa D} - 1)\big)T_F\right) \qquad (2)$$

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5.3.2 From pathogen growth rate to disease metrics

Here we model the relationship from pathogen growth rate (r) to the disease metrics, either the area under the disease progress curve (AUDPC) or the severity at a specified time, T_S, $s(T_S)$.

As before we assume that the disease progress curve increases via a logistic function. It is therefore straight forward to calculate the disease severity at a given time point, T (Equation 3).

$$s(T_S) = \frac{K}{1 + \frac{K - y_0}{y_0} e^{-rT_S}} \tag{3}$$

Similarly, we can integrate over $s(t)$ from $t = 0$ to $t = T$, to calculate the AUDPC in a growing season (Equation 4).

$$\begin{aligned} \mathrm{AUDPC} &= \int_0^T \frac{K}{1 + \left(\frac{K - y_0}{y_0}\right) e^{-rt}} \, dt \\ &= \left[K \left(t - \frac{\log\left(\frac{K - y}{y} e^{-rt} + 1\right)}{-r} \right) + C \right]_0^T \\ &= KT + \frac{K}{r} \log \left(\frac{\frac{(K - y_0)}{y_0} e^{-rT} + 1}{\frac{K - y_0}{y_0} + 1} \right) \end{aligned} \tag{4}$$

5.3.3 From disease metric to yield

Disease-yield relationships can take many forms. For potatoes, as the biomass accumulation in tubers occurs from tuber initiation early in the growing season, yield can be affected by the disease severity throughout the growing season, and integral measurements, such as the AUDPC have been found to be a better predictor of yield than any single time point measurement of either the host or pathogen (Shah *et al.*, 2004). For simplicity, the possibility of blighted tubers causing secondary bacterial soft rots in store is not considered here. The disease-yield relationship of a particular trial can therefore be calculated as a linear relationship between yield and AUDPC (Equation 5), with the intercept being the potential yield Y_0 in the absence of any pathogen (when $\mathrm{AUDPC} = 0$).

$$Y = Y_0 - m \cdot \mathrm{AUDPC} \tag{5}$$

Conversely, for apple scab, only the leaf severity early in the season has been found to affect the disease incidence of fruit, while infected leaves later in the season contribute to overwinter inoculum. However, the fruit severity determines yield. Scab severities > 1% result in an unmarketable apple, and so fruit severity must be kept near zero.

Therefore, to calculate the marketable yield of apples we must first translate from leaf severity to fruit severity, before determining the yield.

Data suggests that fruit severity is related to leaf severity according to $F = 100\left(1 - e^{-\gamma s(T_S)}\right)$, where F is the fruit severity, and γ is a shape parameter, while fruit severity can be converted to incidence by a beta distribution. Fitting to the data suggests a value of $\gamma = 0.5$. This severity, however, is the average severity of fruit, F. Only fruit with a severity >1% will be discarded, and so it is necessary to know the distribution of fruit severity. The distribution of severity on a population of fruit can be described by a beta distribution, $\mathrm{Beta}(\mu\nu, (1-\mu)\nu)$, parameterized by the mean of that distribution, $\mu = F$, and a scaling factor, ν. The incidence of the population is therefore described by the cumulative distribution function of this beta distribution, $I_x(\mu\nu, (1-\mu)\nu)$, and the yield is the proportion of fruit with incidence < 1%.

$$Y = Y_0 \int_0^{0.01} I_x(F\nu, (1-F)\nu) \tag{6}$$

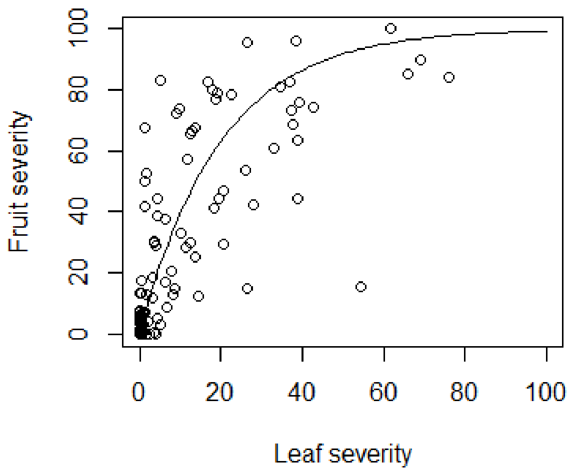

Figure 6. Relationship between the maximum leaf severity within the critical period for apple scab, and the maximum recorded fruit severity. The line depicts the relationship $F = 100\left(1 - e^{-\gamma s(T_S)}\right)$ with $\gamma = 0.25$.

5.4 Determining accuracy

Determining the accuracy of each DSS was not a priority for these DSSs since many validations have been published previously. However we explore a superficial determination graphically to demonstrate that the DSS is at least predicting disease to a useful extent, before proceeding further with the analysis.

While the accuracy of a DSS is typically estimated by experimental validation in which a standard spray control is compared with trials that follow the predictions of a DSS, given the nature of this dataset, we simply explore whether more infection risk periods are associated with a higher disease metric (AUDPC or $s(T_S)$) in untreated trials.

5.5 Determining value

The value of a crop is the profit from selling the crop yield ($P \cdot Y$, where P is the price per unit crop, and Y is the realized yield) minus the costs of expenses. Here we are only considering

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the costs associated with disease treatments, ($C \cdot N \cdot D$, where C is the cost of pesticide, N is the number of applications, and D is the dose), and so calculate the profit over spray costs.

The economic value of the DSSs is defined as the increase in profit over spray costs from following a DSS compared with following a standard spray program:

$$v = P(Y_D - Y_S) - C(N_D - N_S) \tag{7}$$

where Y_D and Y_S denote the yield following a decision support system or following a standard spray program respectively, and N_D and N_S are the number of pesticide applications following a decision support system or following a standard spray program.

By altering the proportion of sprays that fall on IRPs we then explore how yield changes as the fungicide sprays are targeted more or less at IRPs.

Using the equations in Section 4.3 (Equations 2, 4, and 5 for potato late blight; Equations 2, 3, and 6 for apple scab) we estimate the yield for a typical year and vary the proportion of fungicide sprays that target IRPs. From this we estimate the profit over spray costs, and can calculate the value of a spray program, given its accordance with the risk periods predicted by the DSS. The value of a DSS can then be calculated as the difference in profit over spray costs (Equation 7) between a scenario where all fungicide sprays are targeted at IRPs, and a scenario that has the same proportion of sprays target IRPs as a standard spray program.

6 Results

6.1 Potato late blight

6.1.1 Parameter estimation

Parameter estimation was carried out in four stages.

1) r_0, y_0, and θ were estimated from the untreated replicates using non-linear optimization to a logistic function incorporating r_0 and r_I.
2) m and Y_0 were fitted by linear regression between the yield and AUDPC for each trial, and the median taken from the resulting distributions.
3) Median values for T, T_F, and T_I were calculated from the trial data.
4) κ was estimated manually, while P and C were found in literature.

Table 1. Parameter values and descriptions for potato blight

Parameter	Parameter description	Median value
r_0	Disease progress growth rate outside IRPs	0.17
y_0	Initial severity of a trial	0.0005
θ	The multiple of r_0 in IRPs, such that $r_I = \theta r_0$	2.3 for Hutton 2.4 for Smith
κ	Shape of the dose-response curve – the relationship between dose and r	4
m	Slope of the relationship between yield and AUDPC	0.0005

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Y_0	Yield in the absence of any pathogen, being the intercept of the relationship between yield and AUDPC	50 t/ha
T	The total number of days in the simulation	109
T_F	The number of fungicide applications within the growing season	9
T_I	The number of infection risk windows per growing season	40 for Hutton 15 for Smith
P	Price of one tonne of tubers	€225/t*
C	Cost of a fungicide spray	€44/ha†

* https://www.fwi.co.uk/prices-trends/arable-prices/potato-prices; † Guenthner et al., (2001)

6.1.2 Accuracy

For both the Smith period and the Hutton criteria, a greater number of days with high infection risk during the growing season in untreated trials was associated with a greater AUDPC (Figure 7) and a lower yield (Figure 8), suggesting that both criteria correspond with periods of significantly higher disease increase.

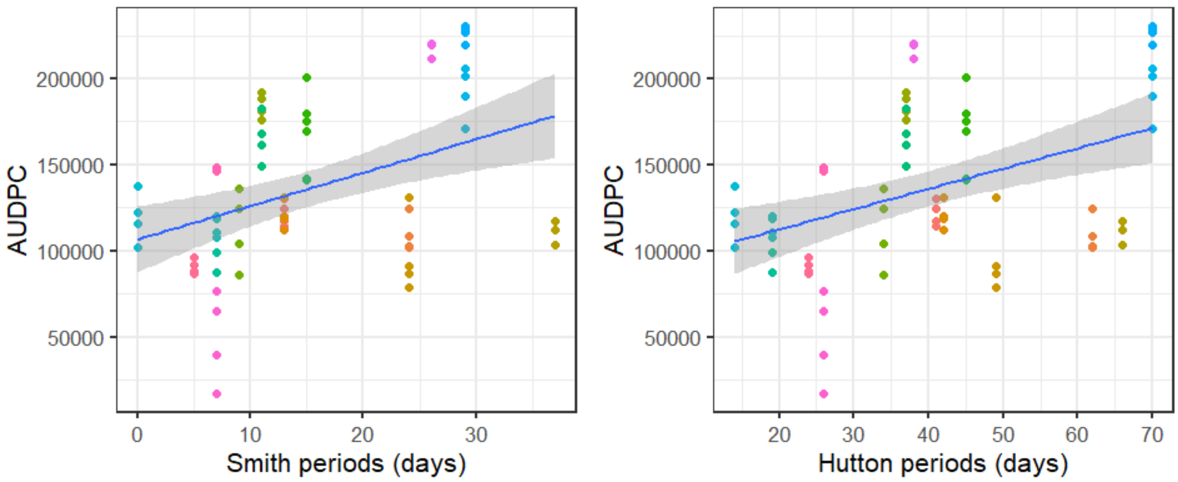

Figure 7. The relationships between the number of Smith (left) and Hutton (right) periods on the area under the disease progress curve (AUDPC) in untreated plots. Each colour represents a different trial, normally with 4 reps.

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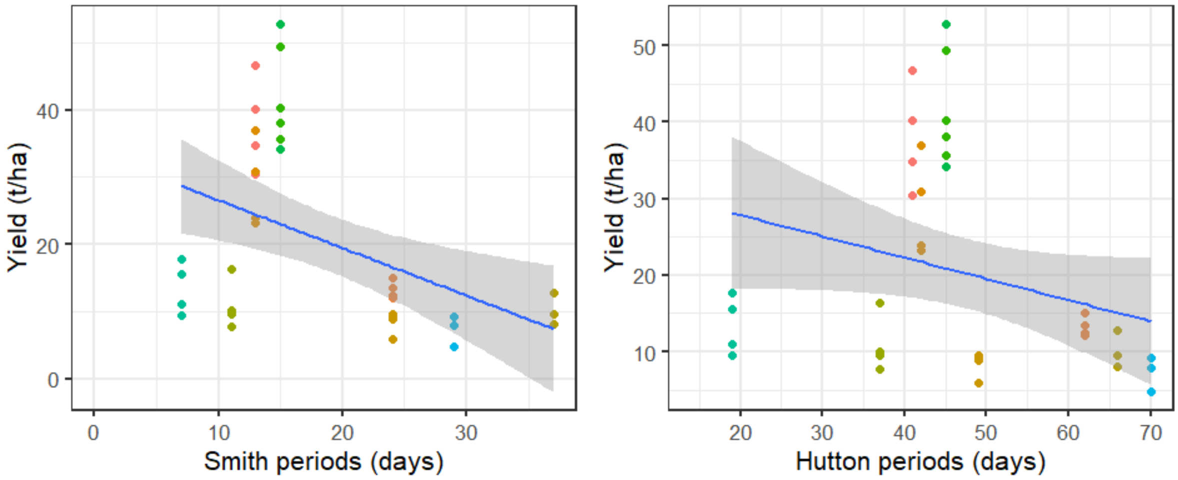

Figure 8. The relationships between the number of Smith (left) and Hutton (right) periods on the yield (AUDPC) in untreated plots. Each colour represents a different trial, normally with 4 reps.

6.1.3 Value

The value of each decision support system in an average epidemic in a typical site is shown in Figures 9 and 10. When the fungicide applications all miss the IRPs (as determined by the DSS) there is a substantial yield loss and, as the proportion of sprays that hit IRPs increases the yield increases (Figure 9). Similarly, as more fungicide sprays are applied, the yield loss is reduced.

Additionally, as the sprays are targeted to IRPs more accurately the profit over spray costs increases (Figure 10). When the fungicides all miss the IRPs the profits over spray costs are relatively low, and as the fungicides affect more of the IRPs the profits increase. However for both the Hutton and Smith criteria, when the fungicide applications all target IRPs the profit over spray cost is maximized by using fewer than 20 sprays.

The value of the Hutton and Smith criteria depends on the number of sprays applied. However, when all sprays are targeted at an IRP, the difference in profit over spray costs between using a DSS or following a standard spray program is maximized when using 10 sprays and could deliver €5000/ha for the Hutton criterion, while the value of the Smith period is maximized when using 7 sprays and could deliver €3590/ha, compared with following a standard spray program (Figure 11). The values presented here, however, are theoretical maximum economic benefits. At this stage of the development of the methodology, practical constraints on the realisation of these benefits are not accounted for explicitly. For example, treatments may be constrained by application interval limitations specified on fungicide product labels.

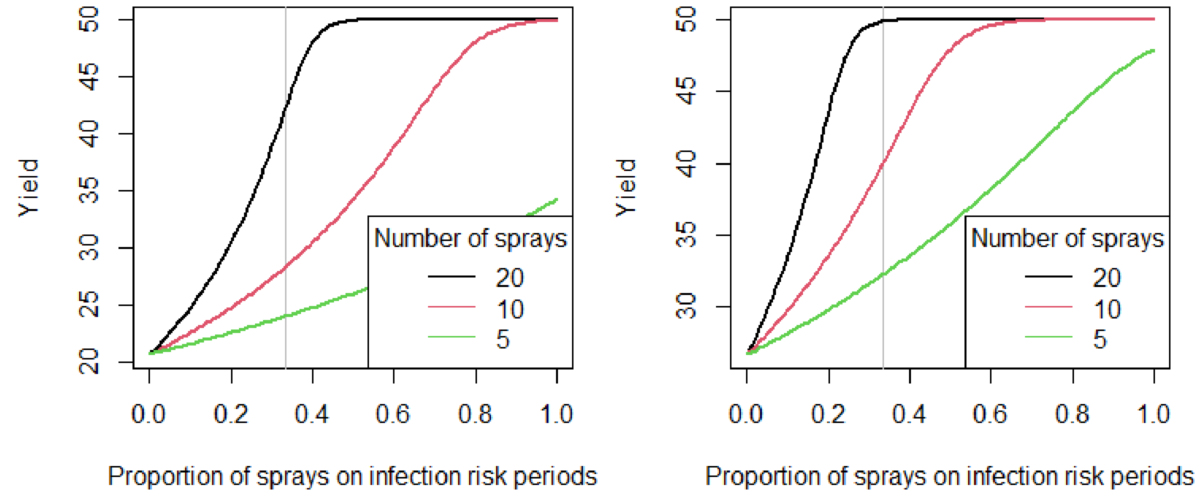

Figure 9. Yield increases as a larger proportion of sprays hit infection risk periods (IRPs) using (left) the Hutton criterion, and (right) the Smith criterion. The vertical line in each graph indicates the standard spray program determined from field trials.

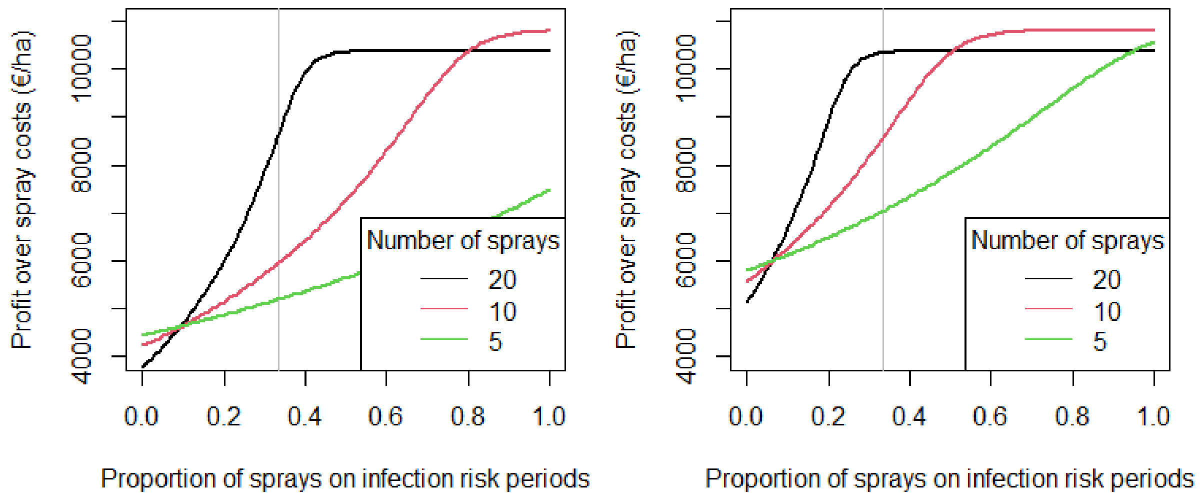

Figure 10. The profit over spray costs plotted against the proportion of sprays on IRPs changes using (left) the Hutton criterion, and (right) the Smith criterion. The vertical line in each graph indicates the standard spray program determined from field trials.

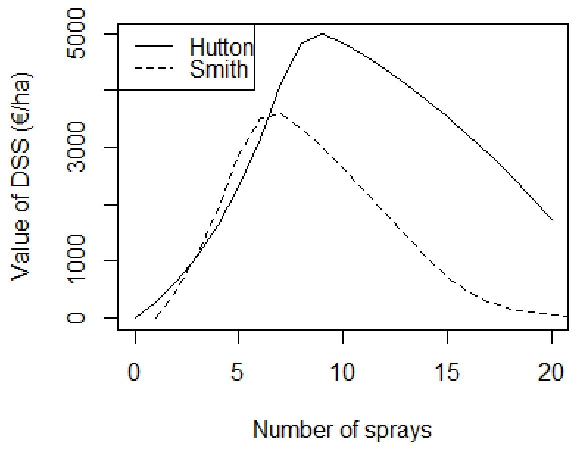

Figure 11. The value of the Hutton and Smith criteria plotted against the number of sprays. Value based on preliminary data.

6.2 Apple scab

6.2.1 Parameter estimation

Parameter estimation was carried out in four stages.

1) r_0, y_0, and θ were estimated from the untreated replicates using non-linear optimization to a logistic function incorporating r_0 and r_I.
2) Median values for T, T_F, and T_I were calculated from the trial data.
3) γ was fit from leaf and fruit severity data.
4) ν was estimated manually, while Y_0, P, and C were found in literature.

Table 2. Parameter values and descriptions for apple scab

Parameter	Parameter description	Median value
r_0	Disease progress growth rate outside IRPs	0.0117
y_0	Initial severity of a trial	0.747
θ	The multiple of r_0 in IRPs, such that $r_I = \theta r_0$	6
γ	Shape of relationship between leaf severity and fruit severity	0.25
ν	Shape of the distribution of severity	1
Y_0	Yield in the absence of any pathogen, being the intercept of the relationship between yield and AUDPC	25 t/ha*
T	The time at which to estimate leaf severity	91
T_F	The number of fungicide applications within the growing season	10
T_I	The number of infection risk windows per growing season	15
P	Price of one tonne of apples	€135/t†
C	Cost of a fungicide spray	€70/ha‡

* Yilmaz et al., (2015); †https://www.fwi.co.uk/machinery/unusual-harvesters-cider-apples;
‡ Tona, Calcante and Oberti, (2018)

6.2.2 Accuracy

The relationship between the number of Mills periods within the specified period (1st April – 1st July) is weak for leaf severity and fruit severity (Figure 12). Nevertheless, a higher proportion of treated Mills periods results in a considerable reduction in both leaf and fruit severity (Figure 13).

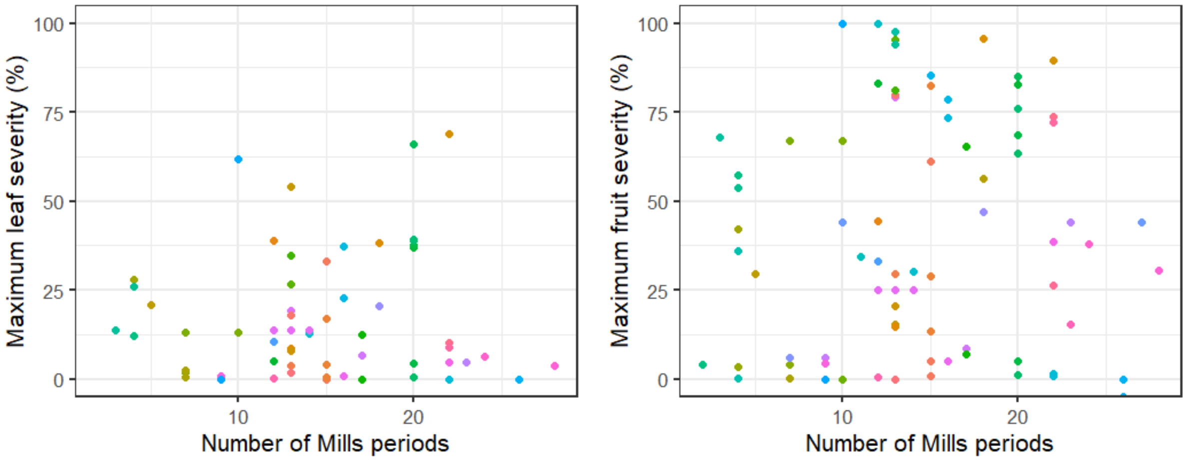

Figure 12. The effect of the number of Mills periods between the 1st April and the 1st July on the maximum leaf severity within that time (left), and the maximum recorded fruit severity (right) in untreated trials.

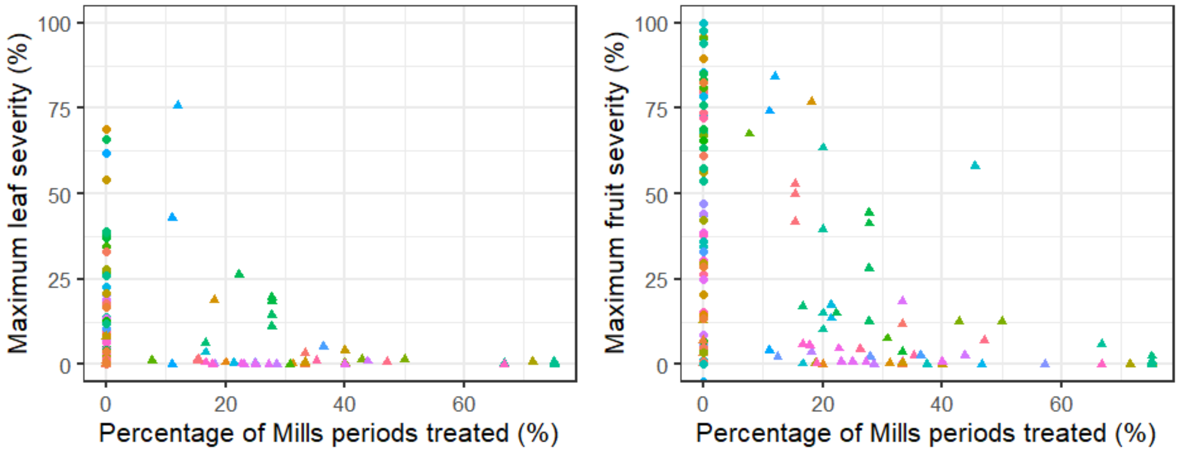

Figure 13. The maximum severity of the leaf (left) and fruit (right) can be considerably reduced by applying them within three days before a Mills period.

6.2.3 Value

Figure 14 shows the yield and profit over spray costs when a given proportion of the fungicides are targeted at IRPs. When none of the fungicides target IRPs there is a large yield loss, and the application of fungicides costs more than the price of the resulting marketable crop. When all the fungicides are targeted at IRPs yield loss greatly reduced and the profit over spray costs is greater than 1000 €/ha with 5 sprays. However, while the yield always increases with the number of sprays, the profit over spray costs does not, with 10 sprays resulting in a greater profit over spray costs than 20 fungicide applications when all the sprays target IRPs.

The value of the Mills criterion is shown in Figure 15. With 10 sprays, the use of the Mills criterion results in >1500 €/ha more profit over spray costs than following a standard spray program. When more than 10 sprays are applied the value of the DSS decreases.

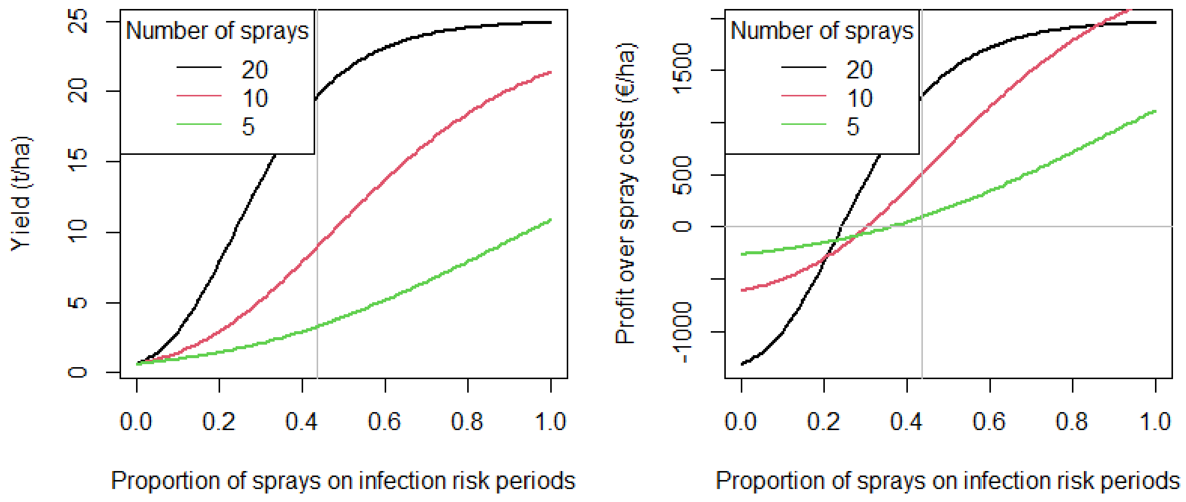

Figure 14. The yield (left) and profit over spray costs (right) plotted against the proportion of sprays targetting infection risk periods. Each of the curved lines represents a different number of spray applications. The gray vertical line in each graph indicates the standard spray program determined from field trials.

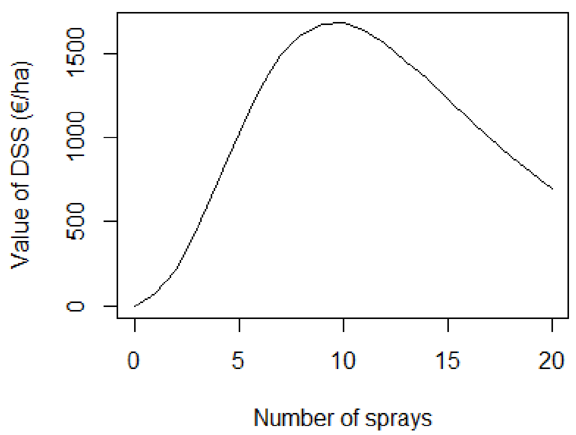

Figure 15. The value of the Mills criterion plotted against the number of sprays applied. Value based on preliminary data.

Horizon 2020

7 Discussion

In this report we have introduced a method that can be used to calculate the value of a decision support system (DSS) and demonstrated its use by calculating the value of the Smith and Hutton criteria for potato blight, and the Mills criterion in apple scab.

Applying fungicides according to timings specified by DSSs is expected to increase the effectiveness of control options, by targeting those applications at periods in which the pathogen is expected to spread more than usual. We have shown in each of the three DSSs examined, that increasing the proportion of sprays that are targeted to infection risk periods (IRPs) as defined by a DSS, results in yield increases, unless pathogen-related yield loss is negligible. In the potato field trials, where sprays were regularly applied every 7-10 days, approximately a third of sprays, on average, targeted an IRP. Nevertheless, even with a 10% increase in sprays affecting IRPs (one extra spray when 10 sprays are applied), a considerable yield increase is expected. In the apple field trials, over 40% of the sprays were considered to affect infection risk periods, and again, an increase in this proportion is expected to provide major yield increases.

While applying fungicide more times is always expected to lead to increases in yield, our method demonstrates that it is not always cost-effective. With 20 sprays (for context, the highest number of sprays applied in field trials of potato late blight and apple scab was 15 and 23 respectively) if the sprays were well-targeted there was little additional disease prevention, and so the fungicide sprays cost more than they delivered. The marginal value of a single fungicide spray decreases as the sprays are better targeted at IRPs. Put another way, by targeting sprays to IRPs, fewer sprays can be applied while maintaining the same profit over spray cost. In each case the value of the DSS was maximized at an intermediate number of fungicide applications, where there are sufficient applications to protect against disease when applied at the appropriate times, and not too many that they are no longer cost effective. It is important to remember that the profit over spray cost given here is not the profit a grower may expect to achieve, but rather the income from the crop minus the disease control costs. Additional costs, whether overhead and variable, were not included in this analysis.

While in this report we have defined a typical disease year, the value of a DSS needs to be applicable to different regions with perhaps very different levels of disease pressure. As such the value of a DSS is likely to be more relevant to the areas in which it was designed and provide less value in areas to which the IRPs are not as suitable. Next, we aim to build on this methodology to examine the value under different levels of disease pressure.

To develop our methods for apple scab and potato late blight, we chose to use DSS with open code. However, a benefit of the methodology presented here is that it does not require knowledge of the implementation of how a DSS determines IRPs, which may be commercially sensitive. The method only requires knowledge of the timings of the predicted IRPs, with which it is possible to determine the average effect of these predicted IRPs on the growth rate of the pathogen population. Given disease-yield relationships from data or the literature, and a knowledge of typical yield and application costs, the value of a DSS can then be estimated. We aim, in future work, to apply this method to the priority DSSs for potato late blight and apple scab as highlighted in Deliverable 4.9.

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