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A decision model for chemical control of aphids in winter wheat with quantification of risk.

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ABSTRACT

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Application of pesticides reduces expected yield loss as well as variation in yield loss due to aphids in winter wheat. However, chemical treatment imposes a burden on farm budget and farm environment. Thus optimization of number and timing of applications is called for. In this study a stochastic programming model is presented which optimises number and timing of chemical treatments of aphids with respect to an economic objective and a risk objective. Loss associated with chemical treatment at different points in time is calculated with simple models based on field experience and laboratory work. Variation in loss is calculated by introducing temperature as a random variable. Results show that the resulting strategies using the risk objective in most cases do not differ from those calculated with the economic objective.

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1. INTRODUCTION

Modern agriculture relies on the input of chemicals to protect crops from excessive losses by insect pests and fungal diseases. Decision strategies of farmers range from prophylactic application of pesticides, so called calendar spraying, to selective treatment of organisms after population numbers have exceeded a threshold value. The latter strategy, called supervised pest control, requires knowledge of the way yield loss is caused by the pest or disease in order to determine the threshold value.

If a farmer sprays prophylactically, he excludes any uncertainty. A farmer who uses field information in his decision accepts uncertainty. This uncertainty can be ascribed to three sources: the accuracy of his (mind-)model on how crop and pests interact, his estimation of the present state of the crop, and the future progress of weather-related variables, such as temperature and rainfall.

Dutch research has contributed to the knowledge on interactions between crop and pests. Mathematical models of crop growth and development, dynamics of pests and diseases, and interactions of harmful organisms with the crop are suitable tools for integration of information (De Wit _et al_., 1978; Zadoks, 1979; Rabbinge _et al_., 1983).

In this paper it is assumed that these models accurately describe the crop-pest system. As sources of uncertainty remain the error in input variables and the future progress of weather-related variables. A decision model is presented which takes account of uncertainty in future values of temperature. The model is to be regarded as preliminary and it will be refined in the future. The ultimate aim of the exercise is to identify sources of variation that greatly contribute to uncertainty in the outcome of a spraying decision, thus indicating gaps in our knowledge as well as showing the flexibility of the modelled system.

In the section to follow, a decision problem is described in terms of five components. These components are then used to develop a decision support system for chemical control of aphids in winter wheat.

2. DESCRIPTION OF A DECISION PROBLEM

Dannenbring and Starr (1981) distinguish five components in any decision problem:

1. the objective that has to be met. The aim of intervention in the crop-pest system may for example be maximisation of yield in monetary or volumetric units, minimisation of energy input or maximisation of net returns.
2. the decision alternatives which describe the ways in which a decision maker can intervene in the system. E.g. buy or sell an item at a specific date, spray or do not spray.
3. uncontrollable events. The decision is affected by events which are beyond the control of the decision maker. These may also be called random variables. Examples are price of grain, price of pesticides and fertilizer, realization of weather-related variables.
4. outcome. Combination of the initial state of the system, a decision alternative and an uncontrollable event results in an outcome. In the case of A decision alternatives and B uncontrollable events the outcomes can be represented by a AxB matrix.
5. decision criterion. This is defined as a logical or rational method selecting the decision alternative that best meets the objective. In order to be able to select among the decision alternatives, the decision criterion must be capable of transforming the outcome in such a way that it is comparable to the objective.

The choice of the decision criterion is influenced by the knowledge available on the uncontrollable event that will happen in the future.

3. DECISION MODEL FOR CEREAL APHID CONTROL IN WINTER WHEAT

3.1 Biological aspects

In Dutch wheat fields, aphids appear some time in June when the crop is flowering. They come from other grass species or from roses. The aphids insert their mouthparts into the plant and withdraw assimilates from them. This causes a reduction in grain yield. Another cause of yield-reduction is honeydew, a solution containing mainly sugars, excreted by the aphids. Deposited on a leaf it interferes with the photosynthesis. Also it seems to accelerate senescence of the leaf.

Aphid numbers increase rapidly, the rate depending on temperature and development stage of the crop. At later development stages the quality of the crop as a source of food declines, resulting in less off-spring per aphid and emigration of winged individuals. Aphid populations are affected by fungi and other insects . Their effect is pronounced later in the season as their population build-up lags behind the aphids'. The injurious presence of aphids in winter wheat covers a period of seven weeks.

3.2 Description of the decision problem

3.2.1 Objective

With regard to objectives for pest control Norton and Mumford (1983) distinguish two types of farmers: investors and insurers. Investment implies that the expected costs of crop protection should not exceed the expected benefits. Insurance can not be evaluated by such an objective criterion: only the farmer can say how much he is willing to spend in order not to have nightmares of devastating aphid outbreaks. This distinction suggests that an optimal policy for investment is fundamentally different from one for insurance.

In this study random factors are incorporated in an investment objective. The decision objective is:

a. the timing of aphicide application has to be such that the expected total loss is minimal over the time-interval $[1,T]$ where T stands for the length of the planning horizon in days, and
b. the probability of total loss exceeding a maximum level, does not exceed a maximum probability.

Total loss is composed of damage by aphids and costs of chemical treatment.

The objective indicates that information is needed on the probability distribution of total loss.

3.2.2 Decision alternatives

The decision alternatives considered here are to treat and not to treat. A decision can be made once a day during the time interval $[1,T]$, representing the growing season. If a farmer treats, an instantaneous death of 90% of the aphid population is assumed. The cost of treatment is 100 Dfl/ha. If no treatment is carried out, no treatment costs are incurred and the population is not affected.

Some simplifying assumptions are introduced: 1. aphids do not appear before flowering, 2. farmers decide on treatment only once a week, and 3. if a decision to treat is made, the application is carried out on the first day of a decision stage, which is defined as the length of time between two decisions. Assumption 1 represents the common situation in the Netherlands, assumption 2 may eventually be changed.

The effect of a decision alternative can be defined more formally. Let $M_1(.)$ be the function describing the management result in terms of percentage kill, $M_2(.)$ the function doing the same in terms of monetary units and C_n a variable expressing the management action at the beginning of decision stage n (n=1,2,...,N with N the number of decision stages) with

$C_n = 0$:= no treatment

$C_n = 1$:= treatment

then $M_1(C_n)$ and $M_2(C_n)$ describe the effect of the decision alternatives in percentage kill of the target organism and in Dfl/ha respectively.

3.2.3 Uncontrollable events

Temperature, treated as the daily average of hourly observations, was introduced into the model as an uncontrollable factor. It affects the relative growth rate of the aphid population in an indirect manner, by way of crop development stage.

Temperature is modelled as a variate obeying a first order Markov process with normally distributed disturbance:

(1) $$\underline{T}_t - E(\underline{T}_t) = \rho_t(\underline{T}_{t-1} - E(\underline{T}_{t-1})) + \underline{e}_t$$

where t := daynumber, with t=1 on the first day of the planning horizon. t=1,2,...,R where R is the last day of the planning period.

$\underline{T}_t$:= temperature on day t

ρ_t := autocorrelation coefficient for temperature on day t-1 and day t

$\underline{e}_t$:= normally distributed random variable

$E(.)$:= expectation operator

The expected temperatures are subtracted to enable calculation of the distribution parameters of $\underline{e}_t$:

$$(2) \quad \begin{aligned} E(\underline{e}_t) &= 0 \\ \sigma^2(\underline{e}_t) &= \sigma^2(\underline{T}_t) - \rho^2{}_t\, \sigma^2(\underline{T}_{t-1}) \end{aligned}$$

The variance of $\underline{T}_t$ and ρ_t was calculated from historic data (30 and 15 years respectively) supplied by the KNMI (Royal Dutch Meteorological Institute).

3.2.4 Outcome

The outcome of the decision process is expressed as loss in Dfl/ha. It consists of the costs of the decision alternative and the loss due to yield reduction by aphids.

At the beginning of decision stage n two types of loss have to be calculated: loss already accumulated in the past (P_n) and loss that may accumulate in the future ($\underline{F}_n$). F is underlined to indicate its stochastic character, which is due to the uncontrollable factor temperature. P_n is deterministic as temperature in the past is known. Added, P_n and $\underline{F}_n$ constitute $\underline{L}_n$, total loss at the beginning of decision stage n:

$$(3) \qquad \underline{L}_n = P_n + \underline{F}_n$$

Two indices are used to designate time, t and n. The index t describes the number of days elapsed since the start of the planning horizon. The index n describes the number of decision stages, with n=1 at the start of the planning horizon.The length of a decision stage in days is represented by the variable g.

The two types of losses were calculated by means of an adapted version of the aphid model used in the Dutch advisory system EPIPRE (Rabbinge and Rijsdijk, 1983; Zadoks, 1984). The model consists of three elements:

- the state vector $X_n(A,D,P)$ defines the state of the system at the beginning of decision stage n and is made up of 3 state variables: the number of aphids A, the development stage of the crop D and the total loss incurred during the preceding n-1 decision stages, P. Indexing of these variables was omitted for reasons of typographical clarity.

- the vector of decisions at the start of decision stage n, C_n, is one-dimensional and consists of the control action $C_n=0$ ('do not treat') or $C_n=1$ ('treat').

- the transformation function $\underline{Z}_n(X_{n-1},C_n)$ describes the development of the system from state X_{n-1} and decision C_n to state $\underline{X}_n$ during decision stage n: $\underline{X}_n = \underline{Z}_n(X_{n-1},C_n)$

The transformation function consists of models describing three processes: crop development, aphid population dynamics and accumulation of loss.

3.2.4.1 crop development

D_t, the crop development at the start of day t, is described by a temperature sum equation. This was calculated from the literature by Van Keulen (pers. comm.):

$$(4) \quad \underline{D}_t = \min\left(\sum_{\tau=1}^{t} (0.0011\, \underline{T}_{\tau-1} + 0.0002),\ 1 \right)$$

and $D_0 = 0$

$\underline{D}_t$ (dimension: day degree) is a random variable as temperature $\underline{T}_t$ is assumed to be stochastic. $\underline{D}_t$ is initialised as 0 at flowering of the crop. The maximum value of $\underline{D}_t$ is 1, which is reached when the crop is ripe.

3.2.4.2 aphid population dynamics

The number of aphids in the population increases exponentially with time.

$$(5) \qquad \frac{\Delta A}{\Delta t} = R(\underline{D}_t)\ \underline{A}$$

where $\underline{A}$:=aphid density (number/tiller)

$R(\underline{D}_t)$:=relative growth rate, dependent on development stage D_t (day^{-1})

t :=time from onset of flowering (day)

The relative growth rate $R(\underline{D}_t)$ is a function of development stage on day t, $\underline{D}_t$:

(6) $$R(\underline{D}_t) = 0.15\ \underline{D}_t + 0.11$$

This describes the observation that population numbers initially increase exponentially. The number of aphids per tiller is found by integrating the rate equation (5):

(7a) $$\underline{A}_t = A_0 \exp\left(\sum_{\tau=1}^{t} R(\underline{D}_\tau) \right)$$

where $\underline{A}_t$ stands for aphid density at the start of day t. A_0 represents the observed number of aphids on t=0.

To account for the carrying capacity of a tiller, an upper limit of 80 aphids per tiller is introduced:

(7b) $$\underline{A}_t = \min\left(A_0 \exp\left(\sum_{\tau=1}^{t} R(\underline{D}_\tau) \right), 80 \right)$$

Equation 7b describes the population increase if no treatment is carried out.

3.2.4.3 accumulation of loss

Here damage is defined as grain yield reduction in volumetric units (kg/ha) and loss as damage expressed in monetary units (Dfl/ha). First damage is calculated. The rate of accumulation of damage is a function of aphid density and development stage:

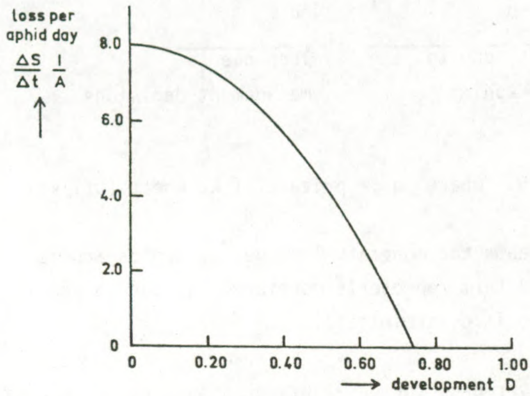
(8) $$\frac{\Delta S}{\Delta t} = \left(\underline{A}_t \left(8.0 - 14.3\ \underline{D}_t^2 \right) \right)^+$$

where S:= damage (kg/ha/day) and max(0,x) is indicated by x^+.

As the model is solved with time-steps of one day, $\Delta t=1$ and $\Delta S=\underline{S}_t-\underline{S}_{t-1}$.

The structure of this relation is based on two facts of experience:

Figure 1. Empirical relation between crop development D_t and daily increase in loss per aphid.



1. aphids present during or soon after flowering (D_t=0) cause the higher damage;
2. aphids present after D_t=0.75 do not cause any damage.

Parameters of the parabola (figure 1) were estimated from experimental work (Rabbinge and Coster, 1984).

Total damage per decision stage is calculated by substituting relations 7b in equation 8 and integrating the result over the days in the decision period. This is described in relation 9.

$$(9)\quad \underline{S}_n = \sum_{t=b(n)}^{l(n)} \left(\frac{\Delta S}{\Delta t}\right)$$

$$= \sum_{\tau=b(n)}^{l(n)} \underbrace{(\min(\ A_0 \exp(\ \sum_{\tau=1}^{t}\ R(\underline{D}_\tau),\ 80))}_{\text{number of aphids}}\underbrace{(\ 8.0\ -\ 14.3\ \underline{D}_t^2\ ))^+}_{\text{damage per aphid}}$$

where
- S_n := loss by aphids incurred in decision stage n (kg/ha)
- A_0 := density of aphids on t=0 (aphids/tiller)
- b(n) := first day of decision stage n (g(n-1))
- l(n) := last day of decision stage n (gn - 1)

This model is used to calculate future loss $\underline{F}_n$ (cf. equation 3) at the start of decision stage n.

$$(10) \qquad \underline{F}_n = \underbrace{q \sum_{i=n}^{N} M_1(C_i)\, \underline{S}_i}_{\text{loss due to aphids}} + \underbrace{\sum_{i=n}^{N} M_2(C_i)}_{\text{loss due to management decisions}}$$

and $q = 0.5$ where $q :=$ price of 1 kg wheat (Dfl/kg).

The first term represents the monetary loss due to aphids and is stochastic, the second term represents monetary loss due to application of a chemical and is deterministic.

Losses already incurred at the onset of decision stage n, P_n (cf. equation 3), are calculated from the number of aphids and the crop development at the start of each of the previous decision stages. The number of aphids and the development stage of the crop between two observations are found by interpolation. For aphid numbers an exponential interpolation is used, for crop development stage a linear interpolation.

$$(11) \qquad P_n = q \sum_{i=1}^{n-1} M_1(C_i)\, S_i{}' + \sum_{i=1}^{n-1} M_2(C_i)$$

where the prime indicates the different method of calculation of A and D, compared to equation 10.

Total loss at the start of decision stage n, $\underline{L}_n$, can now be calculated by adding past and future losses P_n and $\underline{F}_n$:

$$(12) \qquad \underline{L}_n = P_n + \underline{F}_n \quad , \quad 1 \leq n \leq N$$

3.2.5 Decision criterion

The decision criterion constitutes a means of choosing the decision series that best meets the objective. The objective, described in section 3.2.1, can be formalised as:

Solve for every j=1,2,...,N the following problem:

(13) $\min E(\underline{L}_j)$

(14) $\underline{L}_j = P_j + \underline{F}_j$

(15) $P(\underline{L}_j \geq L_{max}) \leq \alpha$

(16) $C_j \in \{0,1\}$

where L_{max} and α are parameters which should be specified by the decision maker.

Note that (13) and (14) represents the investment criterion, (15) the risk constraint and (16) the decision alternatives.

As usual in chance constraint optimization first the set of feasible solutions is determined by applying the chance constraint and next the objective function is minimised.

3.3 Solution heuristic

No attempt was made to solve the optimization problem analytically as the transformation function consists of oversimplified relations, which can be replaced later on by more realistic models. Instead the probability distribution of $\underline{L}_j$ was simulated in a Monte Carlo approach. This type of mathematical simulation is not to be confused with dynamic simulation methods (e.g. De Wit and Goudriaan, 1978). In a Monte Carlo approach the input distribution is sampled, the sample is fed through the model and the resulting output is considered to be a sample of the output distribution. The output sample may be analyzed with standard statistical methods. In dynamic simulation system behaviour at a certain level of integration is explained by descriptive models of elements and their interaction at a lower level.

Here the aim of Monte Carlo simulation is estimation of the critical level probability $P(\underline{L}_j \geq L_{max})$. A crude Monte Carlo method (Hammersley and Handscombe, 1964) was used which involves generating pseudo-random numbers from the distribution of temperature characterised by equations 1 and 2, for every $t \in [1,T]$. Given the state of the system at the onset of decision stage 1 and a series of decisions $C_1, C_2, \ldots, C_N$, the progress of crop development, number of aphids and loss was calculated using the relations described in the previous section. This was repeated a total of 300 times, yielding as many values for total loss $\underline{L}_j$. The sample size was considered sufficient as averages and variances did not vary more than 5% when sampling was repeated. The fraction of values greater than or equal to L_{max} was calculated, which is an unbiased estimator of the critical level probability $P(\underline{L}_j \geq L_{max})$.

The procedure was repeated with different series of decisions $C_1, C_2, \ldots, C_N$. In the reruns, initial status of the crop and progress of temperature were identical to those of the initial run. Thus maximum resolution with respect to effect of different control strategies was obtained.

For j=1, there are 2^N possible decision series containing 0,1,...,N spraying decisions. The computational effort was limited to $\binom{N}{0}+\binom{N}{1}+\binom{N}{2}+\binom{N}{3}+\binom{N}{4}$ as more than 4 treatments against cereal aphids never occur in the Netherlands.

In this way, decision series satisfying the chance constraint were identified. From these the optimal series was selected by calculating the objective function equation 13. Theoretically two or more series might yield the same minimal value for $E(\underline{L}_j)$. If a unique solution is wanted, constraints not part of this model have to be introduced.

The decision problem is solved with rolling planning horizon, i.e. the optimal series for j=1 is calculated and the first decision is implemented. At the beginning of the next decision stage (j=2) the optimal decision series for the remaining N-1 decision stages is identified, given the new status of the system. Again, only the first decision is implemented, etcetera. Thus, risk associated with a decision diminishes as more information becomes available.

3.4 Results

The optimal policy for a hypothetical aphid infestation is shown in table 1 . The planning horizon is divided into decision stages of 7 days, starting on Julian day 165. The initial state of the system is: D=0 (flowering), A=0.17 aphids/tiller, P_1=0 Dfl/ha. Critical level probability and expected loss are calculated for all decision series.

Table 2 lists the more important results. The decision series b-e and h-l satisfy the risk constraint P($\underline{L}_1 \geq 350$) $\leq$ 0.10. Series c from this set involves minimal expected loss. The optimal decision for decision stage j=1 is not to treat, as summarized in table 1.

decision stage j		1	2	3	4	5	6	7
Julian number 1st day		165	172	179	186	193	200	207
field observations	crop development	0	0.13	0.26	0.35	0.51	0.64	0.79
	no. aphids / tiller (%tillers with aphids)	0.17 (6%)	1.76 (50%)	0.25 (10%)	0.05 (1%)	0.14 (5%)	0.49 (20%)	0.05 (1%)
optimal decision		0	1	1	0	0	0	0
$L_{max} - P_j$ (Dfl/ha)		350	328	223	122	120	117	116

Table 1. Control of an aphid infestation in winter wheat in a hypothetical season according to the decision model described in the text. The planning period starts at flowering (D=0) in 14 June (daynumber 165). The chance constraint is P($\underline{L}_j \geq L_{max}$) $\leq$ 0.10, with L_{max}=350 Dfl/ha.

The state of the system at the onset of decision stage j=2 is characterized by D=0.13 and A=1.76, both observed in the field, and P_2=22 Dfl/ha, which was calculated. A number of relevant decision series are listed in table 3. The optimal series in this case is f, indicating that treatment is necessary. Thus, the concept of a rolling planning horizon involves analysis of the decision problem every time new information becomes available.

	decision series	$P(\underline{F}_1 \geq 350)$	$E(\underline{F}_1)$ (Dfl/ha)
a	0 0 0 0 0 0 0	1.00	771
b	1 0 0 0 0 0 0	0.00	203
c	0 1 0 0 0 0 0	0.00	188
d	0 0 1 0 0 0 0	0.00	219
e	0 0 0 1 0 0 0	0.00	251
f	0 0 0 0 1 0 0	0.65	367
g	0 0 0 0 0 1 0	1.00	619
h	1 1 0 0 0 0 0	0.00	214
i	1 0 1 0 0 0 0	0.00	214
j	1 0 0 1 0 0 0	0.00	215
k	0 1 1 0 0 0 0	0.00	220
l	0 1 0 1 0 0 0	0.00	224

Table 2. Probability distribution characteristics of a number of decision series at the onset of the first decision stage of the planning horizon, starting on daynumber 165 (14 June) with D=0, A=0.17 and P_1=0. Length of the decision stage is 7 days. A decision series consists of a series of decisions to spray (1) or not to spray (0) at the start of consecutive- tive decision stages.

	decision series	$P(\underline{F}_2 \geq 328)$	$E(\underline{F}_2)$ (Dfl/ha)
a	0 0 0 0 0 0	1.00	2207
b	1 0 0 0 0 0	0.90	426
c	0 1 0 0 0 0	1.00	569
d	0 0 1 0 0 0	1.00	734
e	0 0 0 1 0 0	1.00	1207
f	1 1 0 0 0 0	0.00	247
g	1 0 1 0 0 0	0.04	275
h	1 0 0 1 0 0	0.15	309
i	0 1 1 0 0 0	0.53	332
j	0 1 0 1 0 0	1.00	382
k	0 1 0 0 1 0	1.00	496

Table 3. Probability distribution characteristics of a number of decision series at the onset of the second decision stage of the planning horizon, starting on daynumber 172 (21 June) with D=0.13, A=1.76 and P_2=22.

In figure 2 a-d the effect of temperature variation on the probability distribution of future loss $\underline{F}_1$ is shown for three decision series on three flowering dates, at A=0.80 aphids/tiller. If only one treatment is carried out costs exceeding 275 Dfl/ha have a greater probability of occurrence at early flowering than at late flowering (fig. 2a, 2b). Early in the season temperature averages are lower than later, causing crops that flower early to develop more slowly as compared to later flowering crops. Therefore aphids are present during a longer period of time, with higher damage as a result. When treating twice (fig. 2c and 2d) aphid numbers are kept lower, consequently the variation in loss is less and the average loss is smaller than with one treatment only.

Figure 2. Effect of starting date and decision series on complement of probability distribution of future loss $\underline{F}_1$. In each case A=0.80 aphids/tiller and D=0. Starting dates are daynumbers 153 (————), 165 (— — — —) and 172 (--------), respectively. Four decision series are evaluated:

1 0 0 0 0 0 0 - figure 2a
0 1 0 0 0 0 0 - figure 2b
1 1 0 0 0 0 0 - figure 2c
0 1 1 0 0 0 0 - figure 2d.

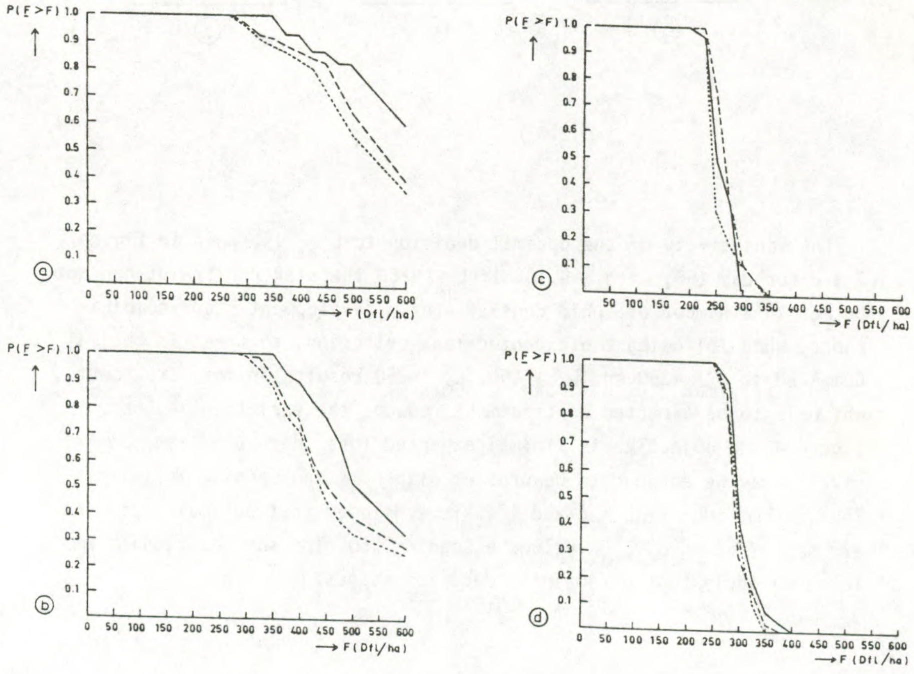
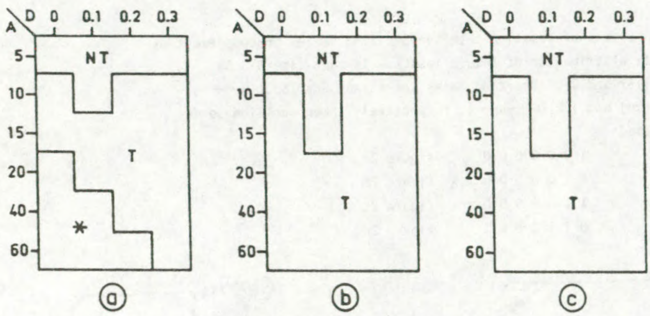


Figure 3. Optimal policy for different combinations of development stage and aphid density at the start of the first decision stage of the planning horizon (daynumber 165), calculated with objective II:

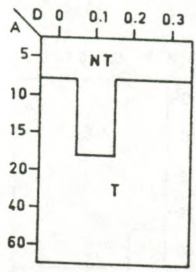
$$\underset{C_1,\ldots,C_N}{\text{minimum}}\ E(\underline{L}_1) \quad \text{subject to} \quad P(\underline{L}_1 \geq L_{max}) \leq \alpha \quad ,$$

where α=0.10 and L_{max}=250 (fig. 3a), L_{max}=350 (fig. 3b) and L_{max}=400 (fig. 3c). T: to treat is optimal; NT: not to treat is optimal. If the risk constraint can not be met (indicated with an asterisk) 'treat' results in the least expected costs.



The sensitivity of the optimal decision to L_{max} is shown in figure 3 a-c for day 165, with α=0.10. If L_{max}=250 the risk constraint can not be met in a number of aphid density - crop development stage combinations. When following the expected loss criterion, to treat is optimal. Compared to L_{max}=350 and L_{max}=400, L_{max}=250 results in more treatments, which is to be expected as treatment reduces the variation in loss. In figure 4 the objective is minimal expected loss. Here the risk constraint may be assumed to be present with L_{max} approaching infinity. Thus, from figures 3b, 3c and 4 it is concluded that optimal decisions are not affected by L_{max} values exceeding 350. The same conclusion was found to apply to the remaining decision stages.

Figure 4. Optimal policy for different combinations of crop development and aphid density on daynumber 165. The criterion for optimization was minimal expected loss $\underline{L}_1$. T: to treat is optimal; NT: not to treat is optimal.



The sensitivity of the optimal decisions to the objective can be evaluated by comparing figures 3, 4 and 5 in which three objectives were employed:

objective I : minimise expected loss (figure 4);

objective II : minimise expected loss, under the constraint of a maximal critical probability level (figure 3);

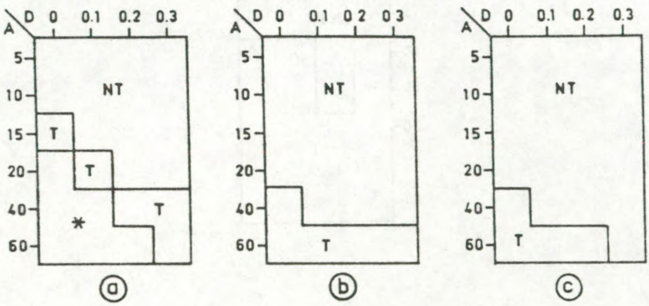
objective III: spray only if the critical probability level is exceeded in case no spraying is carried out (figure 5).

The first objective represents a risk-neutral attitude. In the second one traditional economic considerations are included. In the third objective the decision maker is assumed to postpone use of pesticides until a risk threshold is exceeded, which may be termed an ecological consideration. There is a clear difference between the strategies satisfying objective III and those satisfying I and II. When considering risk as in objective III, considerably less treatment is carried out.

Figure 5. Optimal policy for different combinations of development stage and aphid density at the start of the first decision stage of the planning horizon (daynumber 165), calculated with objective III:

$$C_1=0 \text{ as long as } P(\underline{L}_1 \geq L_{max}) \leq \alpha \quad ,$$

where $\alpha=0.10$ and $L_{max}=250$ (fig. 3a), $L_{max}=350$ (fig. 3b) and $L_{max}=400$ (fig. 3c). T: to treat is optimal; NT: not to treat is optimal. If the risk constraint can not be met (indicated with an asterisk) 'treat' results in the least expected costs.



3.5 Discussion

In this paper chemical control of aphids in winter wheat was formulated as a stochastic optimization problem with a terminal value constraint. The trend in the results agrees with the expectation: loosening the risk constraint and excluding the minimal expected loss requirement results in later treatment.

The figures for loss were calculated with simple models, and approximate reality only roughly. Although unsuitable for implementation purposes, they serve to illustrate a purpose. Improvements can be made by replacing the submodels for loss by more realistic simulation models. Subsequent sensitivity analysis will indicate the simplifications that may be carried out without affecting the optimal decisions.

Temperature was introduced as a random variable. Other sources of variation, e.g. sampling error and accessibility of a field in connection with precipitation, need to be investigated to identify variables that have a major contribution to uncertainty in the outcome of a treatment. In the model presented here, variation in temperature did not have a pronounced effect on optimal decisions.

Reviews on modelling in agricultural management (Anderson, 1972; Shoemaker, 1981) highlight the merits of dynamic programming or similar recursive methods compared to exhaustive search by simulation when faced with multistage decision problems. These techniques can handle non-linear and discontinuous transformation functions to determine the optimal series of decisions in an efficient manner. Measures of risk can be incorporated by imposing penalties on undesirable values of the value-function. For purposes of explicitly calculating risk in the sense proposed here, however, they are not suitable due to their recursive character. Therefore in this study an exhaustive search method was chosen. The major drawback of this method is its inefficiency. Per run only one initial value of the state vector can be considered, whereas in dynamic programming a single computation results in optimal policies for a range of initial values. When considering to incorporate more state or random variables this inefficiency may prove to be inhibitive.

Gonedes and Lieber (1974) describe an inventory decision problem with a structure analogous to the one described in this paper. They were able to transform the problem to a deterministic equivalent and solve it numerically. Thornton and Dent (1984a, 1984b) numerically calculated the probability distribution of loss caused by a disease of wheat. They used utility functions to account for a farmer's risk attitude.

The results of this type of exercise are useful for identifying critical elements of the decision system, thus directing research to missing links. If used as a management game a farmer may compare his decisions to the ones best meeting his objectives. Deviations can be traced back to differences in actual and stated objectives or differences in actual and perceived effects of random factors.

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