IPM Decisions

D4.10 Description of the general outline methods for DSS evaluation of the value of a prediction.

Grant agreement number: 817617

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

Deliverable due date: 31/05/2021 **Date of delivery:** 21/05/2020

Classification: Public

Version History

Version number	Implemented by	PME approval date	Reason
1.0	Joe Helps, Alice Milne & Frank van den Bosch		Deliverable 4.10 – environmental and economic benefits of DSS.

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1 Public Summary

We present a generic framework for evaluating the value of decision support systems (DSS), and then describe how this can be applied in practice for various formulations of the DSS and under different data constraints.

2 Executive Summary

The expected value of a DSS is defined as either (i) the economic, or (ii) the environmental benefit derived from using a DSS over a standard practice. We present a framework describing how these two types of benefit can be calculated for various types of DSS and for various formats of validation data. Specifically, we consider the situations where predictions inform (i) the number of sprays (ii) total dose of pesticides (iii) onset of spraying, and (iv) spray timings. We explain that, to be meaningful, estimates of the expected value of DSS should be accompanied by a quantification of the likely variation in value, hence allowing the user to make a risk-based assessment.

3 Introduction

The value of a DSS is defined as the economic or environmental benefit derived from using a DSS over a standard practice. In the case of economic value, a DSS is seen to be beneficial if by using it the expected 'cost to disease' (the costs caused by disease, such as value of yield loss and costs of control measures) is smaller than that achieved when applying a grower's standard practice. In the case of environmental value, a DSS is seen to be beneficial if its use results in a reduction in the frequency or dose of pesticide sprays applied, with no expected loss in profit compared with standard practice.

For ease of exposition and without loss of generality we present our framework within the context of economic value for disease control. In this case the value of a prediction (V) is defined as the difference between the cost to disease when not following a DSS (C_S) and the cost to disease when following a DSS (C_{DSS}). The expected value therefore becomes

$$\mathrm{E}(V) = \mathrm{E}(C_S - C_{DSS}), \qquad \text{Eqn. 1}$$

where C_{DSS} is the cost to disease when following the spray programme associated with the DSS prediction and C_S is the cost to disease when following a standard spray programme. The cost of applying a given spray programme (q) comprises the cost of the fungicide treatments, the cost of application and the price of the yield lost due to remaining disease and is denoted:

$$C(x, q) = F(q) + PL(x, q) \qquad \text{Eqn. 2}$$

where $F(q)$ is the price of the fungicide programme (including application costs), and $L(x, q)$ is the amount of yield lost when the fungicide programme q is applied in a situation with disease pressure x, and P is the price of a unit of yield.

In the case of the DSS the programme q is derived from a prediction of disease pressure x_{pred}, and we explicitly acknowledge that in our equation by making q a function of x_{pred}

$$\mathrm{C_{DSS}}(x, x_{\mathrm{pred}}) = F\left(q(x_{\mathrm{pred}})\right) + PL\left(x, q(x_{\mathrm{pred}})\right). \qquad \text{Eqn. 3}$$

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That is to say, the cost associated with using a DSS is now a function of the actual disease pressure x, and the predicted disease pressure x_{pred}. The standard programme does not depend on prediction, and so q_s is a fixed standard practice, therefore we denote C_S as a function of x alone

$$C_S(x) = F(q_s) + PL(x, q_s). \qquad \text{Eqn. 4}$$

The expected value of prediction can be calculated from

$$\mathrm{E}(V) = \int_0^{100} \int_0^{100} \{C_{\mathrm{S}}(x) - C_{\mathrm{DSS}}(x, x_{\text{pred}})\} f(x, x_{\text{pred}}) \mathrm{d}x \, \mathrm{d}x_{\text{pred}} \qquad \text{Eqn. 5}$$

where $f(x, x_{\text{pred}})$ describes the joint distribution of the predicted and observed disease pressure. In Eq. 5 we have assumed disease pressure to be in units of percent (hence the integral limits are defined 0 and 100).

To implement the above approach, we must:

(i) derive a distribution describing the joint probability of observing each combination of actual disease pressure and predicted disease pressure, i.e. $f(x, x_{\text{pred}})$

(ii) derive the DSS spray programme recommendation for each value of x_{pred}, i.e. derive $q(x_{\text{pred}})$

(iii) calculate the cost associated with applying these derived programmes given that the true disease pressure was x. That is to say, calculate $C_{\mathrm{DSS}}(x, x_{\text{pred}})$ for each possible combination of x, x_{pred} (one of which will also be $C_{\mathrm{S}}(x)$).

Whilst theoretically possible, in most cases these steps are not practical due to DSS formulation and/or data availability. However, it forms the foundation for more practical approaches as we describe below.

4 Practical implementation

4.1 Data

A key factor in how we implement our assessments is the form of the data available for evaluation. Typically the large data sets that are needed to properly determine the value of DSS are not collected for that specific purpose, rather they are trials data which aim to explore the efficacy of new products in a range of environments by comparing them to standard and untreated spray programmes, or they are a collection of research experiments undertaken by various institutions with no shared protocol. Whilst these data sets can be useful, because they were not designed for the specific purpose of quantifying the value of DSS, the method needs to be adapted to each, as also described in deliverable 4.3.

4.2 To spray or not to spray – that is the question

Our first example relates to the case where we wish to determine whether the number of sprays predicted by the DSS is expected to be economically more optimal than standard practice (the simplest case of this is where the DSS guides whether to treat or not). These types of case study often arise with risk based DSS, where the systems advise when to spray based on some risk criteria (e.g. based on weather). The risk criterion usually relates to a period when infection efficiency of the pathogen is

high. To our knowledge there is no risk prediction model that has been validated on basis of experimental estimates of infection efficiency under different weather conditions. Risk models are virtually always a product of fitting a model to observations of disease severity.

To add to the complexity, often these DSSs offer no prediction of disease pressure (x_{pred}) in terms of % disease. Therefore, all we are able to assess is whether the total number of sprays the DSS predicts is likely to be economically (or environmentally) more optimal than standard practice. This assessment does not account for the fact that if the DSS is based on some underlying biological process then it should also give benefit through improved timing. Therefore, this assessment of value is likely to be conservative.

In this special case, where we can only assess the DSS based on the number of sprays it predicts, the expected value of prediction (Eq. 5) degenerates to

$$\mathrm{E}(V) = \sum_{n} \int_{0}^{100} \{C_{\mathrm{S}}(x) - C_{\mathrm{DSS}}(x,n)\} f(x,n) \mathrm{d}x \qquad \text{Eqn. 6}$$

where n is the predicted number of sprays from the DSS (conceptually equivalent to x_{pred}) , and $f(x,n)$ describes the joint distribution between disease pressure and the number of sprays predicted. The joint distribution can be derived by running the DSS for each site-season available in the trials data. For this data we also have a metric for disease pressure (for example in IPM Decisions deliverable D4.13 we quantified disease pressure x using the untreated plots in the data) giving us paired values of x and n to which we can fit the distribution $f(x,n)$. The yield loss relationship $L(x,n)$ and can also typically be derived from the trials data or models (see Report IPM Decisions D4.13). This provides us the information we need.

4.3 Dose reduction

Some DSSs focus on the potential to reduce pesticide dose. Given that dose can be quantified on a discrete scale of quarter-dose units the analyses of these types of DSS can be framed similarly to above (depending on data availability). That is to say, the expected value can be defined by

$$\mathrm{E}(V) = \sum_{\delta} \int_{0}^{100} \{C_{\mathrm{S}}(x) - C_{\mathrm{DSS}}(x,\delta)\} f(x,\delta) \mathrm{d}\delta \qquad \text{Eqn. 7}$$

where δ is dose unit in this case.

This type of DSS was investigated by te Beest et al. (2009) who evaluated a predictive model of *Zymoseptoria tritici* for economic and environmental benefit. In their case dose was adjusted to one of two levels (δ_l or δ_h) depending on whether a damaging epidemic was predicted. The joint distribution function that they fitted was equivalent to a weighted sum of exponential distribution.

4.4 When to start spraying

Several DSS predict when spraying should start and thereafter it is assumed spraying will occur at regular intervals. In these cases, we often only have data showing the crop loss or damage associated

with starting sprays too early or too late. Typically spraying too early does not result in serious crop loss because of repeated spraying, but there are financial and environmental losses through the unnecessary applications. For this type of case study Eqn.2 becomes the cost associated with starting to spray earlier or later than the optimal timing, t_0 (t_0 is now conceptually equivalent to our unknown disease pressure x) and the cost is given by

$$C(t_0 - t) = F(t_0 - t) + PL(t_0 - t). \qquad \text{Eqn. 8}$$

In this case our formulation of Eqn. 5 is recast as

$$\mathrm{E}(V) = \int_{t_1}^{t_2} \int_{t_1}^{t_2} \{C_{\mathrm{S}}(t_0 - t_s) - C_{\mathrm{DSS}}(t_0 - t_{\mathrm{pred}})\} f(t_0 - t_{\mathrm{pred}}) \mathrm{d}t_0 \, \mathrm{d}t_{\mathrm{pred}} \qquad \text{Eqn. 9}$$

where the probability distribution $f(\tau)$ describes the probability the DSS predicts the timing of the initial spray at times relative to optimal. This can be derived from data on the true timing of the first risk event combined with predictions from the DSS. The cost relationship (Eqn. 8) can be derived from trials data and/or experimental data (where available).

4.5 Timing sprays according to risk

Finally, we consider the situation where there is sufficient data to evaluate whether the DSS appropriately targets risk periods. This situation was evaluated in IPM Decisions deliverable D4.12. To make the analysis tractable within our framework we describe the recommendation in terms of how many sprays are recommended and the proportion of those that coincide with a true risk event. Hence our generic framework becomes

$$\mathrm{E}(V) = \sum_n \int_0^{100} \int_0^1 \{C_{\mathrm{S}}(x) - C_{\mathrm{DSS}}(x, n, p)\} f(x, n, p) \mathrm{d}p \, \mathrm{d}x \qquad \text{Eqn. 10}$$

Here (as above) with sufficient data it is relatively straightforward to characterise $f(x, n, p)$. The analysis of cost is challenging, however, and relies on model-based assumptions of how sprays affect the growth of the epidemic within risk periods and in periods of minimal risk. We give an example of this type of model-based estimate of cost in IPM Decisions deliverable D4.12.

4.6 Uncertainty and risk

In the above, the value of a DSS is presented as a single expected value. This summarises the distribution of likely outcomes from using the DSS and so hides variation and associated risk. Risk is a key factor for growers and so as well as the expected value of the DSS, the variation in the distribution should also be communicated. This can be done either by displaying the distribution of the value (as in IPM Decisions deliverable D4.13, and see below) or by presenting some statistic to summarise risk, such as the probability using a DSS will result in loss above some threshold value. This type of approach has been demonstrated to work well with stakeholder groups who may be less familiar with interpreting distributions (Chagumaira et al., 2021).

Uncertainty can be evaluated using Monte-Carlo methods. The distribution of the value of a DSS, V, can be calculated from estimated distributions of pest measures (such as pathogen severity), combined with relationships between a potential fungicide programme and yield. The DSS of te Beest et al. (2009) evaluated the weather in the 30 days preceding GS31, to determine the likelihood of a large epidemic at GS 75 which, if it occurred, could have a large impact on yield. Specifically, they specified that if a severity larger than 5% was predicted, a greater dose was required to optimise the gross margin. Therefore with the te Beest DSS, if a damaging epidemic is not predicted less fungicide than a standard programme would be suggested, whereas if a damaging epidemic was predicted more fungicide would be advised. To estimate the value of this DSS we therefore need to create a link from the distribution of disease to the realised cost with or without the DSS. With a standard spray programme, we need to empirically estimate two relationships:

1) $x = g(x_0, q_s)$, the realised severity, x, given the severity in untreated trials, x_0, and the standard spray programme, q_s
2) $Y = h(x)$, the yield given a realised severity

Given any untreated severity, x_0, we can therefore work out the expected yield. Together with the cost of a spray programme, and the price per unit yield, we can estimate $F(q)$ and $PL(x, q)$ in Eqn. 2, and therefore the cost of a standard spray programme.

To calculate the expected cost when using the DSS, we include the extra step for the DSS, evaluating the weather in the thirty days prior to GS31, and calculating the required fungicide programme depending on the level of predicted disease, x_{pred}. We can therefore estimate the yield resulting from a DSS from any untreated disease level, x_0.

Finally, to calculate the distribution of the value of a DSS, we draw x_0 repeatedly from empirical data, and calculate the cost using the standard spray program, C_S and using the DSS, C_{DSS}. The distribution of the difference, $C_{DSS} - C_S$ is the distribution of the value of that DSS, V.

5 Conclusions

The generic framework presented has the flexibility to estimate the value of DSS in most situations given the availability of sufficient data to quantify the joint distribution between predicted and actual disease pressure and information to quantify the impact of control on a given level of disease. It is important to present the user with both expected value and a measure of the risk of extreme losses so that they can assess benefits and risks associated with following DSS recommendations.

6 References

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

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