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# Uncertainty Analysis Applied to Supervised Control of Aphids and Brown Rust in Winter Wheat. Part 2. Relative Importance of Different Components of Uncertainty

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*ABSTRACT*

*The components of an existing model for supervised control of aphids (especially* Sitobion avenae*) and brown rust (*Puccinia recondita*) in winter wheat contain uncertainty. Their contribution to uncertainty about model output is assessed. The model simulates financial loss associated with a time sequence of decisions on chemical control as a function of crop development, population growth, and damage. Four sources of uncertainty were quantified: model parameters, incidence sample estimates, future average daily temperature, and white noise. Uncertainty about the first two sources is controllable because it decreases when more information is collected. Uncertainty about the last two sources is uncontrollable, given the structure of the model. Uncertainty about model output, charac-*



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*terized by its variance, is calculated by repeatedly drawing realizations of the various sources of uncertainty, and calculating financial loss after each draw. By processing new realizations of these sources one by one, the contribution of each component to total variance can be assessed using an adapted Monte Carlo procedure. For most relevant initial conditions and decision strategies the sources of uncontrollable uncertainty cause more than half of the uncertainty about model output. White noise in the relative growth rates of aphids and brown rust is the most important source of uncertainty. Resources for improvement of the model are most effectively allocated to studies of the population dynamics of aphids and brown rust.*

## INTRODUCTION

Predictions of costs and benefits of chemical control of pests and diseases at the field level are an essential element of supervised control (Zadoks, 1985). Such predictions can be made using dynamic models which relate pest or disease intensity to financial loss. Usually, uncertainty about the values of parameters and model inputs is ignored and calculations are carried out with average values. In principle, however, uncertainty must be taken into account when relations in the model are non-linear, when the contribution of different sources of uncertainty to output uncertainty of the model is of interest, or when risk has to be assessed.

A decision model for evaluating costs associated with different strategies of chemical control of aphids (especially *Sitobion avenae*) and brown rust (*Puccinia recondita*) in a field of winter wheat was presented (Rossing *et al.*, 1994*b*). It represents an upgraded version of part of the EPIPRE advisory system (Zadoks *et al.*, 1984; Drenth et al., 1989). The model predicts financial loss associated with a particular time series of decisions on chemical control for given initial values of temperature sum and incidences of aphids and brown rust. Aphids and brown rust were considered because they often occur simultaneously. Diseases other than brown rust were omitted in view of the exploratory nature of the study. The effect of uncertainty about model parameters and model inputs on damage thresholds, i.e. densities at which chemical control is just economical for a farmer, was assessed. It was shown that ignoring uncertainty about model parameters and inputs results in damage thresholds which exceed the thresholds calculated under uncertainty, assuming risk-neutrality. Farmers deciding on chemical control based on the deterministic damage thresholds will spray their crops too late, and may incur economically unacceptable financial losses. Thus, as a consequence of non-linear relations in the model, uncertainty must be taken into account when calculating expected costs associated with different strategies of chemical control of aphids and brown rust.

In this paper, the contribution of uncertainty about parameters and inputs of the decision model to uncertainty about predicted financial loss is assessed. The major causes of model output uncertainty are identified for a number of relevant initial conditions and control strategies. Research prioritization is discussed in relation to the possibilities for reducing model output uncertainty.

## MATERIALS AND METHODS

### Description of the decision model

The decision model, which was described earlier (Rossing *et al.*, 1994*b*), simulates financial loss due to attack by aphids and brown rust from ear emergence (DC 55 (Zadoks *et al.*, 1974)) to dough ripeness (DC 83), i.e. approximately from early June till late July, in a commercial field of winter wheat in The Netherlands of, say, 5–10 ha. Financial loss is defined as the costs of yield reduction caused by aphids and/or brown rust plus the costs of eventual control. Costs are calculated at field level. The model is used to estimate the probability distributions of financial loss associated with different strategies of chemical control. A strategy is defined as a series of decisions on chemical control made on the first day of consecutive decision periods of one week. The decisions which can be taken at the start of each week are either chemical control of aphids and/or brown rust or no chemical control. The series of decisions is fixed at the start of the simulation. The model comprises relations which describe the dynamics of crop development, population growth, and damage by aphids and brown rust as a function of the strategy on chemical control. The model inputs include the temperature sum accumulated since the day the crop attained development stage pseudostem elongation (DC 30), the future average daily temperature, and the initial values of aphid and brown rust incidences determined by the farmer.

Uncertainty about the values of input variables and of model parameters was quantified using empirical data (Rossing *et al.*, 1994*b*). Parameters were estimated by regression, the variance–covariance matrix of the estimates providing a measure of parameter uncertainty. Residual variation was ascribed to measurement effects and was disregarded for prediction. In some of the regression analyses, however, residual variances greatly exceeded the variances attributable to measurement

TABLE 1
Sources of Uncertainty in Decision Model

| *Category* | *Component* | *Distribution* |
|---|---|---|
| Parameters | Various | (Multivariate) Normal, Beta |
| White noise | Relative growth rate | Normal |
| | Incidence–density transformation | Normal |
| | Temperature sum–development stage relation | Normal |
| Estimates of initial state | Incidence | Binomial |
| | Temperature sum | —[a] |
| Future average daily temperature | Future average daily temperature | 36 Years of historic data |

[a] Uncertainty is disregarded.

effects. Apparently, the $y$ variable varied in an unpredictable manner, due to causes not accounted for in the regression model. In these cases the residual variation constitutes a source of uncertainty which must be taken into account for prediction of a new situation. The random deviations of the empirical data from the fitted regression model were described as mutually independent, identically distributed, Normal variates. This source of variation is referred to as white noise. The input variable 'initial temperature sum' was assumed to be known with negligible variation. Initial values of aphid and brown rust incidences were subject to observational error. The variation in future average daily temperature was described by 36 years of daily maximum and minimum temperatures measured at the meteorological station of the Wageningen Agricultural University from 1954 to 1990. Thus, analysis of the available information resulted in four categories of uncertainty: model parameters; white noise; estimates of the initial state; and future average daily temperature. In each category one or more components can be distinguished (Table 1). These components represent the smallest independent sources of uncertainty in the model. Uncertainty about the interactions between these model components was assumed to be absent.

**Relative importance of component uncertainty for model output uncertainty**

Uncertainty about model components (Table 1) causes the outcome of the model, financial loss, to be uncertain. Here, the uncertainty about model outcome is characterized by its variance. Model output variance attributable to uncertainty about model component $x_i$ can be assessed in two ways. First, by calculating the decrease in expected model output variance resulting from removal of the uncertainty about $x_i$, and, second, by calculating the expected model output variance remaining after removal of the uncertainty about all components except $x_i$. The first approach is relevant for model parameters and estimates of the initial state where, theoretically, uncertainty is controllable. In these categories uncertainty declines when more empirical data are collected. The second approach is appropriate for the categories white noise and future average daily temperature where uncertainty is uncontrollable.

Jansen *et al.* (1994) developed an adapted Monte Carlo method to assess efficiently the contribution of uncertainty about a model component to model output variance. The method is illustrated in Fig. 1. The procedure starts with a simple random sample of the $Q$, i.c. three, independent components of uncertainty in a model and calculation of model output, which is indicated in Fig. 1 as $f(u_1, v_1, w_1)$. Processing one component at a time, new realizations of the components are drawn by simple random sampling from the appropriate probability distributions. After each draw, model output is calculated and stored. After $Q$ draws, the values of all components have been changed once compared to their initial values, resulting in $f(u_2, v_2, w_2)$ in Fig. 1, and the first cycle is completed. In total $M$ cycles are made. Since the components are changed one by one, the difference in model output between consecutive draws is solely due to variation in one component. The change in model output after $(Q - 1)$ draws is due to variation in all components, except one.

The expected output variance of the full model is estimated as the variance of a column in Fig. 1, each column representing a random sample of the model output distribution. The contribution of a source of controllable variation to model output uncertainty is calculated as the decrease in expected output variance resulting from removal of the

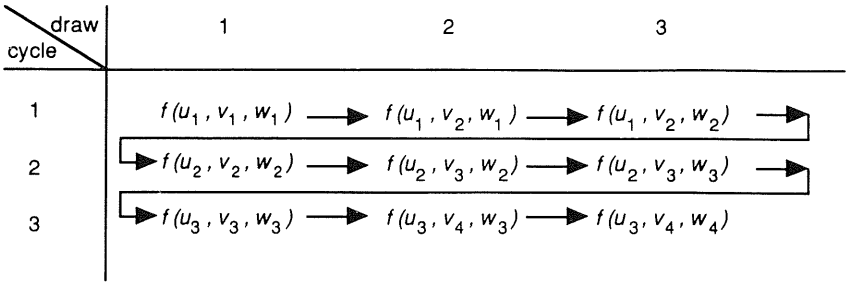


**Fig. 1.** Illustration of the adapted Monte Carlo method for a model f(·) with three sources of uncertainty, $u$, $v$, and $w$. Consecutively drawn random values of, for example, $u$ are denoted by $u_1$, $u_2$, etc. The sample consists of three cycles. After Jansen *et al.* (1994).

uncertainty about one model component. For example, the expected model output variance remaining after removal of the controllable uncertainty about $u$ is estimated as the variance of the differences between columns 1 and 3 in Fig. 1. The contribution of a source of uncontrollable variation to model uncertainty is assessed by the expected model output variance remaining after removal of the uncertainty about all other sources of uncertainty. For example, the contribution of the source of uncontrollable uncertainty $v$ to model uncertainty is estimated as the variance of the differences between columns 1 and 2 in Fig. 1. The variance estimates are used to obtain a ranking of the relative importance of the various components of controllable and uncontrollable uncertainty, respectively.

The estimates of expected model output variance are unbiased and asymptotically normally distributed. Since their (co-) variances can be estimated, the difference between expected model output variances resulting from uncertainty in two components can be tested for deviation from zero.

Note, that after removal of uncertainty in, for example, component $u$ the expected model output variance represents the main effect of $u$, whereas the expected model output variance after removal of uncertainty in all components except $u$ constitutes the main effect of $u$ plus the interaction of $u$ with the other components of uncertainty. Thus, the two variance estimates do not necessarily add up to the full model's output variance.

The decision model and the Monte Carlo procedure are programmed in FORTRAN-77. The analysis of model output was programmed in C (Jansen *et al.*, 1994). Preliminary analyses showed that between 2000 and 32 000 cycles were needed to arrive at sufficiently precise estimates of expected model output variance, i.e. with a coefficient of variation of approximately 0.10, or smaller. The greatest number of iterations was needed for decision strategies which resulted in highly skewed frequency distributions of financial loss.

In the analysis, a distinction is made between white noise and future temperature on the one hand, and model parameters and estimates of the initial state on the other. Uncertainty about white noise and future temperature cannot be reduced without changing the structure of the model, and represents uncontrollable variation. Thus, the uncertainty about financial loss caused by these sources represents a lower bound for model uncertainty. In contrast, uncertainty about model parameters and estimates of the initial state decreases as more information is collected, and represents controllable variation. Therefore, the decrease of uncertainty about model outcome resulting from removing the uncertainty about these sources is the maximum improvement achievable within the framework of the model structure.

## RESULTS

In a previous paper (Rossing *et al.*, 1994*b*) risk-neutral damage thresholds for aphids and brown rust were calculated for temperature sums which correspond with average crop development stages '50% of the ear visible' (DC 55), 'onset of flowering' (DC 61), and 'flowering completed' (DC 69). These temperature sums and incidences of aphids and brown rust are used as initial states in the calculation of the relative importance of the various categories and components of uncertainty. Three strategies of chemical control are evaluated for both aphids and brown rust:

**TABLE 2**

Expected Variance of Financial Loss (Dfl$^2$ ha$^{-2}$) Caused by Different Sources of Uncertainty for Combinations of Three Initial States and Three Decision Strategies (NS, S1 and S2).

APHIDS

| *Sources of uncertainty* | *Initial state* $T_0$ = 165; $I_{0,A}$ = 0·08 *Strategy* | | | $T_0$ = 225°d; $I_{0,A}$ = 0·30 *Strategy* | | | $T_0$ = 320; $I_{0,A}$ = 0·85 *Strategy* | | |
|---|---|---|---|---|---|---|---|---|---|
| | NS | S1 | S2 | NS | S1 | S2 | NS | S1 | S2 |
| All | 45 800 | 715 | 1 370 | 41 100 | 587 | 2 120 | 24 100 | 758 | 5 680 |
| White noise and future temperature | 32 600 | 443 | 1 030 | 30 300 | 342 | 1 700 | 17 800 | 314 | 4 780 |
| Model parameters and estimate of initial state | 13 200 | 272 | 340 | 10 800 | 245 | 420 | 6 300 | 444 | 900 |

BROWN RUST

| *Sources of uncertainty* | *Initial state* $T_0$ = 165; $I_{0,B}$ = 0·01 *Strategy* | | | $T_0$ = 225°d; $I_{0,B}$ = 0·02 *Strategy* | | | $T_0$ = 320; $I_{0,B}$ = 0·08 *Strategy* | | |
|---|---|---|---|---|---|---|---|---|---|
| | NS | S1 | S2 | NS | S1 | S2 | NS | S1 | S2 |
| All | 76 800 | 4 030 | 4 170 | 60 800 | 1 750 | 1 850 | 60 400 | 959 | 1 730 |
| White noise and future temperature | 66 000 | 3 940 | 4 030 | 53 700 | 1 820 | 1 760 | 53 700 | 1 020 | 1 560 |
| Model parameters and estimate of initial state | 10 800 | 90 | 140 | 7 100 | 0 | 90 | 6 700 | 0 | 170 |

$T_0$ represents the initial temperature sum (°d), $I_{0.A}$ the estimated initial aphid incidence (–), and $I_{0.B}$ the estimated initial brown rust incidence (–). Attainable yield is 8 000 ka ha$^{-1}$

**TABLE 3**

Expected Variance of Financial Loss ($Dfl^2\ ha^{-2}$) Caused by White Noise and Future Average Daily Temperature for Three Decision Strategies (NS, S1 and S2) at Initial State $T_0 = 225°d$ (Temperature Sum), $I_{0,A} = 0{\cdot}30$ (Initial Aphid Incidence) and $I_{0,B} = 0{\cdot}02$ (Initial Brown Rust Incidence).

| *Source of uncertainty* | *Strategy* | | |
|---|---|---|---|
| | *NS* | *S1* | *S2* |
| APHIDS | | | |
| White noise and future temperature | 30 300 | 342 | 1 700 |
| White noise in relative growth rate | 23 600a | 198a | 1 260a |
| White noise in temperature sum–crop development stage relation | 697c | 45c | 54d |
| White noise incidence–density transformation | 5 250b | 76b | 595b |
| Future average daily temperature | 4 830b | 137a | 157c |
| BROWN RUST | | | |
| White noise and future temperature | 53 700 | 1 820 | 1 760 |
| White noise in relative growth rate | 41 400a | 1 300a | 1 330a |
| White noise in temperature sum–crop development stage relation | 3 640c | 304d | 256c |
| White noise incidence–density transformation | 13 500b | 507c | 749b |
| Future average daily temperature | 18 500b | 974b | 898b |

Attainable yield is 8 000 kg ha$^{-1}$. Different letters following estimates indicate significant differences within strategies ($p < 0{\cdot}05$).

no chemical control at any time (NS); control at the start of the first decision period only (S1); and control at the start of the second decision period only (S2). Throughout the analysis attainable yield is 8000 kg ha$^{-1}$.

Expected variance of financial loss, the model output of interest, is greatest when no chemical control is carried out for both aphids and brown rust (Table 2). Immediate chemical control results in the smallest expected variance while chemical control at the start of the second decision period results in an intermediate variance estimate. These results correspond to the graphical and numerical results in the previous paper (Fig. 4 and Table 8 in Rossing *et al.*, 1994*b*), which showed that chemical control reduces the range of possible financial losses.

In most cases the categories of uncontrollable variation, white noise and future average daily temperature cause more than 50% of the uncertainty about financial loss (Table 2). More detailed analysis shows that white noise in the relative growth rates of aphids and brown rust usually contributes significantly more to model output variance than other white noise components or future temperature. This is illustrated for an initial

**TABLE 4**

Expected Reduction of Variance of Financial Loss (Dfl² ha⁻²) When Uncertainty About Model Parameters and the Estimated Initial State is removed, for Three Decision Strategies (NS, S1 and S2) at Initial State $T_0$ = 225°d (Temperature Sum); $I_{0,A}$ = 0·30 (Initial Aphid Incidence) and $I_{0,B}$ = 0·02 (Initial Brown Rust Incidence).

| *Source of uncertainty removed* | *Strategy* | | |
|---|---|---|---|
| | *NS* | *S1* | *S2* |
| APHIDS | | | |
| Model parameters and estimate of initial state | 10 800 | 245 | 420 |
| Model parameters: | | | |
| Incidence–density transformation | 300b | 0a | 0b |
| Damage relation | 300b | 0a | 0b |
| Maximum damage | 0b | 0a | 80b |
| Temperature sum–crop development stage relation | 1 000b | 0a | 0b |
| Relative growth rate | 4 900a | 91a | 300a |
| Direct aphicidal effect | 0b | 27a | 230b |
| Effective aphicidal period | 0b | 0a | 130b |
| Estimate of initial state | 0b | 0a | 140b |
| BROWN RUST | | | |
| Model parameters and estimate of initial state | 7 100 | 0 | 170 |
| Model parameters: | | | |
| Incidence–density transformation | 2 300b | 30b | 0a |
| Damage relation | 900b | 0b | 30a |
| Maximum damage | 500b | 0b | 50a |
| Temperature sum–crop development stage relation | 0b | 0b | 80a |
| Relative growth rate | — | — | — |
| Direct aphicidal effect | — | — | — |
| Effective aphicidal period | — | 190b | 80a |
| Estimate of initial state | 800ab | 420a | 90a |

[1] Uncertainty about the mean relative growth rate is disregarded (*see* Rossing *et al.*, 1994*b*).
[2] Direct fungicidal effect absent.
[3] Attainable yield is 8000 kg ha⁻¹. Different letters following estimates indicate significant differences within strategies ($P < 0{\cdot}05$).

temperature sum of 225°d (equivalent to average crop development stage DC 61), and initial aphid and brown rust incidences of 30% and 2%, respectively (Table 3).

The consequences of removing the uncertainty about the sources of controllable uncertainty are illustrated for the same initial state (Table 4). For aphids, perfect knowledge of the parameters describing the relative population growth rate results in the greatest decrease of expected model output variance for the strategies NS and S2. For brown rust, the initial incidence estimate is the most important source of controllable uncertainty when fungicide is applied immediately (S1). However, the decreases of model output variance expected when the various components of controllable uncertainty were fully known, are small.

## DISCUSSION

The contribution of uncontrollable variation to uncertainty about financial loss was generally more important than the contribution of controllable variation. Among the components of uncontrollable variation, white noise in the relative growth rates of aphids and brown rust appeared more important than other sources of white noise, or future temperature. The minor importance of uncertainty about future average daily temperature is not surprising as in the decision model only temperature integrated over time is considered. Such integration results in 'smoothing' of day-to-day temperature fluctuations.

The results of the analysis indicate that, given the structure of the model, efforts to further refine estimates of parameters and initial incidences are not expected to reduce greatly output uncertainty (Table 2). Apparently the research effort put into the development and maintenance of EPIPRE (Zadoks, 1984; Drenth *et al.*, 1989; Daamen, 1991) has yielded sufficiently precise parameter estimates. The uncertainty about financial loss due to the sample estimate of initial brown rust incidence is commensurate with the uncertainty due to the parameter estimates (Table 4). Thus, the sample size for brown rust recommended in EPIPRE appears adequate. For aphids, however, the uncertainty about financial loss due to the sample estimate of initial incidence is substantially smaller than the uncertainty due to the relative growth rate estimate, the largest source of variation (Table 4). Therefore, the recommended sample size for aphids may be decreased without greatly increasing the uncertainty in model predictions.

As white noise in the relative growth rates of aphids and brown rust was of major importance, a significant improvement of the decision model will involve a review of the concepts of population growth. More detailed models, such as the one by Entwistle & Dixon (1986) which takes into account the field-to-field variation in aphid population growth rate, may be needed to reduce the effect of white noise in the decision model.

The coefficient of variation of the estimates of model output variance varied greatly with decision strategy. At $M$ = 2000 cycles the coefficient of variation of the variance estimates was 5–10% for NS while for S1 and S2 values of 25–40% occurred, which necessitated 32 000 cycles to attain the desired precision. Since the computational effort grows quadratically with required precision, computer speed becomes a limiting factor to attain more precise estimates. The reason for the large variance of the estimates for the strategies S1 and S2 is the skewness of the distributions of financial loss (see Rossing *et al.*, 1994*b*).

The structure of the decision model and the various estimates have been assumed valid. As the decision model constitutes an upgraded version of analogous modules in the EPIPRE advisory system which was tested extensively (Reinink, 1986; Drenth *et al.*, 1989), this seems a valid assumption.

The uncertainty analysis has identified the sources of uncertainty of major importance for uncertainty in predicted financial loss associated with a particular decision strategy. The results may be used to set research priorities, and to support pest and disease management. In combination with estimates of the likely gains in knowledge on model components resulting from different research efforts, the results can be used to allocate resources for efficiently reducing uncertainty about model output. When used for decision support in a farm management context, some degree of uncertainty in the model has to be accepted. The consequences of this uncertainty for decision making in supervised control of aphids and brown rust are addressed in a following contribution (Rossing *et al.*, 1994*a*).

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