Predictability and Nonlinear Modelling in Natural Sciences and Economics

edited by

J. Grasman

Department of Mathematics,
Agricultural University,
Wageningen, The Netherlands

and

G. van Straten

Department of Agricultural Engineering and Physics,
Agricultural University,
Wageningen, The Netherlands

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UNCERTAINTY OF PREDICTIONS IN SUPERVISED PEST CONTROL IN WINTER WHEAT: ITS PRICE AND CAUSES

WALTER A.H. ROSSING[1], RICHARD A. DAAMEN[2],
ELIGIUS M.T. HENDRIX[3] & MICHIEL J.W. JANSEN[4,5]

[1] Wageningen Agricultural University, Dept. Theoretical Production Ecology, P.O. Box 430, 6700 AK Wageningen, The Netherlands; [2] Research Institute for Plant Protection; [3] WAU, Dept. Mathematics; [4] DLO-Agricultural Mathematics Group; [5] DLO-Centre for Agrobiological Research.

e-mail: rossing@rcl.wau.nl

Summary

In supervised control, the economically optimal timing of pesticide application is equivalent with the level of pest attack where projected costs of immediate control just equal projected costs of no control. This level is called the damage threshold. Uncertainty about the costs of different strategies of chemical control of aphids (especially *Sitobion avenae*) and brown rust (*Puccinia recondita*) is calculated with a deterministic model. Sources of uncertainty, which comprise estimates of initial state and parameters, future weather, and white noise, are modelled as random inputs. Consequences of uncertainty for damage thresholds are analyzed. The relative importance of various sources of uncertainty for prediction uncertainty is calculated using a novel procedure.

Stochastic damage thresholds are lower than those calculated using average values for sources of uncertainty. Thus, uncertainty causes earlier chemical control of pests and higher input of pesticides. Due to the strongly skewed frequency distribution of costs of no control, the probability of positive return on pesticide expenditure at the stochastic damage thresholds is only 30%. White noise in the relative growth rates of both aphids and brown rust is found to be the most important source of uncertainty. More accurate estimation of parameters and initial estimates in the current model results in marginal reduction of prediction uncertainty only. Reduction of prediction uncertainty and concomitant reduction of recommended pesticide use requires reduction of the uncertainty associated with no chemical control by adopting a different approach to prediction of the population dynamics of aphids and brown rust.

Keywords Uncertainty analysis, Monte Carlo methods, non-linear systems, crop protection

1. Introduction

An important objective of pesticide application is insurance against major crop losses which occur with low probability (Norton & Mumford, 1983; Tait, 1987; Pannell, 1991). In many pathosystems pesticides are very effective in decreasing densities of growth reducing organisms. Although crop loss may occur even at low densities, the extent of loss as well as the variation in loss is usually smaller than at high pest densities. A second, potentially conflicting objective of pesticide application is maximization of (expected) return on expenditure (Norton & Mumford, 1983; Rossing *et al.*, 1993a). Extreme emphasis on insurance occurs when spraying is carried out at regular time intervals without reference to the presence of or damage by the pest. Examples of such prophylactic control strategies are found in control of late blight (*Phytophthora infestans*) in potato and fire blight (*Botrytis* spp.) in various flowerbulb species in the Netherlands.

Supervised control represents a concept of pest management in which maximization of returns on expenditure is emphasized. The level of pest attack at which the projected costs of chemical control just equal the projected costs of no control is called the damage threshold and represents the optimal time of pesticide application. Costs of decision alternatives are usually predicted with mathematical models. Recommended action is passed to farmers in decision support systems.

In this paper the importance of uncertainty for supervised control of aphids (especially *Sitobion avenae*) and brown rust (*Puccinia recondita*) in winter wheat in the Netherlands is investigated. Two questions are addressed. Firstly, to what extent do the damage thresholds for aphids and brown rust change when uncertainty about various components in the mathematical models is taken into account, or, what is the price of uncertainty. Secondly, which sources of uncertainty contribute most to uncertainty about costs associated with a control decision and how can uncertainty about the costs be reduced most effectively.

2. Research approach

2.1 Decision model

A deterministic simulation model is used to predict costs of spray strategies at given initial temperature sum and initial levels of pest attack in a winter wheat field in the Netherlands. A spray strategy consists of a time series of decisions on chemical control of aphids, brown rust or both with fixed time interval of one week. Costs of a strategy comprise the monetary equivalent of yield loss due to pest attack plus the costs of eventual chemical control.

The model consists of submodels describing crop development, population dynamics and damage per unit of pest density. Relations in the model are based on empirical data collected during several years and experiments. Crop development is calculated as a function of temperature sum above a developmental threshold of 6 °C, accumulated from crop development stage pseudo-stem elongation (DC 30, Zadoks *et al.*, 1974).

The submodel on population dynamics is initialized with field observations on aphids and brown rust incidences, i.e. percentage of sample units containing the pest. In the submodel incidence is transformed into density, which is assumed to increase exponentially with time. The relative growth rate of the aphid population is a function of crop development stage. For brown rust the relative growth rate is constant. Aphid-specific pesticides reduce the population to 85% of its pre-spray density and arrest population increase for 12 days after application. In contrast, brown rust specific pesticides do not affect the population present and arrest population increase during 18 days. Damage per pest-unit decreases with crop development stage for aphids and is constant throughout the season for brown rust. A maximum level of damage is imposed for both pests. A schematic representation of the model is shown in Fig. 1. Details are given in Rossing *et al.* (1993b).

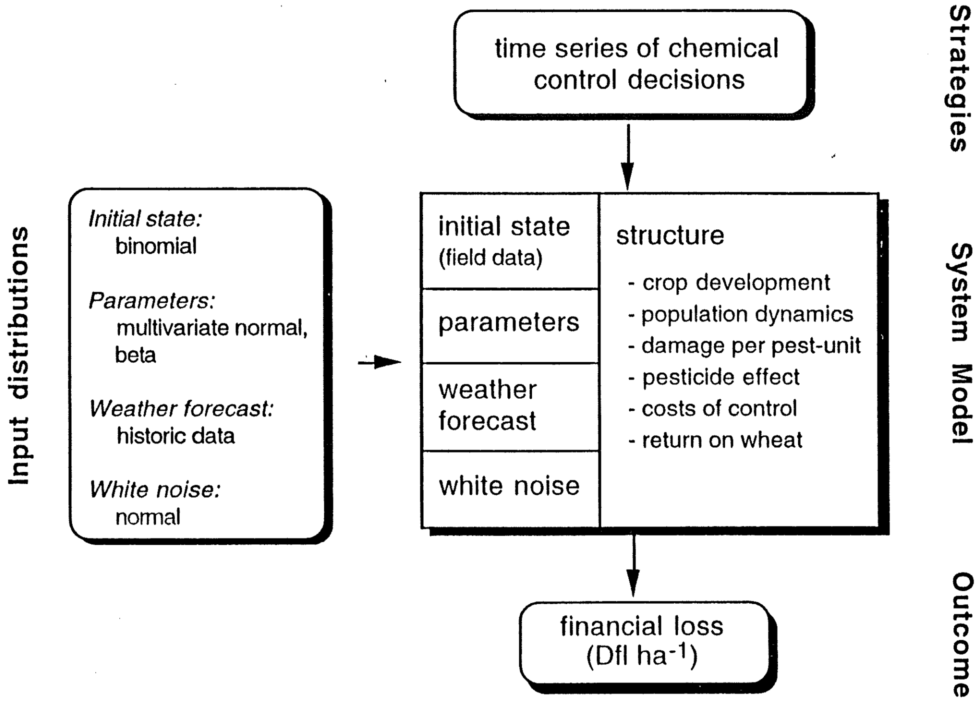

Figure 1. Schematic outline of the decision model.

Uncertainty is modelled as random inputs into the model. Four categories of uncertainty are distinguished (Table 1). Parameters were estimated using field data and regression, the variance-covariance matrix providing a measure of uncertainty. Residual variance was ascribed to measurement effects and was disregarded for prediction. In some data sets the measurement variance could be quantified. In those cases the surplus residual variance was ascribed to natural variability and was included in the model as mutually independent, identically distributed normal variates. This source of uncertainty will be called white noise. Uncertainty about initial incidences of aphids and brown rust was modelled as binomial distributions with parameters depending on the incidence estimates and the sample sizes. Uncertainty about future average daily temperature was described by 36 years of daily minimum and maximum temperature measured in Wageningen between 1954 and 1990.

The categories parameters and estimates of the initial state represent sources of *controllable uncertainty*, since uncertainty may be reduced by collecting additional data. Uncertainty about future average daily temperature and white noise represents *uncontrollable uncertainty*, at least for a given structure of the model.

Table 1. Sources of uncertainty in the decision model.

Category	Component	Distribution
Estimates of initial state	· incidence · temperature sum	binomial _a
Parameters	various	(multivariate) normal, beta
Gaussian white noise	· relative growth rate · incidence-density transformation · temperature sum - crop development stage transformation	normal normal normal
Future average daily temperature	-	historic data (36 years)

[a] Temperature sum is assumed to be known with negligible uncertainty.

2.2 Partitioning of model output uncertainty

The contribution of various sources of uncertainty in the model to uncertainty about costs of a spray strategy is calculated using the procedure described by Jansen *et al.* (1993). Uncertainty about model output is characterized by its variance. Sources of uncertainty are combined in Q groups which are mutually independent. In successive Monte Carlo runs new realizations of independent groups of variates are drawn by simple random sampling from the appropriate distributions, processing one group per run. After Q runs the values of all groups have been changed once, and the first cycle is completed. In total M cycles are made. Differences in model output between consecutive runs are caused by the uncertainty about one group of variates, while differences between runs i and $i+Q-1$ are due to uncertainty about all groups except one. This procedure which was termed *winding stairs sampling*, allows estimation of the full variance of mode output using the independent model outputs Q runs apart. The contribution of a group of sources of uncertainty is estimated as either its top variance, the reduction in total variance resulting from removal of uncertainty about the group, or its bottom variance, the variance remaining when uncertainty about all other groups is removed. Calculation of top variance is useful for groups of variates containing controllable uncertainty, *i.e.* parameters and estimates of the initial state. The top variance represents the maximum improvement of prediction accuracy possible for the given model structure. For sources of uncontrollable uncertainty the bottom variance is a more useful measure of uncertainty. It represents the minimum model accuracy that has to be accepted.

3. Results and discussion

3.1 The price of uncertainty

The damage thresholds for aphids and brown rust in Fig. 2 which are calculated using the

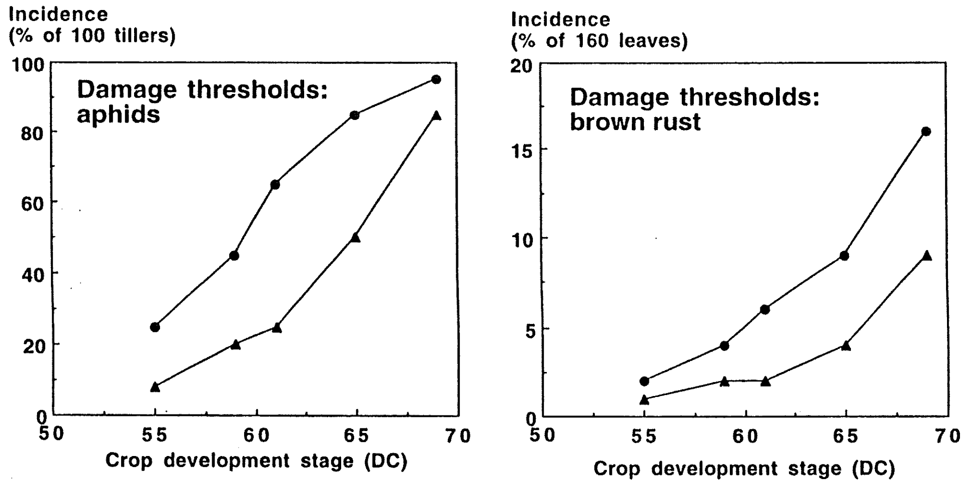

Figure 2. Damage thresholds for aphids (A) and brown rust (B) according the deterministic version of the decision model (— • —) and the stochastic version, run with $M = 500$ (— —).

decision model with random inputs are referred to as stochastic damage thresholds. Also shown are deterministic damage thresholds calculated with
average values of inputs. The stochastic damage thresholds are consistently lower than the deterministic thresholds, reflecting the convexity of the decision model.

The size of the difference between deterministic and stochastic damage thresholds is a measure for the price that has to be paid for uncertainty. Due to uncertainty pesticides are applied at lower pest incidences, leading to on average higher expenditure on pesticide input and a larger burden for the environment than would be economical with perfect information.

In Fig. 3 frequency distributions of costs associated with no chemical control at any time (NC) and immediate chemical control (IC) are shown for a single stochastic damage threshold. Potential costs associated with NC range between almost 0 Dfl ha^{-1} and 1200 Dfl ha^{-1}, with a 90%-percentile of 796 Dfl ha^{-1} (Fig. 3a). The distribution is strongly skewed to the right. In contrast, the 90%-percentile for IC is 214 Dfl ha^{-1} (Fig. 3b). The lower cost threshold of 185 Dfl ha^{-1} is due to the fixed costs of a control operation.

By definition the expected value of the difference in costs between NC and IC (Fig. 4) equals zero, since the initial state represents a stochastic damage threshold. Counter-intuitively, the probability that costs of IC are less than costs of NC is 30%, rather than the intuitive 50%. In other words, although on average immediate chemical control is an economically rational decision at initial incidences equal to or higher than the stochastic damage threshold, the majority of pesticide applications at stochastic damage thresholds are ineffective. The low probability of economic success is caused by the strong skewness of the distribution of costs of no control. This result holds for all stochastic damage thresholds, with little variation in the probability of positive return on expenditure

(Rossing *et al.*, 1993a) and warrants analysis of the causes of uncertainty about costs of NC.

3.2 Causes of uncertainty about costs of no control

In Table 2 the contribution of the various categories of uncertainty to uncertainty about predicted costs of no control of aphids and brown rust is shown for one stochastic damage threshold. Results at other damage thresholds are comparable (Rossing *et al.*, 1993c). The analysis was carried out in several steps, in each step disaggregating the sources of uncertainty. In the first step only controllable and uncontrollable sources of uncertainty are distinguished. Both for aphids and brown rust uncontrollable uncertainty was found to contribute most to total prediction

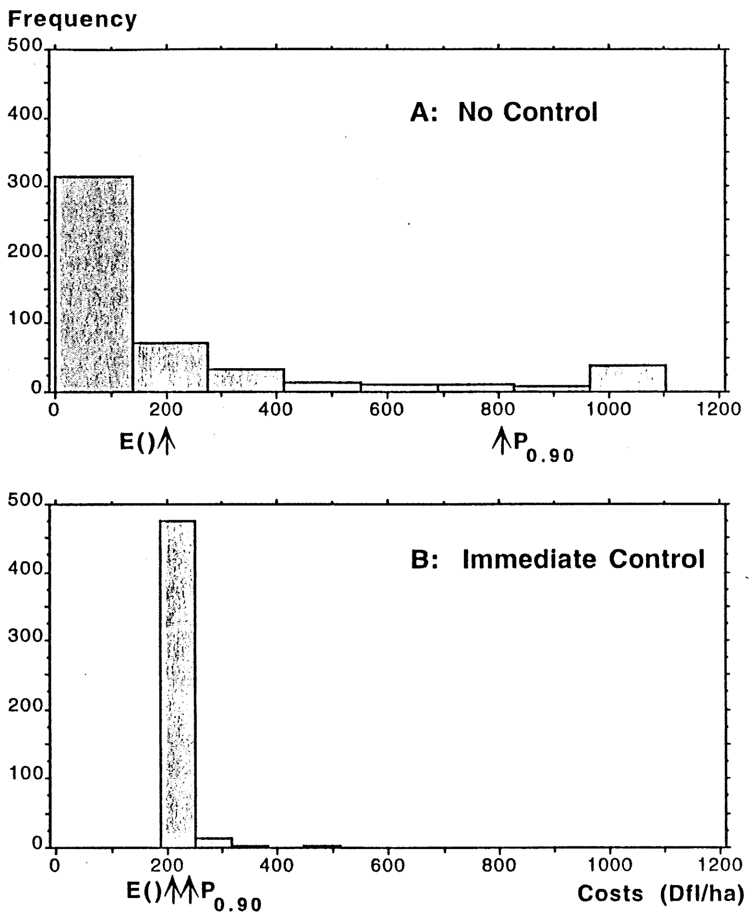

Figure 3. Frequency distributions of costs of no chemical control (A) and immediate chemical control of aphids and brown rust jointly (B) in 500 Monte Carlo runs. Initial state of the system: temperature sum 200 days, equivalent with DC±4 (se), aphid incidence 5% of 100 tillers, brown rust incidence 2% of 160 leaves. Arrows indicate the 0.90-quantile ($P_{0.90}$) or the expected value (E()) of costs.

uncertainty. Further analysis shows that among the sources of uncontrollable uncertainty white noise is far more important than predicted temperature. White noise in the relative growth rates of the pests represents the major source of

Table 2. Expected contribution to model output variance of various sources of uncertainty, as percentage of the variance of the full model, aphids and brown rust separately. Initial states: 25% aphids, 8% brown rust, crop 225 °day. No chemical control at any time.

Source of uncertainty	Contribution (%)	
	aphids	brown rust
Parameter & initial incidence estimate	26[t]	12[t]
White noise in relative growth rate	57[t]	68[t]
White noise in crop development	2[b]	6[b]
White noise in initial density	13[b]	22[b]
Future temperature	12[b]	30[b]

[t] estimate based on top variance
[b] estimate based on bottom variance

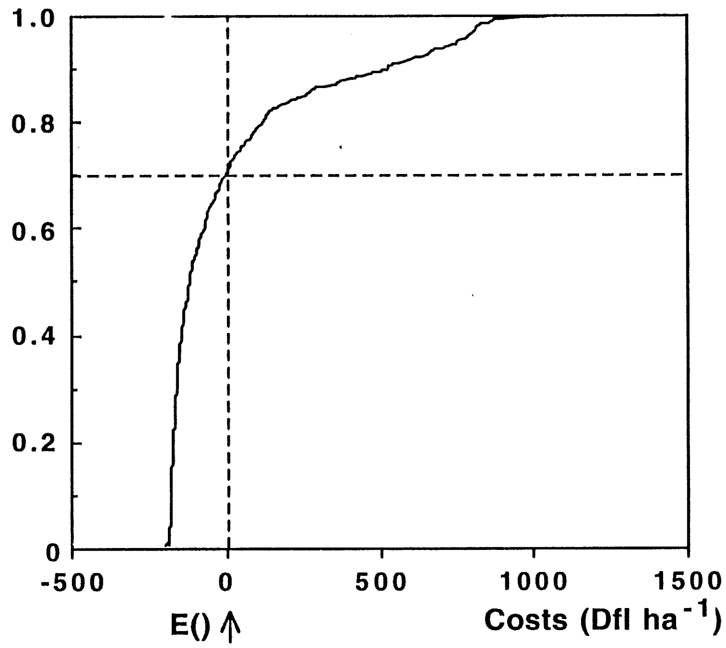

Figure 4. Cumulative relative frequency distribution of the difference of costs of no control and immediate chemical control (NC minus IC) in 500 Monte Carlo runs. For initial state of the system, see caption to Figure 3. The arrow indicates the expected value (E()) of the difference (NC minus IC).

uncertainty (Table 2). Thus, reduction of uncertainty about predicted costs of NC calls for alternative submodels describing pest population dynamics, rather than better determination of parameters and initial conditions.

3.3 Conclusions

This paper focussed on identification and quantification of sources of uncertainty and evaluation of the consequences for prediction uncertainty in pest control. The results of the analysis show that disregarding uncertainty will lead to wrong recommendations to farmers. The possibilities for improving the prediction within the constraints of the current structure of the model are nearly exhausted. Further improvement will require new concepts to be included into the model, especially concerning prediction of population dynamics. Major improvements may be expected when field-specific factors affecting relative growth rates will be taken into account, such as age distribution of the brown rust population and mortality by predators and parasites in the aphid population.

For the purpose of decision support the uncertainty in the model predictions has to be accepted. Rather than ignoring uncertainty or arbitrarily adjusting deterministic results as is done currently in many decision support systems, measures should be designed to assess the degree to which the objectives of pest control, return on expenditure and insurance, are satisfied by various decision strategies. We have proposed such framework for supporting pest control decisions under uncertainty elsewhere (Rossing *et al.*, 1993a).

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