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GRADUATE SCHOOL

A BIOECONOMIC MODEL FOR WEED MANAGEMENT IN CORN AND SOYBEAN

A Thesis

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ABSTRACT

A bioeconomic simulation model of weed management is developed in this research. The model identifies nearly optimal tactics for weed control in corn and soybean, based on weed population density estimates. By incorporating multiple controls and weed species into a dynamic model, it fills a gap between existing multiple species, multiple control static models and single species, single control dynamic ones. Its open design allows it to run with any suitable set of input parameter data.

The model simulates weed germination, growth, reproduction, susceptibility to control treatments, and reduction of crop yields. Three annual weeds are included: mixed green and yellow foxtails, common lambsquarters, and redroot pigweed. Weed control recommendations are made by identifying the optimal control that maximizes expected net income per acre for a one- or two-year planning horizon.

Dynamic stochastic simulation experiments are conducted to test the recommendations module in the context of a synthetic southwestern Minnesota corn and soybean farm. Experiments examine annualized net farm income and herbicide load per acre for a six-year simulation under twenty states of nature. The experiments compare outcomes from various 1) levels of weed population information, 2) economic decision

rules, 3) farm sizes, 4) initial weed densities, and 5) herbicide bans.

Simulation results impute substantial value to weed population information, low initial weed seed levels, and availability of triazine herbicides. They also indicate that the quantity of herbicides used may be reduced if weed management decisions are based upon weed population information.

To Sylvia

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ABBREVIATIONS USED

ac	Acre
ai	Active ingredient
bu	bushels
C	Degrees Celsius
CARA	Constant absolute risk attitude
CC	Continuous corn rotation
CS	Corn-soy rotation
d.f.	degrees of freedom
EPTC	A thiocarbamate herbicide
lb	Pound (453 grams)
m^2	Square meter
MN	Minnesota
NPV	Net present value
OLS	Ordinary least squares regression
POST	Post-emergence
PPI	Pre-plant incorporated
PRE	Pre-emergence
PV	Present value
R^2	Coefficient of determination
SEE	Standard error of estimate
SUR	Seemingly unrelated regression
WLS	Weighted least squares
WSUR	Weighted seemingly unrelated regression

I. INTRODUCTION

1.1 Why Weeds Matter

Weeds cause serious crop losses by competing for light, water, space and nutrients. A study by the Weed Science Society of America estimated the average annual value of U.S. crop losses due to weeds to be $7.5 billion during 1975-79 (Chandler et al.). Corn (Zea mays L.) and soybeans (Glycine max (L.) Merr.) account for over half of these losses.

Herbicides are the preferred method of weed control in the United States. They offer selective weed control that costs less than tillage or hand weeding and controls a broader spectrum of weed species than existing biological controls. Moreover, pre-emergent herbicides offer implicit insurance against the possibility that bad weather will prevent a farmer from destroying weeds by timely tillage once the crop emerges. Ninety-six percent of U.S. corn and soybean cropland was treated with herbicides in 1988. This accounted for 81% of all herbicides applied to U.S. crops that year (Osteen and Szmedra).

A drawback of herbicide use is the potential health hazard posed. Human exposure to herbicides through residues consumed in food is slight, as is the concomitant risk of cancer (Archibald and Winter). However, herbicides contribute significantly to groundwater contamination in rural areas. An estimated 46 million Americans drink water from groundwater supplies that may be contaminated by pesticides, which include insecticides, nematicides and fungicides, as well as herbicides (Nielsen and Lee). Two herbicides were found to be the most widespread pesticide contaminants in a 1988 survey of 500 Minnesota wells. Atrazine was found in 31% of the wells, while alachlor was detected in 3% (Klaseus et al.). Not coincidentally, these are the herbicides most commonly used on corn in Minnesota. Alachlor is also the number two choice for soybeans in Minnesota (National Agricultural Pesticide Impact Assessment Program, NAPIAP).

Herbicides are more likely than other pesticides to enter the groundwater because 1) they are more heavily applied than other pesticides, 2) many are applied directly to the soil in pre-plant incorporated or pre-emergent treatments, and 3) even post-emergent treatments are usually applied when crops and weeds are small and much soil is exposed. Where spray rigs are dumped or washed out, herbicides can create point source contamination in addition to the non-point contamination associated with normal chemical treatment of crops.

The groundwater contamination problem is typically cast as the result of an economic externality: Farmers perceive all the benefits of agricultural chemicals, while paying only some of the costs. In particular, they avoid paying most of the environmental costs of water pollution. The conclusion is that they "overuse" chemicals. The public policy debate around reducing groundwater contamination focusses on introducing incentives or regulations forcing farmers to realize the full social costs of chemical use (Segerson). Policy alternatives recently proposed include bans, taxes, marketable use permits (see, e.g., Gianessi et al.), and public purchase of chemical use rights (Taff and Cox).

1.2 The Role of Information in Weed Management

An alternative explanation for part of the chemical "overuse" is that farmers lack full information for maximization of private net benefits. Profit maximization presupposes that the decision maker has complete information about prices and the production process. Yet at key decision making moments, most farmers possess very limited information on weed populations in their fields and their potential economic effects.

The information problem is due in part to the timing of weed control decisions. Weeds may be controlled using herbicides at three stages during the growing season. Before the crop is planted, herbicides may be incorporated into the soil (pre-plant incorporated, PPI). After crop planting, they may be sprayed onto the soil surface (pre-emergent, PRE). Both of these techniques kill weed seedlings before emerge. After the weed seedlings emerge, they may be killed by tillage or by herbicide (post-emergent, POST). Weed seedlings are visible only prior to the POST treatment. Earlier weed control decisions must be made on the basis of forecasted weed infestations. Ad hoc decisions tend either to follow rules of thumb or to be based upon weed pressure the previous season. But many viable weed seeds in the soil are holdovers from previous years. At best, these decisions are based on weak forecasts of the potential weed problem.

Good information on the weed seed population and associated germination rates is not enough. Crop yield loss due to weeds is the key economic component of the weed problem. Even if all prices and costs are known in advance, evaluating the need for weed control requires three further kinds of information. The first concerns crop yield loss due to each weed species as weed density increases. Such a production function allows estimation of the opportunity cost of failing to control weeds. The second concerns the efficacy of available weed control measures toward the weed species present. Knowledge of likely control efficacy allows prediction of yield loss in the presence of different weed control treatments. The third type of information concerns the rate of seed production and mortality by each weed that reaches maturity. Combined with the first two kinds of information, these weed population growth parameters permit forecasts of possible crop yield loss in future years.

Previous research has highlighted the differences in optimal weed control strategy between dynamic weed-crop models (which include weed population growth parameters) and static ones (which do not). Five studies from the United Kingdom and Australia found that the economic threshold for weed control occurs at a lower weed density in a dynamic model than a static one (Auld et al., Cousens et al. 1986, Doyle et al., Murdoch, Pandey 1989). Doyle et al. and Cousens et al. (1986) found that the dynamic threshold was not reached every year, so optimum herbicide application was lower than conventional practice. In a dynamic bioeconomic model of Colorado continuous corn with two weed variables (aggregate grasses and aggregate broadleaves), King et al. also found optimal herbicide use to be lower than conventional practice. These results suggest that better biological information about weeds in crops could increase long term farm net incomes while reducing chemical use.

No model reviewed has combined dynamic analysis with multiple individual weed species. Nor has any combined dynamic analysis with multiple weed control treatments. Prior efforts have 1) modeled the weed management problem dynamically with aggregated weeds and a single control (King et al.), 2) modeled it dynamically with a single weed species and a single control (Auld et al., Cousens et al. 1986, Doyle et al., Murdoch, Pandey 1989, Taylor and Burt), or 3) modeled it statically with many individual weed species and control treatments (Kells and Black, Kidder et al., Lybecker et al. (1991b), Wilkerson et al. 1991). Pannell (1989a, 1989c) has modeled static control of a single species in a single crop with variable rates of a single treatment. Cousens et al. (1987b) have stressed the need both for multi-species weed models and for stochastic modeling.

A dynamic, multiple species, multiple control bioeconomic weed management model has the potential to identify weed management strategies that are more profitable than those currently in use. Based upon results from previous dynamic weed-crop studies, it is also expected that such a model will recommend less herbicide use over the long run than conventional practices which entail regular spraying.[1] In this respect, the model may facilitate the substitution of management for agricultural chemicals that has been advocated by proponents of low-input agriculture (Daberkow and Reichelderfer). The value of weed population information is the key to the model's usefulness.

The value of weed population information depends in part upon the farmer's ability to act upon it. For farmers, weather makes the time interval for effective action a

[1] It is important to recognize, however, that such herbicide reductions occur only in the long run. In early years, a dynamic weed control strategy is likely to call for more weed control than a static one, in order to reduce the weed seed population.

random variable. Apland (1988) has defined field time as the "time during which conditions are satisfactory for field work" (p. 1). The prevalence of pre-emergent herbicide applications on Minnesota corn and soybean farms can be interpreted as a response to the risk that rainy weather will impede field access for timely cultivation, rotary hoe or post-emergent herbicide treatment.

For a weed model to be of practical value as a management decision tool, it needs to perform well under a wide range of environmental conditions. This calls for model evaluation in a context which simulates both environmental variability and farm resource constraints.

The analytical approach followed in this study is computer simulation of the biological and economic environment. As Jock Anderson has noted, simulation is useful when "the degree of control and isolation imposed on a formal experiment may prevent ready extrapolation to the less-controlled real world" (p. 35). This is certainly true of agronomic experiments in weed control. Simulation can accommodate rapid experimentation with a stochastic system which, under field conditions, is only observable once each season. By generating sets of outcomes from applying management strategies to random variables, it allows statistical evaluation of results. In addition, sensitivity analysis of a simulation model can aid investigators in identifying those research areas likely to offer the greatest returns.

1.3 Objectives

The problem to be examined in this research is how information concerning weed population dynamics can be used to improve farmer decisions on weed control. "Improve" in this sense means increase the farmer's expected utility, where expected utility refers to the farmer's preferences over different probability distributions of projected net returns.

The initial objective is to design and validate a dynamic bioeconomic model for control of multiple weed species in corn and soybean. The model should include a variety of control alternatives. It should provide recommendations on weed control both before and after weed seedlings emerge.

The second objective is to apply the bioeconomic model to evaluate weed control strategies by stochastic simulation. Strategies to be evaluated will include static and dynamic decision rules. The value of weed population information will be estimated for these under a range of scenarios with different crops, crop rotations, producer risk attitudes, and initial weed pressure.

The third objective is to apply the best decision rule to predict farm-level impacts of bans on atrazine and the triazine herbicides. Impacts on both farm net income and chemical use will be examined.

1.4 Hypotheses

This research will test a set of hypotheses using results from multi-year stochastic simulations with the weed management model. The following nine null hypotheses are stated in falsifiable form:

H1. Strategies using weed population information yield discounted net income streams equal to those that do not.

H2. Strategies using weed population information result in applying amounts of chemicals equal to those that do not.

H3. For a given level of information, strategies using dynamic economic decision rules yield discounted net income streams equal to ones using static rules.

H4. For a given level of information, strategies using dynamic economic decision rules result in applying amounts of chemicals equal to ones using static rules.

H5. An increase in acreage farmed with the same labor and machinery set does not affect the discounted net income stream per acre.

H6. Low and high initial weed seed populations will result in equal discounted net income streams.

H7. Low and high initial weed seed populations will generate equal amounts of chemical application per acre.

H8. Herbicide bans will not affect the stream of discounted net income.

H9. Herbicide bans will not affect chemical application per acre.

The thesis is organized into six chapters. In Chapter 2, the economic theory of pest management is reviewed, with special attention to weeds and to model evaluation under uncertainty. Chapter 3 describes the simulation model in detail. Chapter 4 presents the procedures used to develop parameter estimates to run the model and to validate it. Chapter 5 presents results from the deterministic and stochastic simulation models. It discusses outcomes of stochastic simulations used to a) estimate value of weed population information, b) evaluate alternative decision rules, c) compare results from different initial weed seed densities, d) evaluate the importance of timely weed control, and e) compare herbicide policy alternatives. Chapter 6 summarizes the contribution of the model and identifies opportunities for future research.

II. A CONCEPTUAL MODEL OF WEED MANAGEMENT ECONOMICS

The weed management decision aid developed in this research builds upon a conceptual model of pest management economics. The model is formulated as an economic control problem subject to a set of biological processes. This chapter presents the theoretical basis for the normative decision aid developed subsequently. It further presents a framework for ex ante testing of the decision aid.

2.1 Economics of Pest Management

Pest control inputs differ from other agricultural inputs in that they do not directly increase output, but instead reduce losses caused by a damage agent (e.g., a noxious insect, weed or plant disease). The general model of pest management in crops is concisely summarized by Feder. It presupposes the existence of a damage function giving crop loss as a function of pest numbers. Pesticide usage can reduce pest numbers via a "kill function" which generates the proportion of the pest population controlled for a given amount of pesticide applied. With respect to application rate, the kill function is assumed to have a positive first derivative and a negative second derivative on the closed interval [0,1]. Treating other variable costs as fixed, a slightly modified version of Feder's profit function can be written,

$$\Pi = P\{Y^0 - D(W*[1-k(H)])\} - cH - C^0 \qquad \textbf{(2.1)}$$

where Π denotes profit, Y is crop yield, P is product price, D is the yield loss or damage function, W is the number of pests, $k \in [0,1]$ is the kill function, H is the amount of pesticide used, c is pesticide unit cost, and C^0 denotes variable costs unrelated to pest control. The superscript 0 denotes pest-free levels. It is assumed that damage increases with weed density ($D'(W) > 0$) and efficacy increases with treatment dosage ($k'(H) > 0$) but is independent of weed density ($k'(W) = 0$).

As it stands, pests and pesticides each constitute a single variable in equation (2.1), as though each represents a homogeneous group. Single pest models are useful for analytical purposes; however, they abstract considerably from reality. Yet even in the insect control economics literature, multispecies models are rare (Boggess <u>et al.</u>, Regmi). Weeds are far from homogeneous. They vary not only in the level of damage each species inflicts on the crop, but also in the susceptibility of each to different control treatments. Consequently, both individual weed species and control treatments must be explicitly included in the model. The model can be simplified by recognizing that most pesticides are applied at recommended rates. However, the differentiability of equation (2.1) is sacrificed. Instead, a discrete level of expected profit is associated with each control alternative. Rewriting equation (2.1) as an optimization problem using small letters to denote vectors and capitals to denote scalars,

$$\max_{h} \pi = P\{Y^0 \iota_j - D([\iota_i \iota'_j - k(wsp,h)]'w)\} - (c'I_j)h - C^0 \iota_j \quad (2.2)$$

where π is a j vector of net revenues corresponding to weed control treatments h, w is an i vector of weed species densities, wsp is an i vector of weed species identifiers, h is a j vector of control treatments, k is an (ixj) matrix of weed mortality functions relating each weed species to each control treatment, c is a j vector of unit costs associated with treatments h, ι_i is an i vector of ones, ι_j is a j vector of ones, and I_j is a (jxj) identity matrix.

2.1.1 Economic management of a biological system

Biological dynamics add another layer of complexity. Weed seeds deposited in one season will either die or germinate over a period of years. A dynamic economic model requires endogenous functions for the seed bank and resultant weed density levels. For planning horizons extending beyond one season, outcomes of management practices need to be discounted.

Assuming that the farm manager's utility is defined on discounted cumulative net income at the end of a planning horizon, management strategies can be evaluated using the net present value of accumulated profits (NW) discounted at rate r. The dynamic version of equation (2.2) thus becomes,

$$\max_{h} NW_T = \sum_{t=0}^{T} \frac{P\{Y_t^0 \iota_j - D(w_t^h)\} - (c_t' I_j) h_t - C_t^0 \iota_j}{(1 + r)^t} \tag{2.3}$$

subject to the equations of motion,

$$w_t = w(s_{t-1}) \tag{2.4}$$

$$s_t = s(s_{t-1}, w_t, w_t^h) \tag{2.5}$$

$$w_t^h = [\iota_i \iota_j' - k(wsp, h)]' w_t \tag{2.6}$$

where NW_T is a j^T vector of net wealth positions in period T contingent upon the T-period path of j control treatments followed. $w(s_{t-1})$ is an i vector germination function relating the current number of weeds to the seed bank for each species, with $w'(s_{t-1}) > 0$ assumed. w_t^h is an i vector of weeds surviving to compete with the crop and to reproduce. s is an i vector function associating end of season weed seed bank density (s_t) with seed bank density in the previous season, (s_{t-1}), cumulative weed seedling germination during the season (w_t), and seed production by weeds surviving to reproduce (w_t^h) It is assumed that $s'(s_{t-1}) > 0$, $s'(w_t) < 0$, and $s'(w_t^h) > 0$.

The seed bank state variables link control activities in one period to repercussions in subsequent ones. Under the assumptions stated above, differentiation of equation (2.3) with respect to the arguments of the seed bank equation (2.6) reveals that net wealth is decreasing in weed seed bank and weeds at harvest in any time period. The decrease is greatest in the early periods of the planning horizon because resulting increases in the weed seed bank cause increased weed populations and yield losses of longer duration. The derivative of net wealth with respect to cumulative weed germination is indeterminate, since germination is associated with both decline of the seed bank and increase in number of weeds at harvest. On the basis of these signs alone, it is clear that the dynamic problem in equations (2.3-2.6) is considerably more sensitive to control actions than the static problem in equation (2.2).

The dynamic maximization problem is framed here as one in which the control treatment is the choice variable. This requires a word of explanation. Since the existing weed management literature[1] generally concerns a single control treatment, it tends to focus upon treatment rate and weed density as choice variables. Two management strategies are typically examined: 1) take weed density as given and choose the treatment rate that maximizes utility, or 2) take the treatment rate as given and choose the weed density threshold at which to apply it. Moffitt and Pannell (1990) have both demonstrated that the optimal rate approach of the

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[1] Cousens et al. (1986), Doyle et al., Murdoch, Pandey, and Taylor and Burt examine a single weed in a single crop; King et al. and Lybecker et al. (1988, 1991a) look at two or three weed species aggregates in a single crop.

first strategy insures profits that will always be at least as high as those for the weed density threshold approach.

In practice, herbicides are applied at or near the recommended rates published on their labels. Typically, the "kill function," giving weed mortality as a function of herbicide rate, is unknown outside the manufacturer's laboratories. For practical purposes, the optimizing farm manager is obliged to take application rates (and expected efficacy) as given. This study works from the premise that realistic choice variable is which control treatment to apply (at the recommended rate). "No control" is included in the treatment set, so there is an implicit threshold weed density determining whether or not to choose the "no control" option.

2.1.2 Thresholds for weed control

To characterize the density threshold for weed control, Auld et al. have defined a net gain function, $G(\cdot)$, as the gain in net revenue, $\pi(\cdot)$, from controlling weeds. In static form from equation (2.2), this is simply

$$\max_{h} G(w^{hr}, P, C^{r}) = \pi(w^{hr}, P, C^{r}) - \pi(w^{h0}, P) \qquad (2.7)$$

where $w^{hr} = [\iota_i \iota_j' - k(wsp, h^r)]' w^{h0}$ denotes the j vector of post-control weed populations corresponding to the j vector of treatments h^r at the recommended rate, w^{h0} denotes the uncontrolled population of weeds at harvest, and

$c^r = (c'I)h^r$ is the cost of control at the recommended rate. Note that $G(\cdot)$ can take negative values if the cost of weed control exceeds its benefits. The threshold of interest here, variously termed the "economic-injury level" (Stern et al.), the "action threshold" (Moffitt et al., Moffitt and Farnsworth) or the "economic threshold" (Cousens 1987) is the weed density w^{h0*} satisfying $G(w^{h0*}) = 0$. This is the pest population density "at which the cost of control measures equals the increased return on yield which would result" (Cousens 1987, p. 15).[1] This leads to the decision rule that weeds should be controlled at any pre-treatment density w^{h0} exceeding the threshold w^{h0*},

$$h = \begin{cases} h^{r*} \; if \; [D(w^{h0}) - D(w^{hr*})] \geq \dfrac{c^{r*}}{p} \\ 0 \; otherwise \end{cases} \tag{2.8}$$

where h^{r*} denotes the weed control that maximizes net revenues at recommended application rates, w^{hr*} denotes the resulting i vector of post-control weed species populations, and c^{r*} denotes the combined chemical and mechanical costs of weed treatment at the recommended rate.

However, the static economic threshold ignores the fundamental recursion relationship inherent in this dynamic

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[1]Note this differs from Headley's classic marginalist definition of the economic threshold as "the population that produces incremental damage equal to the cost of preventing that damage" (p. 105). Headley assumes that pesticide rate is a control variable as well as the pest population level at which to apply the pesticide.

problem: The value of the current state is a function both of its value <u>per se</u> and of the value of future states that can be reached from it. This is the essence of Cousens' (1987) dynamic "economic optimum threshold." Failure to control weeds in the current period not only reduces current crop yields. If aggregate weed seed production is density-independent, it also leads to greater weed reproduction, which reduces returns in the next and subsequent periods.

The dynamic optimum weed control path is expressed using the tools of dynamic programming. To simplify the notation of equations (2.3-2.6), retain w_t^h and h_t, letting x_t represent all other variables. If the problem is solved backwards from the final stage, then by Bellman's principle of optimality, the optimal path may be found by solving at each prior stage for the control that maximizes the value of the current stage plus that of the subsequent actions. Adapting the structure used by Kennedy to the notation at hand, the recursive solution equation to the dynamic programming problem in equations (2.3-2.6), can be stated,

$$V_t\{w_t^h\} = \max_{h} \; [\pi_t\{w_t^h, x_t, h_t\} + V_{t+1}\{S\{w_t^h, x_t, h_t\}\}] \tag{2.9}$$

where $V_t(\cdot)$ is the current period value function, π_t is current period net returns, $V_{t+1}(\cdot)$ is the discounted value function for the next period, $S(\cdot)$ (borrowed from the seed bank equation) is the transition function linking period t with period (t+1), t=T...1. By assumption, the initial condition is given and a transversality condition fixes the value of the terminal state.

Applying this notion to Auld et al.'s formulation of equation (2.8), define $DV_{t+1}(w_t^h, x_t, h_t)$ as a value of future yield damage function. Then, revising equation (2.8), the dynamic economic threshold can be expressed as the weed density in period t that solves the dynamic version of (2.7) for w_t^{h0*} generating the decision rule,

$$h = \begin{cases} h^{r*} \; if \left[D(w_t^{ho}) - D(w_t^{hr*}) - DV_{t+1}\{w_t^{hr*}, x_t, h_t\}\right] \geq \dfrac{C^r}{P} \\ 0 \; otherwise \end{cases} \quad \textbf{(2.10)}$$

Under the assumptions of equations (2.3-2.6), damage is an increasing function of weeds at harvest, which in turn are indirectly an increasing function of weeds at harvest -- and hence of weed control -- in the previous period. As Figure 2.1 illustrates, this implies that 1) the dynamic net gain function ($G^D(w)$) lies above the static one ($G^S(w)$), and 2) the dynamic economic optimum threshold (w_0^{0*}) lies at a lower weed density than the static economic threshold (w^{0*}).

2.2 Simulation versus Optimization

The weed management problem is one of finding an optimal weed control strategy over the farm manager's planning horizon. As such, an optimization algorithm such as mathematical programming or dynamic programming would

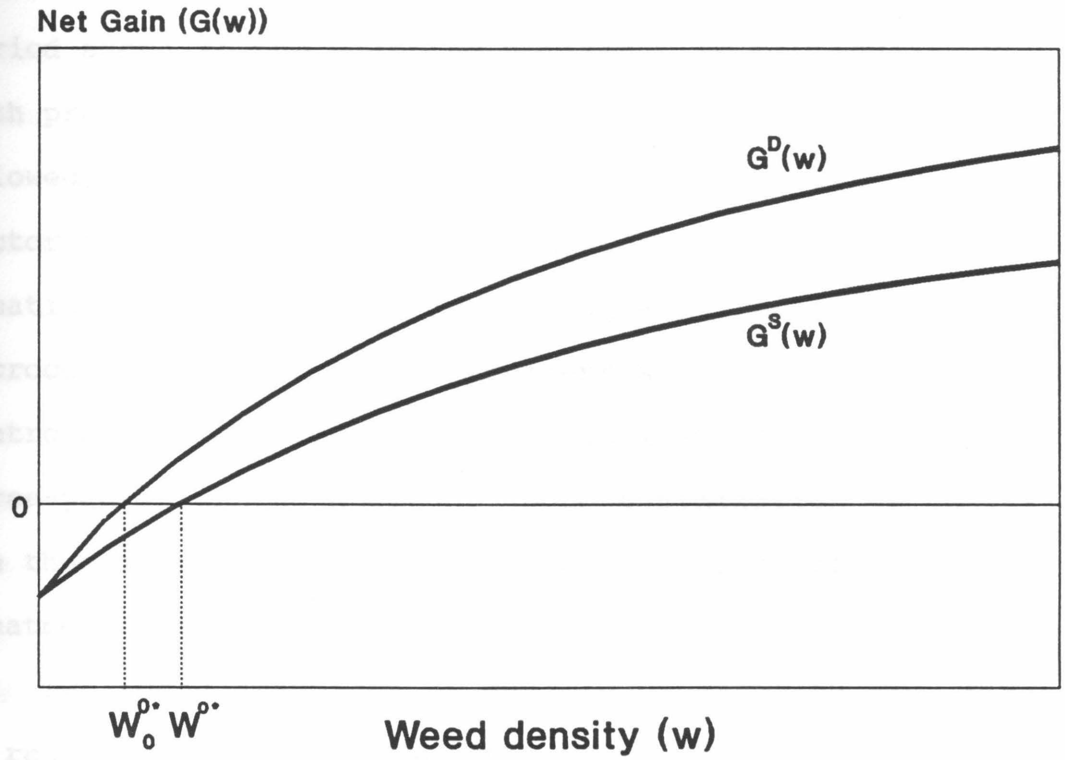

Figure 2.1: Dynamic and static net gain functions compared.

seem appropriate. Unfortunately, both present serious computational drawbacks related to the fact that at each time period after initialization, state variables explicitly depend upon the sequence of previous controls. This creates a formidable data storage problem analogous to that of numerous state variables in a control problem (Moffitt and Farnsworth). The dimensionality problem can be surmounted only by accepting a "near optimal" solution incorporating few controls and making simplifying assumptions to reduce the number of state variables (Taylor and Burt, Zacharias and Grube). For an integer mathematical programming model the dependence of states on prior controls implies that the number of "activities" grows exponentially with each time period added to the planning horizon. In particular, if both pre- and post-weed emergence control treatments are allowed, the length of the discounted cumulative profit vector associated with the dynamic control problem in equations (2.3-2.6) becomes unmanageable, especially on a microcomputer. For 10 pre-emergent and 8 post-emergent controls, 512,000 net wealth values must be evaluated over a three-year planning horizon. Both optimization techniques are thus impractical for more than a handful of control treatments or very few periods.

Two added drawbacks of dynamic programming are, first, it requires assigning discrete values to the state variable(s). For the weed seed bank state variables, this can distort the process of biological reproduction. Second, modeling multiple weed species aggravates the already daunting dimensionality problem.

Simulation is well suited to the representation of large, complex systems (Orcutt) and their inherent stochasticity (J. Anderson). Moreover, it is more flexible and freer of dimensionality problems than the optimization techniques considered. For these reasons, it has been used in other recent economic analyses of biological pest management (Boggess et al., King et al., Regmi, Reichelderfer and Bender). This study's objective of designing an economic framework for a set of biological submodels makes paramount the need for flexibility and structural openness. Consequently, simulation was chosen as the analytical method.

Simulation requires accurate representation of the systems being modeled. For weed management, those systems are largely biological. Given the choice of simulation over optimization methods, identifying decision rules for approximately optimal management strategies becomes important. Specific approaches to biological modeling and economic decision rules are presented in Chapter 3. One of the rules employed is, in fact, a dynamic programming optimal control over a two-year time horizon.

2.3 Evaluation of Model Recommendations

The weed management model presented above abstracts from reality in two important ways. First, it is deterministic, relying upon expected values of yield loss and weed population change in order to develop recommended strategies. Second, it ignores constraints on farm labor, management and machinery resources. In fact, uncertainty touches farm production in a variety of ways. Weather conditions affect crop growth, weed germination and growth, and the availability of workable field days. Field time constraints imposed by labor and machinery endowments combined with inclement weather limit the potential for timely management.

If untimely management causes reduced yields, then a management strategy that is optimal from a per-acre, deterministic standpoint may not be so in a whole-farm, stochastic framework. One operating hypothesis based upon this difference is that farmers "overapply" pre-emergent herbicide for fear they will lack the time to apply post-emergent weed control.

In order to test the sensitivity of model recommendations to the uncertainties and time constraints inherent in farming, prior evaluation is in order. Ex ante evaluation of the recommendations model is carried out through stochastic simulation of weed and crop management in a whole farm framework. The whole farm framework introduces intraseasonal timeliness considerations to the general model of equations (2.3-2.6). Crop yield penalties are associated with untimely completion of management tasks such as planting and weed control. The weed-free yield of equation (2.3) is reformulated as Y_τ^0,

$$Y_\tau^0 = Y^0(1 - \delta_\tau) \qquad \textbf{(2.11)}$$

where $\delta_\tau \in [0,1]$ is the proportion of potential crop yield lost by time τ during cropping season t. Actual crop yield may be further reduced by weather-induced treatment efficacy failures or the infeasibility of post-emergent treatments beyond a given stage in the weed or crop life cycle.

For a farm with more than one field, discounted cumulative farm net income is defined as the summation over all fields of discounted cumulative per-acre net income times the acreage (A_f) of each field (f). Let π_{ft} denote net revenue per acre from field f in season t (as in the numerator of equation (2.3)), except that Y^0_τ substitutes for Y^0. Then discounted cumulative farm net income (FNW) at the end of the planning horizon is

$$FNW_T = \sum_{t=0}^{T} \sum_{f=1}^{F} \frac{A_f \pi_{ft}}{(1 + r)^t} \tag{2.12}$$

2.3.1 Choosing among distributions of discounted net income streams

Stochastic simulation generates distributions of discounted cumulative farm net incomes. Choosing among these distributions requires assumptions about farm manager attitudes toward risk.

Expected utility theory provides a framework within which attitudes toward risk can be examined. Under the assumptions that preferences are ordered, continuous, and independent, there exists a utility function **u** such that 1) for any risky prospect **x** or **y**, **u**(**x**) > **u**(**y**) if and only if **x** is preferred to **y**, and 2) the expected utility of a risky prospect equals the utility of the expectation of the risky prospect (Arrow, Hernstein and Milnor).

Within the context of expected utility theory, two general approaches can be taken to choosing among empirical distributions of revenue gains. The method of stochastic dominance identifies general classes of preferences over which outcome distributions can be classified as risk efficient or not. Alternatively, single valued utility functions associate specific levels of utility with a given attribute. Certainty equivalent money metrics of utility can be developed from some single-valued utility functions. These allow interpersonal utility comparisons. This research assumes specific single valued utility function forms in order to make more discriminating comparisons than are possible using stochastic dominance.

According to the definition of Keeney and Raiffa, "a decision maker is risk averse if he prefers the expected consequence of any nondegenerate lottery to that lottery" (p. 149). One measure of risk aversion that is invariant to linear transformations of the utility function is the Pratt-Arrow coefficient of absolute risk aversion, λ. This is defined as $\lambda \equiv -u''(\pi)/u'(\pi)$, where u is the individual's utility function for attribute π. The Pratt-Arrow coefficient can be interpreted as the rate of change in marginal utility of π (Raskin and Cochran).

Comparing the utility of decision makers with different levels of risk aversion is complicated, and especially difficult without a common measuring unit. One money metric of utility is the certainty equivalent, "the amount **x** such that the decision maker is indifferent between (lottery) **L** and the amount **x** for certain," where **L** is a lottery yielding various possible levels of outcome variable $\mathbf{x}_i$ with associated probabilities (Keeney and Raiffa, p. 143). A family of functional forms that lends itself to money metric comparisons of expected utility is that corresponding to constant absolute risk attitudes, given by

$$u(\pi) = \begin{cases} -e^{-\lambda\pi} & \text{for } \lambda > 0 \\ \pi & \text{for } \lambda = 0 \\ e^{-\lambda\pi} & \text{for } \lambda < 0 \end{cases} \tag{2.13}$$

where **e** is the natural exponent (Keeney and Raiffa, p. 167). Constant risk attitude utility functions allow evaluation of weed management strategies over a range of specified levels of risk aversion or preference. The money metric of utility provided by the easily-calculated certainty equivalent is the means of doing this. For these functions, the certainty equivalent of $\mathbf{u}(\pi)$, π_{ce}, for a distribution of outcomes on π, is

$$\pi_{ce} = \begin{cases} -\dfrac{\ln E[-u(\pi)]}{\lambda} & \text{for } \lambda > 0 \\ E[\pi] & \text{for } \lambda = 0 \\ -\dfrac{\ln E[u(\pi)]}{\lambda} & \text{for } \lambda < 0 \end{cases} \tag{2.14}$$

where **E** is the expectations operator (Robison and Barry, p. 38).

2.3.2 Value of weed population information

The value of information to a decision maker with a specified utility function can be inferred from the difference in certainty equivalents between information states (Byerlee and Anderson, Regmi). Byerlee and Anderson use the notion of compensating variation to make an important distinction between the value of a prediction and that of a predictor. The former is the amount of money which would leave a decision maker indifferent between the posterior expected utility of maximizing expected utility with prior information and that of having done so with the prediction. The value of a predictor must be judged over the range of stochastic states which it purports to predict. The predictor's value is the amount of money which would leave the decision maker indifferent between the posterior expected utility of maximizing expected utility with prior information and the integral over all states of nature of having done so with the prediction. This definition of the value of a predictor will be applied to estimate the value of weed population information from stochastic simulation results.

With broad brush strokes, this chapter has laid out a conceptual model of weed management along with methods for evaluating its performance. The next chapter presents a computer model that implements the ideas introduced here.

III. THE SIMULATION MODEL

The simulation model described in this chapter makes operational the theoretical model presented in Chapter 2. It is composed of two parts: a recommendations module (WEEDSIM) and a whole farm model (WFARM). The former generates *ex ante* weed control recommendations using information about weed seed or seedling populations combined with expected rates of weed germination and crop yield loss due to weeds. The latter simulates the labor and machinery resource constraints and probabilistic field time constraints that characterize actual farms. The simulation model is written in Microsoft QuickBasic (version 4.5); a listing of the computer program may be found in Appendix A.2. This chapter describes the structure and program flow of the simulation model.

Both the recommendations module and the whole farm model are designed to be flexible and open to evolution. Flexibility is incorporated in two ways. First, the program is written in modular fashion. Virtually all program operations are executed by procedures called from the main program. These can be modified or replaced without harming the operation of the larger model, so long as the required values are passed back from the subroutine to the main program. Second, all numerical parameters required to run the model are read in as text files. Hence, without changing any program code, input parameters can be changed as desired. The model's flexibility is intended to facilitate its evolution as biological modeling advances. It is anticipated that some of the simple subroutines currently based on statistically estimated relationships will eventually be supplanted by biological process models.

3.1 Structure of the Recommendations Module

The purpose of the recommendations module is to identify the most attractive treatment strategy. Three types of decision rules are available. All three require crop yield predictions for the current season. One also incorporates yield predictions for the next season. These predictions rely upon a system of biological equations that predict yield loss, weed control, weed germination, and evolution of the weed seed bank. This section will begin with a discussion of the decision rule alternatives and proceed to examine their biological data requirements.

The recommendations module runs on a set of parameter data files. Appropriate files may be prepared by any researcher capable of supplying suitable coefficients for the weed germination, weed seed production and mortality, and crop yield equations that run the model.[1] Additional input files include data on the cost, rates and efficacy of weed control treatments. Initial values supplied by the user include crop name, rotation, expected price and expected weed-free yield, the discount rate, variable costs per acre, and weed seed or seedling density per square meter (by species). The weed density values are critical -- they provide the necessary initial values for simulation of expected weed populations and resulting crop yield loss.

The program flow of the WEEDSIM recommendations module is illustrated in Figure 3.1. Based upon initial weed seed counts provided by the user, WEEDSIM calculates expected pre- and post-planting weed germination. Every possible PPI and PRE weed control treatment included in the model is evaluated jointly with every possible POST treatment. For each PPI/PRE and POST pair, the expected yield is calculated from the expected density of weeds at harvest. The associated present value (PV) of net returns is calculated from user-supplied cost and crop price information. If the user has specified a dynamic (e.g., two-year) decision rule, the model calculates the expected change in the weed seed bank for each species, and then evaluates all PPI/PRE and POST weed control combinations for the following year, starting from each combination in the initial year. WEEDSIM recom-

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[1] Procedures used for statistical estimation of the parameters used in this thesis are outlined in Chapter 4.

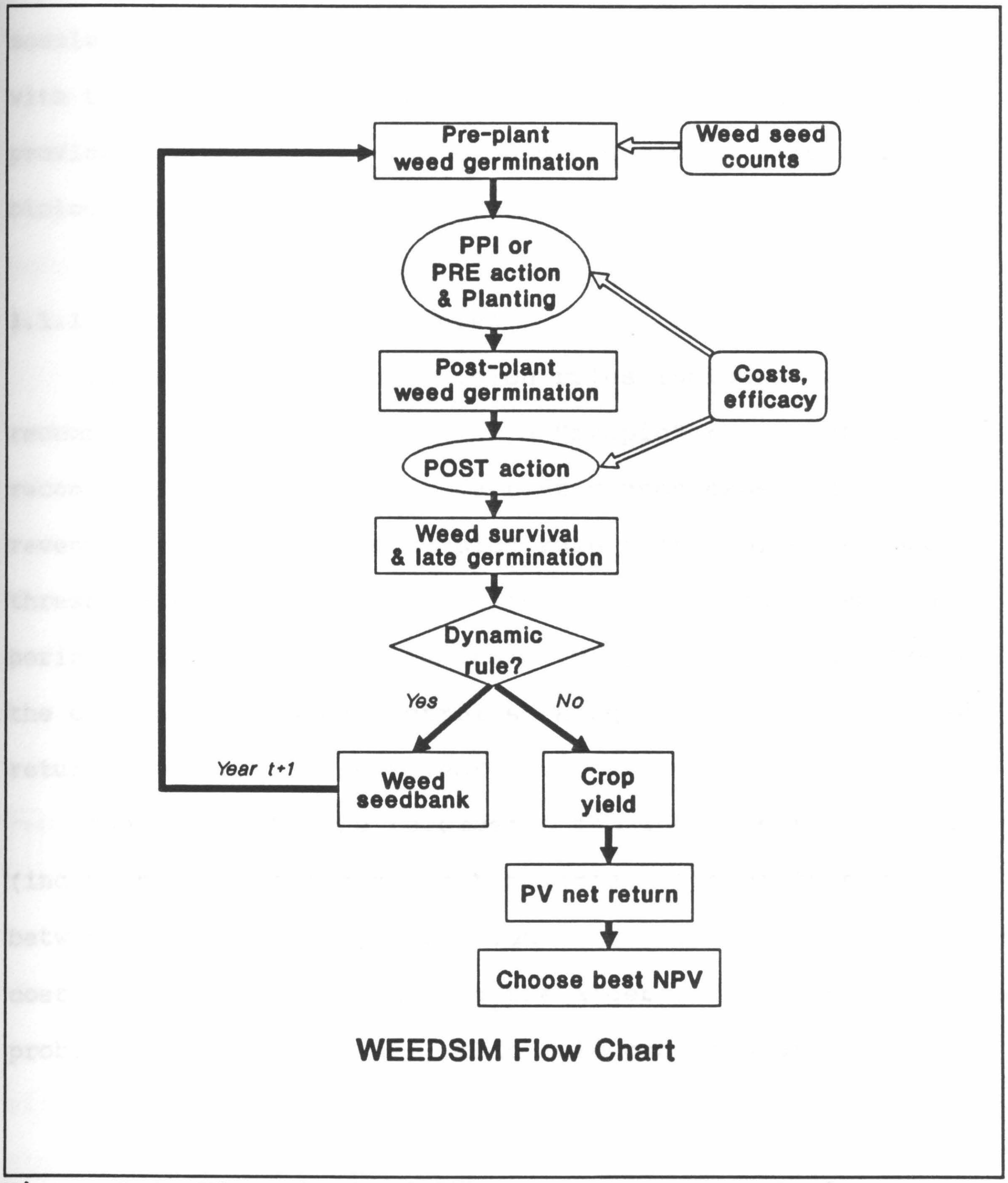

Figure 3.1: Flow chart of the WEEDSIM recommendations module.

mends the PPI/PRE and POST pair for the initial year that generates the highest net present value (NPV) for the specified decision rule. The post-emergence recommendations module, PostWEEDSIM, is identical, except that it begins with the "POST action" stage using weed seedling counts provided by the user. The economic decision rules and the biological submodels are discussed below.

3.1.1 Economic decision rules

The three economic decision rules included in the recommendations module are: 1) a "myopic" rule that makes recommendations maximizing current season expected net revenue, 2) a "cautious myopic" rule that applies a lower threshold for weed control to the same one-year planning horizon, and 3) a "foresighted", two-year rule that chooses the current year weed control strategy based upon expected returns over the current year and the next.

The "myopic" rule recommends the weed control action (including "no control") that maximizes the difference between the value of yield saved in the current year and the cost of treatment. Recalling the algebraic statement of the problem in equation (2.7), this rule can be stated:

$$\max_{h} G(w^{hr}, P, c^{r}) = \pi(w^{hr}, P, c^{r}) - \pi(w^{ho}, P)$$

Based upon initial weed seed counts provided by the user, the model forecasts weed density and its impact on current year crop yields. Expected yields are calculated for all combinations of pre- and post-emergent weed control. From the resultant expected net revenue values (calculated in subroutine WSPostRev), the model selects the highest (using the sorting subroutine WSTopRevMyopic) and makes its recommendation accordingly. This is the kind of decision rule employed in the multiple weed species bioeconomic models currently available or in development for field use (Lybecker et al., 1991a, Wilkerson et al., 1991).

The "cautious myopic" decision rule (also implemented by WSTopRevMyopic) is designed to recognize that a dynamic optimal weed control strategy maintains a lower equilibrium weed population than a static one. The "cautious myopic" decision rule recommends weed control when it is nearly profitable--but not quite, given a single year planning horizon. This results in performance over time that may be superior to the strictly myopic rule. Mathematically, the "cautious myopic" rule is a variant of the myopic one:

$$\max_{h} G(w^{hr}, P, c^{r}) = \pi(w^{hr}, P, c^{r}) - (1-\theta)\pi(w^{ho}, P) \qquad \textbf{(3.1)}$$

where $\theta \in [0,1]$ represents the proportion by which the no control base case is decreased. The rule implies greater willingness to treat weeds than in the myopic profit-maximizing case. It seeks to mimic the optimal dynamic weed control threshold at w_0^{0*} in Figure 2.1, while still using the more easily computed myopic net gain function $G^s(w)$. It does so by lowering the net gain threshold for implementing weed control from 0 to $-\theta\pi(w^0)$, as shown in Figure 3.2. Computationally, it is equivalent to the myopic rule, except that it uses $(1 - \theta)\pi(w^0)$ as the base case in selecting the optimum treatment rather than $\pi(w^0)$. The "cautious myopic" rule is related to the benefit-cost ratio (B/C) criterion used by Regmi. However, with more than two treatments, present value of net revenue is a better measure, since a suboptimal strategy may appear attractive under the B/C criterion if its cost is low.

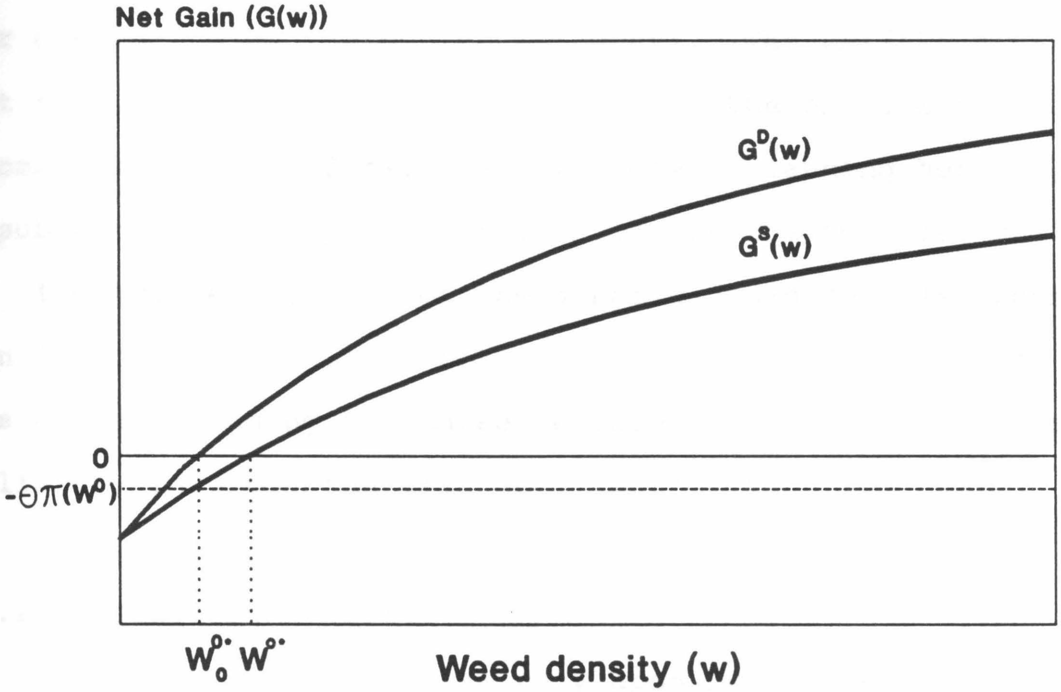

Figure 3.2: "Cautious myopic" decision threshold emulates the dynamic threshold with a static one.

The two-year decision rule forecasts expected yields one year into the future. In order to do this, it predicts seed production by those weeds that reach maturity under each weed control scenario in the current year, using subroutine WSSeedBank. This creates as many predicted initial seed bank conditions for year 2 as there are paired PPI/PRE and POST control treatments. For each predicted initial weed seed bank in year 2, the model repeats the procedure of predicting expected yield for each weed control treatment, using subroutine WSNextYear. Finally, the model selects the combination of treatments in years 1 and 2 that yield the highest expected present value of net wealth over the two year period (using subroutine WSTopRev). The PPI/PRE treatment for year 1 from this combination is the one the model recommends. In the final year of a given planning horizon, it substitutes a myopic decision rule for the two-year rule.

The two-year rule uses the dynamic decision rule (equation (2.10)) to obtain an optimal control over a two-year time horizon. Among the three decision rules, only this one explicitly incorporates weed seed reproduction and death.

3.1.2 Biological submodel

All three decision rules rely upon predictions of weed infestations and estimates of their impact upon crop yield. The biological submodel generates these through a set of subroutines simulating each step in the process of weed growth and competition with the crop.

Two analytical approaches are possible for predicting biological phenomena: process simulation and statistical estimation. Where process simulation is feasible, it is the more desirable of the two, because it explicitly includes environmental factors which tend to enter statistical estimation as dummy variables or unexplained disturbance.

The only process model now available that is suited to this weed management model is the Forcella (1991) weed germination predictor, which is still under development. While advances in process modeling of weed-crop competition have recently taken place (e.g., Maxwell and Ghersa, Wilkerson, et al. 1990, Williams et al.), they have not yet reached the point of modeling multiple weeds. As biological process simulation moves forward, subroutines or object files could easily be made compatible with this model.

For the time being, statistical estimation provides the best means available of predicting biological processes. This section offers an overview of the relevant biological literature and functions included in the model.

3.1.2.1 Weed population dynamics

Careful modeling of the germination, reproduction and mortality of weed plants and seeds is crucial to a dynamic weed management model. Virtually all prior attempts to simulate weed populations have focused upon a single grass weed species in a single crop. In similar weed control models, Cousens et al. (1986) incorporated innate dormancy based on seed age in a wild oat population model, and Doyle et al. built in induced dormancy based on seedbank depth in a blackgrass population. Taylor and Burt, followed by Pandey and Pandey and Medd, modeled the wild oat seed bank as a function of the seed bank in the previous period and wild oat seed panicles at harvest. King et al. modeled the seed banks of both aggregate grass and aggregate broadleaf weeds as linear functions of the seed bank in the previous period and the number of weeds at harvest. The Taylor and Burt, Pandey, Pandey and Medd, and King et al. models all ignored the dormancy issue.

Experimental evidence suggests that weed seed germination occurs as a proportion of the seeds in the seed bank (Cavers and Benoit, Forcella 1990, 1991). For simplicity, this model treats weed seedling germination as a Markovian process, ignoring dormancy. In the absence of weed control, weed seed germination in stage τ of the growing season can be specified as

$$w_{\tau it} = \alpha_{\tau i} s_{it-1} \tag{3.2}$$

where $w_{\tau it}$ is seedling germination by weed species i in stage τ, s_{it-1} is the seed bank of weed species i in the previous season, and $\alpha_{\tau i}$ is a parameter representing the proportion of weed seeds of species i germinating during stage τ. Note that $\alpha_{\tau i}$ may be estimated as a coefficient, or treated as a function itself. In the Forcella germination model, cumulative seasonal weed germination is simulated as $\alpha_i = \alpha_i(\mathrm{AGDD})$, where AGDD is cumulative April growing degree days.

For management purposes, weed seedling germination in row crop fields takes place in three stages: prior to crop planting, after planting, and after post-emergent weed control. Germination prior to crop planting, w_{0it}, follows equation (3.2). Only weed species tolerant of cool weather germinate in significant numbers at this stage. These weeds are killed by the crop planting operation, but their numbers require tracking since they represent a loss from the soil seed bank. Weed seedlings germinating with the crop seeds, w_{1it}, represent a competitive threat to the crop. Due to the use of pre-emergent herbicides, germination and emergence are not necessarily equivalent. Weeds that emerge can be expressed as those that germinated and survived any control treatment,

$$w_{ijt}^{e} = w_{1it}[1 - k(wsp_i, h1_{jt})] \tag{3.3}$$

where $h1_{jt}$ is a dummy variable for pre-emergent weed control treatment j in period t. Some of these surviving weeds may be killed by post-emergent weed control treatments, $h2_{jt}$. Weeds that get established with the crop and compete for more than four to six weeks cause the greatest reduction in crop yields (Stoller et al.). Some weed seedlings emerge after post-emergent treatment, w_{2ijt}. These compete weakly with the crop. However, some reach reproductive maturity and set seed. Weeds at harvest can be expressed as,

$$w_{ijt}^{h} = w_{ijt}^{e}[1 - k(w_i, h2_{jt})] + w_{2ijt} \tag{3.4}$$

where $h2_{jt}$ is post-emergence weed control treatment j, and w_{2ijt} is weed emergence following post-emergent weed control.

WEEDSIM, the recommendations module, simulates these steps through four procedures. WSWeedGerm accepts parameters for the number of weed species being modeled, initial weed seed counts for each, and germination rates for each species before and after planting. It returns expected weed density (w_{1it}) and an updated seed bank for each weed species. WSPreTrt accepts input parameters for the number of weed species, number of PPI and PRE weed treatments, PPI and PRE efficacy ratings, operating costs for field cultivator and sprayer, herbicide rates and unit costs, field size, and variable cost/acre. It calls a weed survival function (Surv), passing weed species and treatment type, to obtain the proportion of weeds of each species surviving each type of treatment. WSPreTrt allows either a PPI or a PRE weed control, but not both. It returns the expected density of weeds surviving PPI/PRE treatment, along with the associated cost and treatment identity. WSPostTrt executes similar functions on the weed densities output from WSPreTrt to predict the number of weeds surviving each combination of PPI/PRE and POST treatment.

The soil seed bank is the link between seasonal weed populations. It contains a stock of viable seeds which grows with the deposition of new seeds and shrinks through seed death and germination. By reducing the number of weeds surviving to reproduce, weed control practices affect seed bank growth.

Reproducing weeds add seeds to the soil seed bank. Abstracting from the age and size of individual weeds, their mean contribution is a simple multiple of the number of weeds at harvest, w_{ijt}^{h}. These seeds join the survivors from the previous season, determining the current seed bank, s_{it},

$$s_{it} = (1 - \sum_{S=0}^{2} \alpha_{si} - \beta_{i}) s_{it-1} + \gamma_{i} w_{it}^{h} \tag{3.5}$$

where $\Sigma\alpha_{si}$ represents the number of seeds of species i lost through germination during the S=3 stages of period t, β_i represents those lost through seed death in the soil, and γ_i represents mean seed production per mature weed.

The recommendations module implements the seed production equation via procedure WSSeedBank. This returns updated seed bank densities based upon parameters for number of weed species, end-of-season weed densities, mean seed production per weed, seed mortality rates, and previous year seed densities updated to subtract cumulative germination during the season.

3.1.2.2 Weed control efficacy

Weed control "efficacy" refers to the toxicity of a control treatment toward the target weed. As implied by the function k(wsp,h), it is determined by the choice and quantity of the control input, h, and the susceptibility of the weed species, wsp.

Herbicide efficacy ratings for treatment at recommended rates are available by weed species (e.g., Durgan <u>et al</u>.). These are expressed as a set of discrete levels, such as "poor," "fair," "good," or "excellent," which correspond to quantiles. Because recommended rates are fixed, the weed control function for a given treatment jumps discontinuously from a stated efficacy level to zero if some condition for efficacy fails. For herbicides sprayed upon the soil before weed seedlings emerge (pre-emergent herbicides), a common condition is that sufficient rain fall to move the chemical into the soil layer where weed seeds are germinating. For herbicides sprayed on weeds that have already emerged (post-emergent herbicides), common conditions are 1) that no rain wash the chemical from the weed leaves within four hours of spraying, and 2) that weeds be at a susceptible life cycle stage.

The kill function employed here takes the form,

$$k(wsp_i, h_j^r) = \kappa_{ij} w_i,\ \kappa_{ij} = \begin{cases} k_{ij} & if\ conditions\ suitable \\ 0 & otherwise \end{cases} \tag{3.6}$$

where h_j^r is treatment j applied at the recommended rate and k_{ij} is the proportion of weeds of species i killed as a result. As noted above, the recommendations module implements this using the Surv function, which transforms efficacy ratings from Durgan <u>et al</u>. into survival rates based upon weed species and treatment type. The input data file includes additional information on efficacy of mechanical weed control methods.

The fact that some POST treatments are not efficacious for weeds or crops greater than a specified size makes it desirable to model plant growth. Since only the 4-6 weeks after crop planting are of interest, a rudimentary growth equation will suffice. For this short period, the average height of a plant species, ph_i, can adequately be modeled as a simple quadratic function of the number of days after planting, $ph_i = \delta_i(DAP)^2$. This form appears to work acceptably for both crops and weeds. Efficacy thresholds stated in terms of number of leaves are readily converted to height format due to the high correlation between height and leaf number. When plants exceed the height threshold for POST efficacy of a given treatment, its efficacy is assumed to be nil, as in equation (3.6).

3.1.2.3 Yield loss due to weeds

The appropriate form for modeling yield as a function of weed density is much debated. Most researchers agree that the yield function is nonlinear, although some hold that a linear form is suitable approximation within the range of weed populations found in farmer's fields (Marra and Carlson).

There is general agreement that crop yields decline to some minimum level at high weed densities, since weed-weed competition becomes more important than weed-crop competition. The debate centers around what occurs at low densities. The issue is clouded by the high variability of crop yields at low weed densities. Zimdahl (1980) argues that the yield function takes a sigmoidal form. Yield loss is negligible at low weed populations, since there is no significant competition for resources between crop and weed. There has been little verification of this theory, as only King et al. have fit a sigmoidal functional form to data.

Cousens (1985a) counters that crop yield loss per weed is greatest at low weed densities. When weeds are few, they grow larger and compete more vigorously with the crop. To capture this, he proposes the hyperbolic yield function:

$$Y = Y^0\left[1 - \frac{Iw}{100(1 + Iw/A)}\right] \qquad \textbf{(3.7)}$$

where Y^0, I and A are parameters to be estimated from data. I represents percentage loss in crop yield per unit of weed density as density approaches zero, and A represents the maximum percentage crop yield loss asymptote as weed density approaches infinity. The hyperbolic form, illustrated in Figure 3.3, is approximately linear at low weed densities. At high densities it becomes asymptotic to the minimum yield level (Y_{min}) given by $Y^0*(1-A/100)$. Cousens found this functional form to outperform 18 others from previously published studies, based on residual sums of squares and F-test comparisons when fit to 22 sets of weed density-crop yield data.[1]

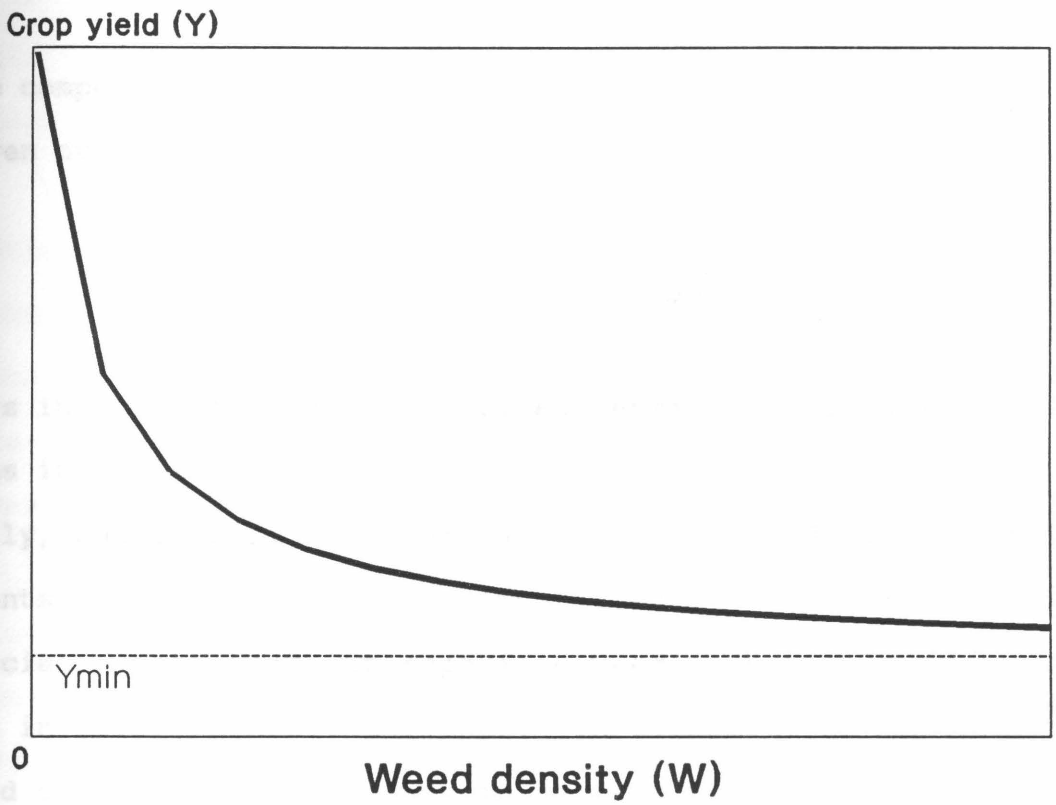

Figure 3.3: Crop yield as a hyperbolic function of weed density.

One multivariate formulation of equation (3.7) is presented in equation (3.8), where the subscript i denotes the weed species.

[1] None of these studies used a sigmoidal form.

$$Y = Y_0\left[1 - \frac{\sum_i I_i w_i}{100\left(1+\sum_i I_i w_i/A\right)}\right] \qquad (3.8)$$

The competitive effect of an additional weed of species n is given by the derivative in equation (3.9).

$$\frac{\partial Y}{\partial W_n} = I_n\left[\frac{-Y_0 A^2}{100\,(A+\sum_i I_i W_i)^2}\right] \qquad (3.9)$$

This implies that as the combined density of all weed species in a field increases, crop yield declines monotonically, but at a diminishing rate. The individual I_i coefficients implicitly serve as competitive indices for each weed species. Note that interspecific weed competition is implicit in (3.8), since the competitive effect of an additional weed of one species depends in part on the density of the other species.

The hyperbolic form is the most appealing for several reasons. The hyperbolic and logistic forms are preferable to the linear one because they bring prior knowledge about plant ecology to an otherwise unconstrained statistical estimation problem. Moreover, the linear form can generate negative yields at high weed densities. The ready interpretation of its coefficients makes the hyperbolic form more attractive than the logistic <u>a priori</u>. When the linear, logistic, and hyperbolic forms were compared for this study, the hyperbolic form provided the best statistical fit, based upon log likelihood function and the standard error of estimate (SEE). In fact, the hyperbolic form is rapidly gaining acceptance (Stoller et al.), although its nonlinearity makes estimation somewhat more cumbersome than for the linear or linearized logistic forms.

To implement the yield function, the recommendations module procedure WSPostTrt calls function Yield2. Yield2 returns a predicted yield based upon input parameters for number of weed species, crop identity, weed-free crop yield, late-season weed density, and weed-crop competition parameters.

The structure of the WEEDSIM recommendations module is illustrated in Figure 3.4. The initial biological subroutines predict the expected weed infestation and expected response to controls. The recommended treatments are determined by the economic decision rule chosen.

3.2 Structure of the Whole Farm Model

The WEEDSIM module generates weed management recommendations for a typical acre of corn or soybean field. The whole farm shell for the recommendations module, WFARM, both captures the effects of limited time and machinery, and allows modeling of stochastic phenomena (weather in particular). This permits evaluation of the recommendations

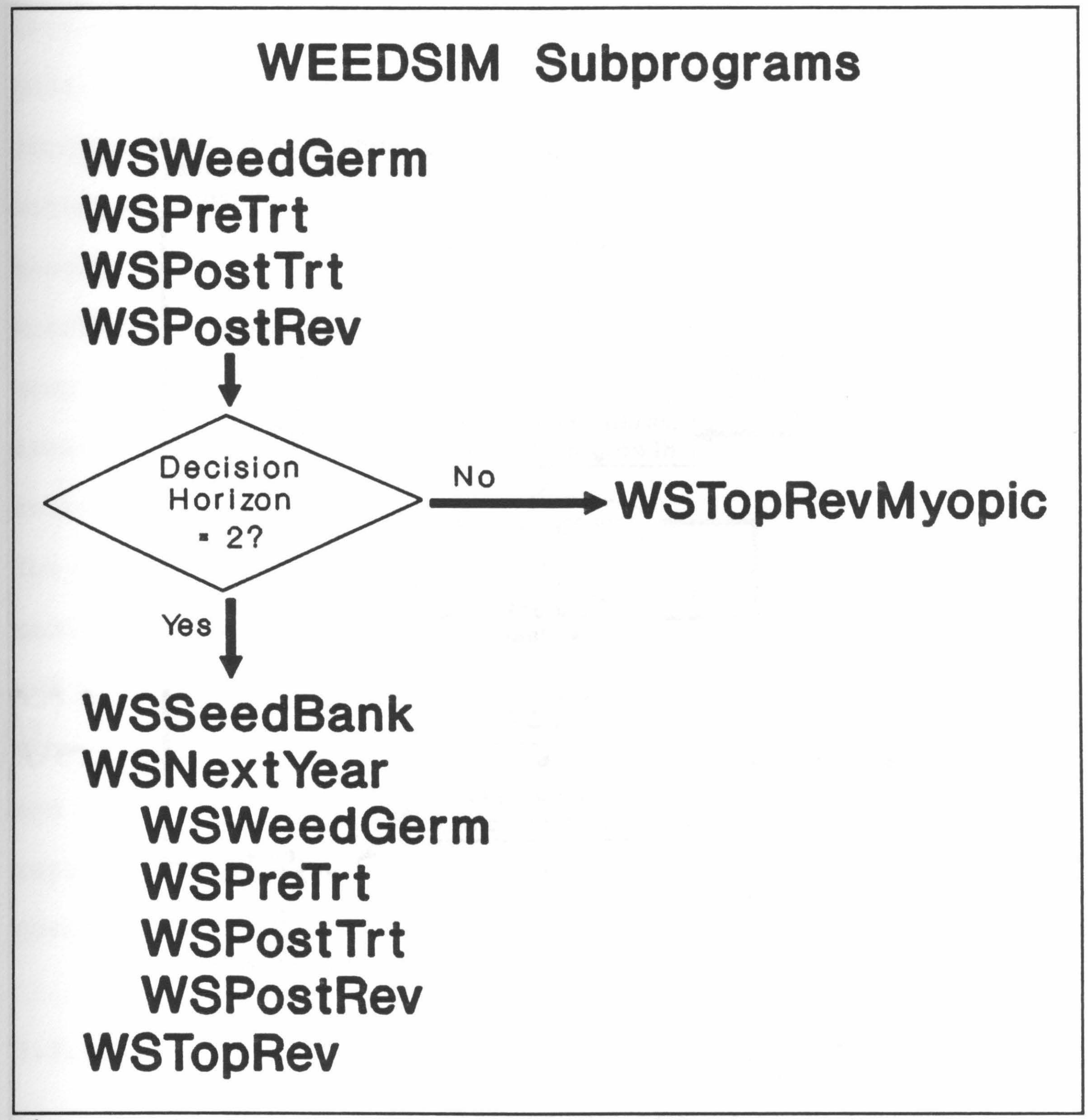

Figure 3.4: Structure chart of the WEEDSIM module.

module through stochastic simulation, before testing it on real fields.

The flow of the WFARM model is illustrated in Figure 3.5. WFARM begins a simulation season by choosing a year at random from a historical data file. The year record includes data on maximum weed-free yield, precipitation,

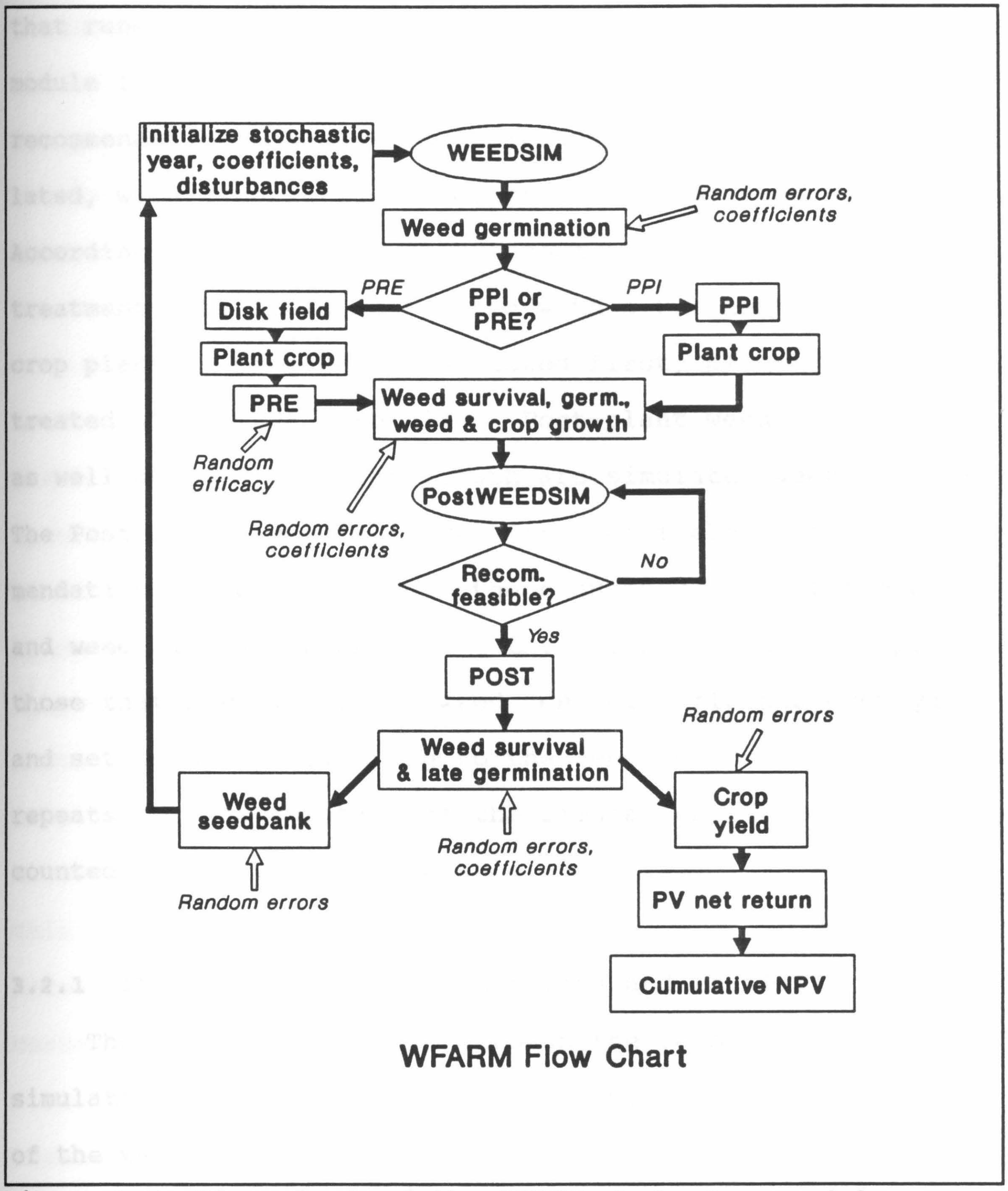

Figure 3.5: Flow chart of the WFARM whole farm model.

workable field days, and simulated total weed germination. WFARM also draws pseudo-random coefficients and disturbance terms from data files associated with each of the equations that runs the WFARM model. Then the model runs the WEEDSIM module for each field, to obtain a PPI/PRE weed management recommendation. Next weed pre-plant germination is simulated, with associated losses from the weed seed bank. According to whether WEEDSIM recommended a PPI or a PRE treatment, the field is treated with a PPI herbicide and the crop planted, or else it is disked first, planted and treated with a PRE herbicide. Post-plant weed germination as well as weed and crop growth are simulated week by week. The PostWEEDSIM module is run for each field. If the recommendation is feasible given the simulated size of the crop and weed, it is implemented. Late-germinating weeds plus those that survived prior weed control influence crop yield and set seed, contributing to the weed seed bank. The cycle repeats for the duration of the simulation period, with discounted net returns accumulated annually.

3.2.1 The role of timely operations and rainfall

The WFARM model steps through the season week by week, simulating crop and weed biology as well as implementation of the weed control recommendations, in light of available precipitation and field working days. By tracking individual activities in each field, late planting can be penalized and untimely weed treatments ruled out.

Planting is the first operation to trigger timeliness penalties if delayed too long. The penalty reflects losses incurred when crops in a northerly climate fail to attain the optimal number of growing degree days. Yield penalties for planting after the optimal period (implemented by subroutine Ypen) are stepwise in time for both corn and soybean (Gunsolus 1990a). As farm size increases, these penalties come into play.

Timeliness for post-emergent weed control is related to weed and crop size. Efficacy ratings for many post-emergent chemical and mechanical weed control measures are contingent upon the size of the weeds or crop. The model simulates plant growth during the first few weeks after emergence using simple quadratic functions of days after planting (in subroutines CropGrowth and WeedGrowth). Recommended treatments may become infeasible or ineffective when the weed or crop grows too large for a given treatment. The model allows re-evaluation of the recommended weed control plan at this point, taking as given the pre-emergent treatment already implemented. Of course, revised plans incur higher costs or provide poorer efficacy.

Apart from timeliness matters, herbicide efficacy is another important factor subject to environmental vagaries. Pre-emergent chemical weed control requires at least a half inch of rain within one week of application to attain rated efficacy levels. Failing this, efficacy is nil. The only recourse is post-emergence weed treatment. On the other hand, pre-plant incorporated and post-emergence control treatments are assumed to have deterministic efficacy. In the first case, soil moisture is presumed sufficient to bring the chemical into contact with germinating weed seeds. In the latter case, it is supposed that if rain threatens, a farmer will not spray or rotary hoe.

3.2.2 Sequence of whole-farm model operations

The specific subprograms that implement the operations illustrated in the WFARM flow chart (Figure 3.5) are shown in Figure 3.6. The resource base for the model farm includes farm acreage, machinery type and size, and labor. Parameters for these are input by the user at the start of a model run. Other parameters read from sequential data files upon initialization of the model include weed treatment rates and costs (read by GetHerbData); treatment efficacy ratings (read by GetKillData); machinery costs and rates of operation (read by subroutine GetMachData); weed growth, expected germination and population dynamics equation coefficients (including coefficients for auxiliary variance equations; read by subroutine GetWeedParm3); crop growth, expected yield and maximum yield loss percent coefficients (read by GetCropData); and weed-crop competition coefficients (read by GetCompData).

At the outset of a season, the whole farm model runs the WEEDSIM recommendations module for each field on the farm. Recommendations are developed based upon expected weed seed germination and maximum yield levels. The whole farm model then implements the recommended weed management plan, subject to random weed germination, weed seed production, weed-free crop yield, weed-induced crop yield loss, time available for field work, and herbicide efficacy.

Crop and weed growth as well as farmer management are simulated field by field. The model starts each simulation season by reading the number of weekly available field working days, weekly precipitation, maximum yields, and predicted weed species germination rates (Forcella 1991) from a data file (using subroutine GetYear). It proceeds by reading from a file of random coefficients and additive error terms associated with the estimated equations (via subroutines GetStateBetas and GetStateErrors). Actual numbers of germinated weeds at each stage (pre-plant, post-plant and post-cultivation) are generated by subroutine CalibrateGerm, which adjusts the expected yearly germination levels for dependence upon seed density and heteroscedastic errors. The germination calibration equations utilize randomized coefficients as well as additive random error terms (from GetStateBetas and GetStateErrors). These take the form,

$$w_{\tau it} = (\hat{\alpha}_{i\tau} + \epsilon_{\alpha\tau i})\, s_{it-1} + u_{i\tau} \tag{3.10}$$

where $\alpha_{i\tau}$ is estimated germination of weed species i at stage τ, $\epsilon_{\alpha i\tau}$ is additive random coefficient error, and $u_{i\tau}$ is additive random equation disturbance.

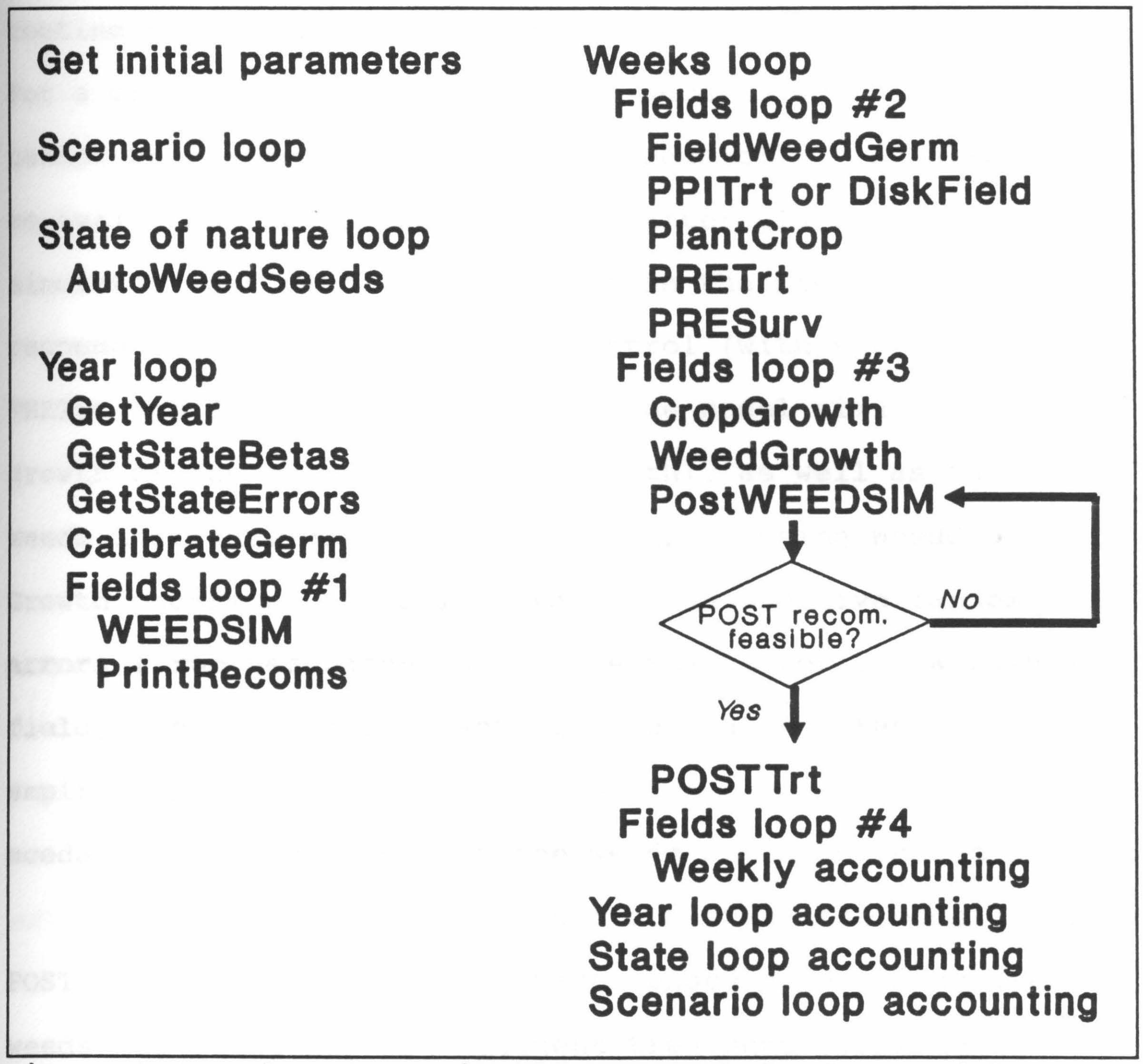

Figure 3.6: Subprograms in the WFARM whole farm model.

Simulated field management begins the first week that corn can be planted, around the week of April 19-25 in southwestern Minnesota. Weed seedling emergence prior to crop planting is simulated first (with subroutine FieldWeed-Germ). Field cultivation (with subroutine FieldCult) and incorporation of any recommended PPI herbicide (with subroutine PPITrt) follows, up to the available number of field working days that week.[1] Crop planting is next (with subroutine PlantCrop), if the crop can be planted that early. For a crop requiring warmer soil, such as soybean, which cannot be planted before May, the feasibility of planting is re-evaluated the following week. After planting, the model simulates weed seedling emergence in the presence of any recommended pre-emergent weed control (with subroutines PRETrt and PRESurv). Each week, the model simulates the growth of the crop (using CropGrowth), as well as those weeds that survive PPI and PRE control (using WeedGrowth). Growth occurs at randomized rates plus additive random errors (from GetStateBetas and GetStateErrors). Within a field, they remain constant for the season. Based on empirical results, errors for the two crops are heteroscedastic, while those for the weeds are homoscedastic.

Since weed germination is stochastic, the model revises POST weed control recommendations based upon the number of weeds surviving any pre-emergent treatment (implementing subroutine PostWEEDSIM). This is essentially a call to WEEDSIM, taking as given post-plant weed emergence and any already implemented soil-applied weed control. Post-emergent weed control by rotary hoe begins the week following planting. For chemical treatments, it begins 2-3 weeks

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[1] Only conventional tillage is included in the whole farm model. Some reduced tillage practices require no preplant field cultivation unless pre-plant incorporated herbicides are used.

after planting. Ensuing weed survival is simulated in subroutine WSPostTrt. The final weed densities used to calculate crop yield and additions to the weed seed bank are simulated in the main program.

At any stage in this sequence, the tasks may be interrupted by the end of available field time in the week. At this time, the week's activities are tallied. For each field, costs are accrued and the density of remaining seeds in the soil updated. Planting dates are recorded, since weed-free yield is reduced from the maximum level according to the delay between the optimum planting time and the one achieved in a given field.

At the end of a simulated year, stochastic yields and weed seed densities are calculated for each field. As estimated equations for these were homoscedastic, random errors from GetStateErrors are simply added to expected values calculated from other arguments developed in the model. Since the expected values are either composites from several data sets (yield coefficients) or values imposed from review of the literature (seed reproduction coefficients), these coefficients are not randomized. Costs, net revenue, and the weed seed bank state variables are updated. Simulation proceeds to the next year (following implementation of subroutine InitializeYear), if another is called for in the planning horizon.

The whole farm model is nested in a "state of nature" loop used for stochastic simulation. States of nature are drawn at random from input data files. The states include 1) the year parameters obtained with GetYear, 2) the random coefficient deviations from the mean in GetStateBetas, and 3) the random disturbance terms associated with individual fields obtained with GetStateErrors. In a given simulation year, equation coefficients and error terms vary from field to field, but the year parameters (maximum crop yield, expected weed germination, rainfall, field days) are constant for all fields.

When multiple scenarios are run, an outer set of loops is added to control the experimental factors varied under the different scenarios. The simulation runs summarized in Chapter 5 had two outer scenario loops, one for decision rules, and one for initial weed seed density settings.

3.2.3 Controllability of the biological system

The biological components of the simulation model essentially provide an accounting of seed and weed numbers. Whether the model is capable of maintaining an equilibrium weed seed population depends upon the parameters supplied and the stochastic errors generated.

The biological system is controllable in a given year if there exists a PPI/PRE and POST treatment pair such that the seed bank for each weed species can be reduced by the outset of the next season. While this should not be a formidable requirement, two quite different conditions can impede controllability. First, random disturbances in a given season may make short-term controllability impossible. When random errors are large, as may be the case for heteroscedastic equations, stochastic model results may far diverge from expected values. Second, mixing parameters estimated from data sets using different measurement methodologies can lead to explosive simulated weed populations. Seed counts, in particular, may differ by orders of magnitude according to the method used (compare, e.g., seed counts in King et al. and Forcella and Lindstrom 1988b). Since germination rate estimates are based on the previous season seed count, the same density of observed seedlings may lead to vastly different germination coefficients. When estimating parameters from data, it is advisable to estimate the group of weed population dynamics equations from the same set of data.

This note of caution sets the stage for the next chapter. Chapter 4 presents the methods employed to develop and validate the set of parameter estimates used to test the simulation model.

IV. DATA AND ESTIMATION

The simulation model described in Chapter 3 requires parameters provided through input files. This chapter describes the development of the input parameter sets used to run the WEEDSIM and WFARM models. It reports methods used to generate correlated pseudo-random variables to simulate error terms for the stochastic simulation experiments discussed in chapters 5 and 6. Where out-of-sample data were available, it also reports results of equation-by-equation validation tests.

Input parameters for the model are developed for the weed species that are economically important to corn and soybean farmers in southwestern Minnesota. Since tillage tends to keep biennial and perennial weeds from getting established in row crops, these are all annuals. They include: green and yellow foxtails (<u>Setaria viridis</u> (L.) Beauv. and <u>S. glauca</u> (L.) Beauv.), redroot pigweed (<u>Amaranthus retroflexus</u> L.), and common lambsquarters (<u>Chenopodium album</u> L.). In addition, yield loss estimates for other weed species are presented in instances where they were present in significant numbers.

Parameters are developed using a variety of techniques, according to the quality and availability of suitable data. Germination rates are predicted using the Forcella (1991) growing degree days model combined with 1985-86 agronomic field trial data from the U.S. Department of Agriculture North Central Soil Conservation Research Laboratory in Morris, Minnesota. Seed production is estimated from that same data set. Yield loss parameters are estimated using eleven sets of agronomic trial data for Upper Midwest corn and soybean. Weed control efficacy ratings are drawn from extension literature (Durgan et al.). Finally, days available for field work, precipitation, and growing degree days are obtained from historical records at the Southwest Experiment Station of the University of Minnesota, Lamberton, Minnesota (Ford, Fuchs). All statistical estimation was carried out using SHAZAM version 6.2 (White et al.).

The 1985-86 Morris data set is the only one available for Minnesota that includes observations on weed seed density, emerged weed seedling density, and crop yield over more than one year. Consequently, its strengths and weaknesses have important ramifications for the quality of the parameters estimated. The data were generated through an agronomic experiment examining the impact of different tillage methods upon weed seed movement and emergence in corn, soybean and wheat crops[1] (Forcella and Lindstrom 1988a, 1988b). Weed seed densities were estimated from soil samples of the experimental plots. Six soil cores were

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[1]Data used for this thesis include only the corn and soybean plots.

sampled from each conventional tillage plot, representing 1:5218 of the top 10 centimeters of soil. Emerged weed seedling densities were estimated from counts of sample quadrates placed in the field plots. The weed seedling sampling quadrate covered 1:369 of the plot surface. Seed and seedling samples did not necessarily come from the same locations within a plot. Samples were counted before crop planting, after crop emergence, and after mid-season lay-by cultivation. The research plots were split, with two thirds of each plot treated with PPI and PRE herbicides and one third left untreated in each year of the experiment. The late-season weed count was performed only on the treated sub-plots. The post-emergence weed count was conducted on the treated plots only in 1985.

The weed count procedure allows pre-plant weed seed germination to be estimated from all plots. Post-planting weed germination can be estimated from the untreated sub-plots, while post-cultivation germination can be estimated from the treated sub-plots. Late-season weed counts included only seedlings that emerged after cultivation. Hence, total weed density in the crop row may be inferred as the sum of post-emergence density and post-cultivation density, where post-cultivation density on untreated sub-plots is assumed to be the same as on the treated ones.[1] Total

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[1]Forcella (1991), personal communication.

weed density is the basis for estimation of weed-crop competition and weed seed production coefficients.

Substantial sampling error contributes to the variance of estimated equations. Since seed density estimates are extrapolations from a rather small sample, their variability is quite high. Weed seedling density estimates come from larger areas that are not necessarily coincident with the seed samples. Hence, considerable sampling error enters into germination proportion estimates and weed seed production estimates, as has been observed elsewhere (Ball and Miller, Wilson et al.). To a lesser extent, this is also true of weed-crop competition estimates, since yields were measured from the entire plot area, not just the areas sampled for weed density. Total late-season weed density is inferred from earlier weed density estimates, rather than direct sample counts.

4.1 Weed population dynamics functions

4.1.1 Germination functions

Weed seedling germination parameters are required by the WEEDSIM and WFARM models for weed germination 1) before crop planting (WSWeedGerm and FieldWeedGerm), 2) after crop planting (WSPreTrt and PRETrt), and 3) after lay-by cultivation (WSPostTrt and POSTTrt). Two methods are available to develop weed seedling germination parameters. The first is to estimate them statistically from the 1985-86 Morris data. The second is to simulate them using the Forcella (1991) seedling emergence model.

The potential of statistical estimation for attaining reliable coefficient estimates is limited by the reliability of the data. First, the weed seed density and seedling emergence data are themselves estimates extrapolated from relatively small samples. The associated sampling variance considerably augments the expected variance of a regression equation. This is especially true of the post-emergence and post-cultivation weed counts, for which only half the 144 observations were usable. Second, examination of the data reveals that germination rates were dramatically higher in 1985 than in 1986. This could be modeled statistically using dummy variables, but that still would not explain the difference in a manner easily applied to a simulation model. Third, the presence of many plots in which no seedlings of a given weed species emerged suggests that tobit regression would generate the best coefficient estimates. However, tobit residuals have poorly defined properties, particularly regarding correlation with residuals from related equations. While tobit regression forecasts the probability that the mean of the dependent variable will be zero, it cannot predict specific cases of zeroes. Residuals calculated by subtracting predicted values from actual values may have a highly skewed distribution. Yet regression residuals are required for stochastic simulation.

The Forcella (1991) emergence model offers a non-statistical alternative. It forecasts weed seedling emergence in the absence of herbicides. The model predicts the rate of weed seedling emergence as a function of cumulative growing degree days (GDD) for the month of April. A GDD is defined as the average of the high and low daily temperatures in degrees Celsius minus ten. The Forcella emergence equations for all three weed species in the model are non-linear functions with a single maximum. In effect, if April is too cool or too hot, fewer weeds than the maximum will emerge. Denoting Y as emergence rate and X as cumulative April GDD, Forcella's emergence equations are as follows:

foxtail, $Y = 0.0205*0.9587^{X}*X^{2.4958}$

lambsquarters, $Y = -8.1326 + 1.3876*X - 0.0127*X^{2}$

pigweed, $Y = 16766.9*(7.68E-29)^{1/X}*X^{-1.4679}$

All three functions have biologically reasonable forms, although the lambsquarters quadratic predicts negative emergence if April GDD are fewer than 6.2 or more than 103.0. Predicted emergence rates as a function of GDD are illustrated in Figure 4.1.

The Forcella germination model offers a clear explanation for the disparity between the two sample years. However, it lacks the statistical richness of a 144 case data set. Indeed, Forcella's simulation equations were

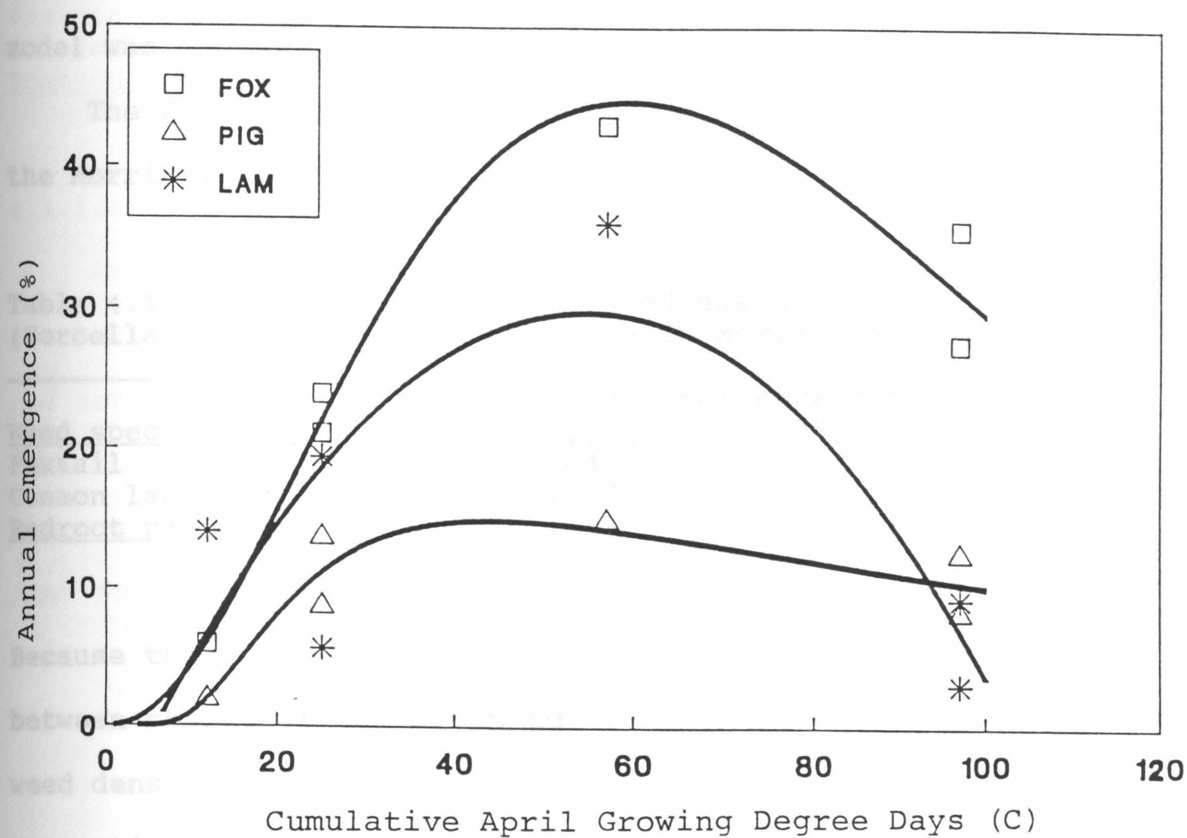

Figure 4.1: Total emergence of three weed species as related to growing degree days in April (from Forcella, 1991)

developed from a very small time series data set. Compared with the tobit residuals problem, however, there is no difficulty in calculating artificial "pseudo-residuals" as the difference between actual seedling emergence numbers and those predicted by applying the Forcella predicted rates to the observed seed bank.[1] Given these strengths and the general objective of developing reasonable parameter values for incorporation into the simulation model, Forcella's model was chosen.

The Forcella predicted emergence rates corresponding to the Morris 1985-86 data set are presented in Table 4.1.

Table 4.1: Predicted cumulative weed emergence rates (Forcella model) for 1985 and 1986 in Morris, Minnesota.

	Predicted emergence rate	
Weed species	1985	1986
Foxtail	.447	.061
Common lambsquarters	.297	.067
Redroot pigweed	.142	.020

Because the Forcella emergence rates do not distinguish between stages of the cropping season, the 1985-86 Morris weed density data were partitioned in order to identify the proportion of total weed emergence that occurs at each stage. Mean emergence proportions by stage of the season are presented in Table 4.2. They are consistent with the results published by Chepil.

[1]The term "pseudo-residuals" is adopted in order to reserve the word "residuals" for those obtained from a statistically estimated predictor.

Table 4.2: Weed seedling emergence proportions for three stages of the cropping season (Morris, MN, 1985-86).

	Weed species		
Stage of the season	Foxtail	Lambsquarters	Pigweed
Pre-planting	.18	.40	0
Post-crop emergence	.72	.54	.92
Post-cultivation	.10	.06	.08

4.1.1.1 Calibration of the Forcella germination predictor

Predicted weed density is calculated as the product of cumulative emergence rate, emergence proportions per stage and estimated weed seed density. Pseudo-residuals were generated by subtracting the predictions from actual values. The pseudo-residuals were regressed on weed seed density to test for systematic bias. In anticipation of spatially correlated seed data (due to the presence of weedy strips in the untreated sub-plots), seemingly unrelated regression (SUR) was applied to the emergence pseudo-residual equations for all three species. Results suggested that bias was present in most cases, with predicted germination rates deviating from actual ones in a linear or quadratic relation to seed density. This was corrected by calibrating the pseudo-residuals against weed seed numbers.

The calibration regressions for pre-plant weed emergence are presented in Table 4.3. The Breusch-Pagan Lagrange multiplier test for contemporaneous correlation (Judge et al., p.456) generated an insignificant $\chi^2(3)$ value of 0.72, so ordinary least squares (OLS) regression was applied. Pseudo-residuals representing the difference between actual pre-planting weed densities and the Forcella predicted values were regressed on seed density and squared seed density. As no pigweed seedlings emerged at this stage, pigweed was omitted. The significance of the regressions ($F(2,141) = 30.63$ for foxtail and $F(2,141) = 360.73$ for lambsquarters) suggested a need for calibration. Logarithmically transformed absolute residuals from the first set of regressions were regressed on the same independent variables to test for heteroscedasticity. Significant evidence of nonconstant variance was present for lambsquarters, $F(2,141) = 8.26$. Weighted least squares (WLS) regression of the pseudo-residuals was performed, using the standard error of estimate as the weighting factor.

The unweighted foxtail and weighted lambsquarters calibration regressions imply that for both weeds, the Forcella predictor under-estimates pre-plant weed densities when seeds are few, and over-estimates them when seeds are many. As both equations are quadratic, at extremely high seed densities, the sign of the mis-calibration reverses itself. For weed seed densities in the 0-3000 seeds/m^2 range, however, the Forcella predictor over-estimates at high densities. Over-estimation is particularly severe for lambsquarters. The presence of significant intercept terms in both regressions is at first perplexing, since if no seeds are present, we expect no seedling emergence. The intercept term is, in fact, a compensation for seed sampling

Table 4.3: Calibration regressions of the pre-planting weed density pseudo-residuals.

Weed species	d.f.	Coefficient Constant	Seeds	$Seeds^2$	SEE	R^2
Pseudo-residuals (OLS)						
Foxtail	141	12.92	-0.031	0.22E-5	26.7	.30
		(4.37)	(-5.09)	(2.36)		
Lambsquarters	141	3.41	-0.11	0.26E-3	4.3	.84
		(7.01)	(-16.3)	(23.63)		
Log absolute residuals (OLS)						
Foxtail	142	2.11	1.3E-4		0.9	.02
		(24.71)	(1.52)			
Lambsquarters	142	0.63	0.0017		0.9	.05
		(6.98)	(2.87)			
Weighted pseudo-residuals (WLS)						
Lambsquarters	141	2.76	-0.090	2.1E-3	1.9	.46
		(6.36)	(-10.57)	(10.54)		

Note: t-statistics presented in parentheses.
d.f. denotes degrees of freedom.
SEE denotes standard error of estimate.

error evident in cases where the density of emerged weeds observed in experimental plots exceeded the estimated seed density.

Similar calibration regressions were applied to weed densities observed after crop emergence. In this case, the Breusch-Pagan $\chi^2(3)$ statistic was 5.90 for the unweighted and 10.96 for the weighted systems. These statistics are significant at the 20% and 5% levels, respectively, so seemingly unrelated regression (SUR) was applied to the pseudo-residuals. The heteroscedasticity tests were followed as above, using a logarithmic transformation of the absolute residuals. Results, presented in Table 4.4, again suggest that the Forcella model under-estimates weed emergence at low seed populations and over-estimates it a high ones.

Table 4.4: Calibration regressions of the post-planting weed density pseudo-residuals.

Weed species	d.f.	Coefficient Constant	Seeds	$Seeds^2$	SEE	R^2
Pseudo-residuals (SUR)						
Foxtail	70	14.70	-0.068		117.4	.24
		(0.95)	(-4.79)			
Lambsquarters	70	4.09	-0.044		12.1	.16
		(2.45)	(-4.06)			
Redroot Pigweed	69	-3.63	0.028	-1.7E-5	13.0	.08
		(-1.58)	(2.14)	(-2.25)		
Log absolute residuals (OLS)						
Foxtail	69	1.93	0.0026	-0.31E-6	1.3	.40
		(9.26)	(6.20)	(-4.61)		
Lambsquarters	70	1.33	0.0021		1.2	.05
		(7.83)	(1.93)			
Redroot pigweed	70	1.51	6.3E-4		1.1	.03
		(9.61)	(1.45)			
Partially weighted pseudo-residuals (SUR)						
Foxtail(wtd.)	70	11.12	-0.084		2.3	.13
		(2.92)	(-3.49)			
Lambsquarters	70	3.91	-0.042		12.1	.16
		(2.33)	(-3.83)			
Redroot pigweed	69	-3.37	0.0026	-1.7E-5	13.1	.07
		(-1.48)	(1.95)	(-2.14)		

Note: t-statistics presented in parentheses.

The calibration regressions for weed emergence following lay-by cultivation also used SUR, since the Breusch-Pagan $\chi^2(3)$ statistics were significant at the 5%

level (10.05 for the unweighted and 31.34 for the partially weighted systems). Because the partially-weighted SUR matrix was not positive definite as originally formulated, constant terms were dropped. The results are presented in Table 4.5. The table suggests that calibration of the

Table 4.5: Calibration regressions of the post-cultivation emergence weed density pseudo-residuals.

			Coefficient			
Weed species	d.f.	Constant	Seeds	$Seeds^2$	SEE	R^2
Pseudo-residuals (SUR)						
Foxtail	70	1.11	-0.0072		12.3	.23
		(0.69)	(-5.16)			
Lambsquarters	70	0.59	-0.0063		2.1	.13
		(2.02)	(-3.34)			
Redroot Pigweed	70	0.16	-0.0011		1.3	.02
		(0.82)	(-2.08)			
Log absolute residuals (OLS)						
Foxtail	69	0.40	0.0015	-1.6E-7	1.4	.18
		(1.83)	(3.38)	(-2.35)		
Lambsquarters	70	-0.45	9.4E-4		1.0	.02
		(-3.37)	(1.07)			
Redroot pigweed	70	-0.54	-1.4E-4		1.0	.00
		(-3.98)	(-0.36)			
Partially weighted pseudo-residuals (SUR)						
Foxtail(wtd.)	71		-0.0059		2.6	
			(-2.60)			
Lambsquarters	71		-0.0041		2.1	
			(-2.50)			
Redroot pigweed	71		-8.6E-4		1.4	
			(-2.11)			

Note: t-statistics presented in parentheses.

pseudo-residuals is most important for foxtail and lambsquarters predictions, which are slightly over-estimated at moderate to high seed densities. Since the weeds that emerge after mid-season cultivation tend not to be controlled, their reproduction makes an important contribution to the weed seed bank (Forcella and Lindstrom 1988b). Hence, calibration of these is important.

Final parameter estimates retained from the calibration regressions are 1) the unweighted foxtail and weighted lambsquarters least squares estimates for pre-planting weed emergence, 2) the partially weighted SUR estimates for post-planting weed emergence, and 3) the weighted foxtail and unweighted lambsquarters SUR estimates for post-cultivation weed emergence.

4.1.1.2 Validation of the calibrated germination predictor

The calibrated germination functions were validated against out-of-sample data from 1990 field trials at the USDA North Central Soil Conservation Laboratory in Morris, Minnesota. The data came from two sites. The 16 observations from the Central Farm contain very high weed seed densities for all three species modeled. The 24 observations from the North Farm generally have low weed seed densities. Jointly, they represent a wide range of weed pressures.

The procedure followed was to input observed seed counts as initial values into the Forcella emergence model, as calibrated by the equations presented above. Predicted seedling densities before crop planting, after crop planting and after lay-by cultivation were generated. The predicted densities were then subtracted from actual 1990 densities to generate a set of residuals. These residuals were adjusted for heteroscedasticity using the 1985-86 auxiliary regression results. The distributions of adjusted 1990 residuals were compared with the distributions of the 1985-86 estimation residuals using a χ^2 goodness-of-fit test.

The χ^2 statistic is used to test the null hypothesis that the predicted values (1990 residuals) are independently, identically distributed random variables from the same cumulative distribution function (CDF) as the observed (1985-86) ones. Since all parameters of the observed 1990 empirical distributions are implicitly known, the test statistic is calculated as follows:

$$\chi^2 = \sum_{j=1}^{J} \frac{(N_j^a - N_j^p)^2}{N_j^p} \tag{4.1}$$

where J is the number of adjacent categories into which observations are grouped, N is the number of observations in each group, the superscript a represents estimation residuals from the Morris 1985-86 trials, and the superscript p represents residuals from the predicted weed density values in 1990 (Law and Kelton, pp. 194-198). In each case, predicted 1990 observations were sorted in ascending order and grouped into six categories containing roughly equal numbers of residuals. Frequency counts for the same categories were taken from the actual residuals of the 1985-86 weighted regressions. Results for the weed seedling emergence residuals are presented in Table 4.6.

Table 4.6: Chi-square goodness-of-fit test for residuals from 1990 predictions of weed seedling emergence relative to the 1985-86 estimation residuals.

Timing of emergence	Foxtail	Lambs-quarters	Redroot Pigweed
Pre-plant	127.86	14.37	29.57
Post-plant	13.46	22.00	47.11
Post-cultivation	67.78	59.06	156.27

Note: $\chi^2(5)$ critical values at the 90% and 95% confidence levels are 9.24 and 11.07, respectively.

The discrepancy between the distributions of forecasted residuals and estimated ones is large. The problem comes from two sources: 1) the narrow range of weed seed densities in the original 1985-86 data set, and 2) the choice of intra-seasonal germination proportions based on the 1985 case alone. Lambsquarters 1990 residuals were sharply negatively skewed, indicating serious underprediction of emergence at all three stages. This is due in part to the large negative quadratic term in the pre-plant emergence equation. The 1985-86 Morris data set includes no seed densities higher than 750 seeds per square meter. The quadratic term proved much too negative when applied to the 1990 data set, which included plots with over 4500 seeds/m^2. Indeed, negative lambsquarters densities were forecast in some cases. Foxtail 1990 emergence residuals indicated overprediction of emergence at the pre-plant stage, but underprediction at the later stages. Pigweed 1990 emergence residuals were generally more kurtic than the 1985-86 ones; also, post-cultivation emergence was underpredicted.

Table 4.7: Descriptive statistics on weed seed density in the Morris 1985, 1986 and 1990 data sets.

Weed species and Statistic	Year 1985	1986	1990	All 3 years
Number of observations	72	72	40	184
Foxtail				
Mean	251	700	1808	765
Standard deviation	536	1187	2608	1573
Minimum	0	19	0	0
Maximum	3177	7095	12071	12071
Lambsquarters				
Mean	42	118	746	225
Standard deviation	89	152	1105	595
Minimum	0	0	0	0
Maximum	522	780	4268	4268
Redroot pigweed				
Mean	73	320	1161	406
Standard deviation	58	386	998	668
Minimum	0	38	0	0
Maximum	189	1963	3599	3599

4.1.1.3 Recalibration of the Forcella germination predictor

Because the goodness-of-fit tests indicate that the estimated weed emergence equations are not valid, the equations were re-estimated including the 40 additional observations from the 1990 Morris data. The chief reason for doing this was that the 1990 data include a much wider range of weed seed densities than the 1985-86 data. The differences are summarized by the descriptive statistics in Table 4.7.

The revised estimates are presented in tables 4.3R, 4.4R and 4.5R. The null hypothesis of no contemporaneous correlation was rejected for all three sets of equations. Significant evidence of heteroscedasticity was also present in the logarithmically transformed absolute residuals of every equation. Variances all took quadratic forms which increase at moderate to high weed seed densities and then decline at extremely high seed densities.

The revised weighted regressions all exhibit less sensitivity to high weed seed densities. In particular, the coefficient on the pre-plant lambsquarters pseudo-residuals weighted equation drops by a factor of forty, from -2.1E-4 to -5.2E-6. Coefficient signs in the pre-plant equations are otherwise similar. However, contrary to the original calibration equations, the revised post-plant equations imply that the Forcella model **under**predicts as seed density increases, linearly for foxtails and pigweed, quadratically for lambsquarters. The same is true of post-cultivation germination, where the revised weighted pseudo-residuals equations increase linearly with weed seed density. Plots of the uncalibrated and recalibrated weed germination functions are presented in appendix figures A1.1 - A1.3.

Table 4.3R: Revised calibration regressions of the pre-plant weed density residuals including the 1990 Morris data.

Weed species	d.f.	Constant	Seeds	$Seeds^2$	SEE	R^2
		Coefficient				
Pseudo-residuals (SUR)						
Foxtail	181	7.21	-0.012	1.0E-6	27.2	.08
		(2.96)	(-3.89)	(2.84)		
Lambsquarters	181	-1.08	0.024	-4.7E-6	11.7	.29
		(-1.11)	(5.94)	(-3.57)		
Log absolute residuals (OLS)						
Foxtail	181	1.77	6.9E-4	-6.1E-8	0.9	.23
		(21.63)	(6.86)	(-5.15)		
Lambsquarters	181	0.66	0.0027	-6.0E-7	1.1	.28
		(7.24)	(7.04)	(-4.95)		
Weighted pseudo-residuals (WSUR)						
Foxtail	181	6.93	-0.011	9.7E-7	2.7	.05
		(3.97)	(-2.24)	(2.35)		
Lambsquarters	181	0.74	-0.014	5.2E-6	1.9	.22
		(2.01)	(-2.64)	(4.09)		

Note: t-statistics in parentheses.

Table 4.4R: Revised calibration regressions of the Morris post-planting weed density residuals including 1990.

		Coefficient				
Weed species	d.f.	Constant	Seeds	$Seeds^2$	SEE	R^2
Pseudo-residuals (SUR)						
Foxtail	109	-14.07	0.156	-7.7E-6	224.0	.41
		(-0.54)	(5.73)	(-2.50)		
Lambsquarters	109	-1.55	0.075	-8.8E-6	25.8	.70
		(-0.56)	(8.46)	(-3.19)		
Redroot Pigweed	109	-6.43	0.086	-1.7E-5	38.7	.51
		(-1.29)	(6.43)	(-3.48)		
Log absolute residuals (OLS)						
Foxtail	109	2.91	0.0010	-7.8E-8	1.3	.34
		(19.76)	(6.56)	(-4.41)		
Lambsquarters	109	1.17	0.0025	-5.1E-7	1.3	.30
		(8.51)	(5.24)	(-3.44)		
Redroot pigweed	109	1.91	0.0021	-6.1E-7	0.9	.33
		(16.54)	(6.57)	(-5.19)		
Weighted pseudo-residuals (WSUR)						
Foxtail	110	1.01	0.078		2.4	.36
		(0.18)	(9.02)			
Lambsquarters	110	2.24		6.9E-6	2.7	.13
		(2.32)		(4.76)		
Redroot pigweed	109	1.32	0.026		3.2	.53
		(0.78)	(11.87)			

Note: t-statistics presented in parentheses.

Table 4.5R: Revised calibration regressions of the Morris post-cultivation emergence weed density residuals including 1990 data.

Weed species	d.f.	Coefficient Constant	Seeds	$Seeds^2$	SEE	R^2
Pseudo-residuals (SUR)						
Foxtail	110	1.98	0.023		51.4	.42
		(0.37)	(9.01)			
Lambsquarters	110	0.28	0.0060		3.5	.65
		(0.79)	(13.78)			
Redroot Pigweed	109	-1.60	0.022	-3.8E-6	8.2	.63
		(-1.50)	(7.34)	(-3.54)		
Log absolute residuals (OLS)						
Foxtail	109	1.41	0.0011	-8.2E-8	1.3	.36
		(9.54)	(6.82)	(-4.65)		
Lambsquarters	109	-0.52	0.0019	-3.8E-7	1.0	.34
		(-4.97)	(5.42)	(-3.34)		
Redroot pigweed	109	0.22	0.0024	-6.1E-7	1.0	.38
		(1.69)	(6.48)	(-4.52)		
Weighted pseudo-residuals (WSUR)						
Foxtail	110	-2.82	0.024		2.0	.68
		(-2.67)	(17.71)			
Lambsquarters	110	0.26	0.0040		2.9	.07
		(1.33)	(3.43)			
Redroot pigweed	110	0.67	0.0052		1.7	.09
		(2.16)	(5.93)			

Note: t-statistics presented in parentheses.

4.1.2 Seed production

After weeds go to seed, the soil seed bank contains all those seeds from the previous season that have not been lost through germination or seed death as well as the new seeds that were deposited by the weeds that survived to reproduce. The seed bank is updated at the end of each season by the WSSeedBank procedure in WEEDSIM and in the year-end accounting loop in WFARM. Rewriting equation (3.5) in stochastic form,

$$s_{it} = (1 - \sum_{s} \alpha_{is} - \beta_{i}) s_{it-1} + \gamma_{i} w_{ijt}^{h} + e_{it} \tag{4.2}$$

where α_{is} is the proportion of seeds of species i germinated during growth stage s (s=0,1,2), $\beta_i \epsilon [0,1]$ is the proportion of seeds of species i that die in the soil, $\gamma_i \epsilon [0,\infty]$ is the average number of seeds deposited by each weed of species i at maturity, and e_{it} is a disturbance term.

Defining $\hat{s}_{3it-1} \equiv (1 - \Sigma\alpha_{is})\hat{s}_{it-1}$, equation (4.2) can be estimated as follows,

$$s_{it} = f_1\hat{s}_{3it-1} + f_2 s_{t-1} + f_3 w_{ijt}^{h} + e_{it} \tag{4.3}$$

where $f_1 = 1$, $f_2 = -\beta_i$ and $f_3 = \gamma_i$.

As with the seedling emergence calibration regressions, there is reason to suspect that the error term in equation (4.3) will be spatially correlated. The Breusch-Pagan test generates the $\chi^2(3)$ test statistic 5.41, which exceeds the conservative critical value $\chi^2(3,.20)=4.64$. Because some evidence of spatial correlation is present, the three equations were estimated as a system.

A further methodological issue is proper specification. The presence of two predetermined right-hand side variables calls into question whether the error term might be correlated with the independent variables. The system of equations was estimated using both SUR and three-stage least squares (3SLS), where 3SLS used early and late-season weed biomass as instrumental variables. The Hausman specification test was applied to the seeds per weed coefficient estimates to test the hypothesis that the SUR estimates are consistent (given that they are more efficient than 3SLS). Results for the foxtail, lambsquarters and pigweed estimates, respectively, were 1.44, 1.72, and 0.77. As none of these exceeds the $\chi^2(3,.05)$ critical value of 3.84, the SUR estimates were retained.

The seed bank data include numerous outliers. A preliminary attempt to screen the data for influential observations identified eight of the 36 observations which exhibited high potential leverage (h_i) accompanied by high studentized residuals or DFBETAS statistics (Belsley et al.). Rather than drop 22% of the sample, it was decided to proceed with all observations.

Seemingly unrelated regressions were performed on the system of three weed seed equations with the restriction that the coefficient on $s_{3it-1}, f_{1i} = 1$. Results are presented in Table 4.6. As the equations lack an intercept, their significance must be judged from t-ratios. The hypothesis of homoscedasticity could not be rejected upon regressing absolute residuals from the SUR equations on the same independent variables.

Table 4.8: SUR estimates of weed seed mortality and reproduction coefficients with all observations (n=72).

Weed	Seeds3(1985)	Seeds(1985)	Seeds/weed(1986)
	Coefficient estimates		
	f_{1i}	f_{2i}	f_{3i}
Foxtail	1	-0.78	12.3
		(-2.66)	(2.95)
Lambsquarters	1	-0.50	6.5
		(-2.41)	(2.21)
R. pigweed	1	1.19	8.8
		(2.27)	(1.04)

Note: t-ratios in parentheses.

Two aspects of the results in Table 4.8 are disconcerting. First, the average seed production estimates (f_{3i}) are extremely low. Forcella and Lindstrom (1988b) obtained similar results for 1985 from harvesting samples of weed seed heads from conventional tillage treatments in the same fields. This can partly be explained by the fact that these weeds were mostly small, late-emerging ones (Forcella, personal communication, 1991). Buhler[1] (1991a) has found that weeds surviving herbicide treatment produce far fewer seeds than survivors of exclusively mechanical treatments. Nonetheless, seed production by the two broadleaved species was expected to exceed substantially that by the foxtails. Second, the seed death coefficient estimate on the previous

[1] Unpublished single year research results from the Rosemount experiment station in 1990 found giant foxtails to produce a mean of 1180 seeds/plant under rotary hoe and cultivation, versus only 120 seeds/plant under PRE and POST herbicide treatment. Seeds/plant for Pennsylvania smartweed were 510 and 0 for the same treatments.

seed bank term (s_{it-1}), f_{2i}, which is expected to lie in the interval $[-(1-\Sigma\alpha_{is}),0]$, falls outside that interval in two cases. In the foxtail equation, it drops below $-(1-\Sigma\alpha_{1s}) = -0.55$, although the coefficient estimate remains within a 95% confidence interval of that threshold. In the pigweed equation, however, f_{23} is greater than zero, so much so that the hypothesis $\beta_3 \in [-(1-\Sigma\alpha_{3s}),0]$ can be rejected with 95% confidence. These results confirm the converse of Ball and Miller's observation that, "low correlations between seed counts and weed counts indicate that seed count estimates alone were poor predictors of weed flora" (p. 372).

Proceeding by imposing restrictions from theory in spite of the pigweed seed death coefficient estimate, the pigweed coefficient, f_{23}, was set at -0.10 and the foxtail one, f_{21}, at -0.45. These imply seed carryover of 76% for pigweed and 10% for foxtail, respectively. The seed production regression results from the added restrictions imply seed carryover of 20% for lambsquarters. Presented in Table 4.9, the resulting seed production estimates are still extremely low.

Table 4.9: Restricted SUR estimates of weed seed mortality and reproduction coefficients with all observations (n=72).

		Coefficient estimates	
Weed	Seeds3(1985)	Seeds(1985)	Seeds/weed(1986)
	f_{1i}	f_{2i}	f_{3i}
Foxtail	1	-0.45	8.8 (2.55)
Lambsquarters	1	-0.53 (-2.66)	6.0 (2.12)
R. pigweed	1	-0.10	13.1 (1.62)

Seed production estimates in the literature are higher by several orders of magnitude. Under cultivated conditions, seed production has been reported at 100,000 to 200,000 seeds/m^2 for green foxtail (Cavers and Benoit), 14,400 to 41,900 seeds/plant for common lambsquarters (Crook and Renner), and 117,000 for redroot pigweed (W. Anderson). Two points about these high numbers should be kept in mind. First, many of the seeds are not viable. Chepil found the percent of fresh germinable seed to be 11-76% for green foxtail, 42-55% for common lambsquarters, and 71-83% for redroot pigweed. Second, high seed production figures mostly come from plants that grew the entire season and were undamaged by herbicide.

As a compromise, two estimates of viable seed production were developed for each species. Seed production by plants emerging after lay-by cultivation is assumed to be that presented in Table 4.9. Based upon Buhler's (1991a) preliminary results concerning seed production by herbicidedamaged weeds, seed production by weeds emerging prior to lay-by cultivation and surviving to reproduce is assumed to be 90, 120 and 130 seeds/plant for foxtails, lambsquarters and pigweed. This multiplies the estimated coefficients by ten for foxtail and pigweed, and by twenty for lambsquarters (to bring it in line with pigweed). It is assumed that all fields are treated with herbicide at least once in the season, so no herbicide-free seed production estimates were developed.

Rather than specify seed mortality explicitly, leaving surviving seed bank carryover as residual, both are calculated as fixed proportions of the seeds that do not emerge, based on the 1985 values. While the proportions are those that obtained in 1985, at least this approach does not impose exact mortality percentages on each succeeding year, based on 1985. Denoting the carryover proportion, $\omega_i = 1 - \Sigma\alpha_{is} - \beta_i$, since $\omega_i + \beta_i = 1 - \Sigma\alpha_{is}$, given simulated α_i, the known ratio $\omega_i/(\omega_i + \beta_i) = \hat{\omega}_i/(1 - \Sigma\hat{\alpha}_{is})$, where $\Sigma\hat{\alpha}_{is}$ is simulated total emergence, $\hat{\omega}_i$ is the new ω_i, and the new $\beta_i = 1 - \Sigma\hat{\alpha}_{is} - \hat{\omega}_i$. The mortality proportions of non-germinated seed numbers so calculated were foxtails, 0.714; lambsquarters, 0.818; and pigweed, 0.116. These estimates imply that pigweed seeds have significantly greater longevity than those of the other two species. The literature on weed seed mortality in the soil is very scanty. In two five-year experiments, Chepil found seed losses after five years, unaccounted for by germination, to be 23-64% for foxtails, 36-49% for common lambsquarters, and 54-63% for redroot pigweed. He concluded that since no foxtail had germinated in the last two to three years, all 23-64% of foxtail seed were dead. Lambsquarters and pigweed, however, continued to germinate in small numbers. Given that seed viability declines at an exponential rate (Roberts and Feast), it is reasonable to suppose that no more than five percent of the original seeds survived. This puts mortality at 31-44% for lambsquarters and 49-58% for pigweed. By comparison, results from applying the mortality proportion coefficients to expected Forcella germination rates based upon 1974-90 Lamberton data are 52%, 68% and 11% for foxtails, lambsquarters and pigweed, respectively.

One positive aspect of the low seed production estimates is that they counterbalance the relatively high seed germination rates from the Forcella model.[1] This is especially true of late season weed emergence, which is largely uncontrollable. High seed production rates could violate the controllability condition on the simulation model, namely, that the population of viable weed seeds diminish under the most potent control strategy.

[1] The high germination rates are an artifact of using a germination test to count viable seeds.

4.2 Yield function

The crop yield function in the simulation model is executed by function Yield2. Data used to estimate coefficients for it were obtained from several sources. Weed density and yield data come from rainfed trials at five agricultural experiment stations in Minnesota and Wisconsin. In all, there are six sets of corn yield data and five of soybean yield data for the year 1989 plus the 1985-86 Morris data set, which covers both crops.

Data from a variety of locations in the upper Midwest offer an opportunity to evaluate the stability of the yield loss coefficients estimated. That they are mostly from a single year is a serious drawback, since temperature and rainfall are important determinants of crop yield, weed germination and losses caused by weeds. Climate across several locations in the same region is undoubtedly correlated, meaning that different years are needed in order to represent a range of environmental conditions.

The yield function is assumed to follow the hyperbolic form given by equation (3.8) with an additive error term, **u**, which is independently and identically distributed (i.i.d.) normal $N(0,\sigma^2)$. Under these conditions, it can be estimated by maximizing the logarithmic normal likelihood function

$$L = -(n/2)\ln(2\pi) - (n/2)\ln(\sigma^2) - (1/2\sigma^2)u'u$$

where σ^2 denotes the variance and $\mathbf{e} = \mathbf{Y} - \mathbf{f(w)}$ is the resulting residual (Judge <u>et al</u>., p. 523).

The yield function was fit to corn and soybean yield data and densities of foxtails (green, yellow and giant), common lambsquarters, redroot pigweed and velvetleaf (Abutilon theophrasti Medic.). Parameter estimates for the corn yield function are presented in Table 4.10. Those for the soybean yield function are presented in Table 4.11. General background on the data is provided in appendix table A1.1. Since coefficient estimates are asymptotically normally distributed (Judge et al., p. 506), asymptotic t-values are reported in parentheses for hypothesis tests.

In general, weed-free yield (YWF) estimates for both crops are close to expected values of 150-160 bushels/acre for corn and 40-50 bushels/acre for soybean. Except for several insignificant negative estimates, the competition coefficients (IFOX, ILAM, IPIG, and IVEL) fall within a reasonable range. However, none of the estimates of pigweed competition in corn or lambsquarters competition in soybean is significantly different from zero at the 5% confidence level.

Table 4.10: Corn yield as an unrestricted hyperbolic function of weed density in seven Minnesota and Wisconsin research trials.

Equation	Site[2]	d.f.	S.E.E.	Coefficient estimate[1] YWF	A	IFOX	ILAM	IPIG
C1	L	16	7.8	155.2	93.1		0.46	
				(28.4)**	(0.30)		(0.78)	
C2	L	44	13.4	164.3	37.7	4.20	-1.13	
				(60.6)**	(2.79)**	(1.70)*	(-0.20)	
C3	M	43	17.2	149.8	6.8E7	0.83	1.00	1.98
				(40.9)**	(0.01)	(2.43)**	(0.26)	(1.05)
C4	W	89	24.3	168.1	133.2	0.90	7.06	-12.69
				(30.9)**	(3.61)**	(4.12)**	(1.42)	(-0.44)
C5	A	57	22.8	132.9	85.4	-0.31	10.90	18.34
				(11.5)**	(4.18)**	(-0.39)	(1.82)*	(1.38)
C6	A	60	19.2	143.6	126.9		5.39	
				(25.8)**	(3.52)**		(3.46)**	
C7	M[3]	64	14.5	106.3	34.3	0.89	3.75	-2.06
				(23.3)**	(5.01)**	(1.65)	(1.50)	(-1.27)

Note: In the tables that follow, asymptotic t-values are presented in parentheses. One and two asterisks denote significance at the 10% and 5% probability levels of Type II error. Large numbers are presented in scientific notation, where "x En" denotes x * 10^n.

[1] The following equations contained other broadleaved weeds with I coefficient estimates as follows:

C1: Mixed broadleaves: 1.98 (0.70)
C4: Velvetleaf: 7.13 (1.57), Common ragweed: -8.48 (-1.84)*
C5: Velvetleaf: 3.61 (2.25)**, Other broadleaves: 2.44 (0.79)
C6: Velvetleaf: 2.85 (4.12)**
C7: Other weeds: 2.21 (1.17).

Equations C1 and C7 included dummy variables for low input management practices and dummy variables, respectively.

[2] In this and subsequent yield tables, "site" refers to the year 1989 unless otherwise indicated. Sites are:

A - Arlington, WI; R - Rosemount, MN
L - Lamberton, MN; W - Waseca, MN
M - Morris, MN.

[3] Years 1985-86 in pooled sample. YWF represents 1985 yield; coefficient estimate for 1986 dummy is 50.6 (7.61)**.

Table 4.11: Soybean yield as an unrestricted hyperbolic function of weed density in six Minnesota and Wisconsin research trials.

Equation	Site	d.f.	S.E.E.	YWF	A	IFOX	ILAM	IPIG
				Coefficient estimate[1]				
S1	L	16	4.5	41.9	5.8	6.06		
				(7.77)**	(0.47)	(0.79)		
S2	W	24	6.9	49.1	90.7	0.17	6.61	-1.48
				(5.95)**	(7.63)**	(1.57)	(1.60)	(-0.29)
S3	W	138	6.1	38.0	126.7	0.68[2]	-2.65	3.86
				(17.5)**	(15.1)**	(5.24)**	(-0.98)	(5.05)**
S4	L	33	11.3	42.8	2.4E11	0.35		
				(17.7)**	(0.00)	(3.70)**		
S5	R	58	4.5	29.4	126.5	1.54	1.80	-0.45
				(28.9)**	(2.26)**	(2.96)**	(0.63)	(-1.24)
S6	M[3]	28	3.6	38.7	28.1	0.72	0.14	-0.10
				(30.0)**	(1.79)*	(1.02)	(0.23)	(-0.14)

[1] The following equations contained other broadleaved weeds with I coefficient estimates as follows:

S1: Mixed broadleaves: -69.2 (-0.84)
S2: Velvetleaf: 0.21 (0.26)
S3: Velvetleaf: 6.03 (3.45)**
S5: Nightshade: 1.14 (1.26)
S6: Other weeds: 2.50 (1.22).

Equations S1 and S6 included dummy variables for low input management practices and waterlogged plots, respectively.

[2] Foxtails were measured in dry weight units (g/m^2), which are not directly comparable with density units. A regression of foxtail density on dry weight using 1989 Lamberton data found considerable unexplained variability (R^2=0.12).

[3] Years 1985-86 in pooled sample. YWF represents 1985 yield; coefficient estimate for 1986 dummy is 9.1 (3.63)**.

Estimates of maximum yield loss (A) are less satisfactory. Five of the 13 exceed 100, implausibly suggesting yield loss over 100%. The A parameter estimates do not offer an obvious candidate for a "typical" yield loss level to impose. The median A for corn is 93.1. For soybean it is 108.6. As weed density approaches infinity, yield loss can be expected to become quite high. A reasonable hypothesis is A = 90%. In Table 4.12, results of that hypothesis test are presented.

Table 4.12: Results of hypothesis test that maximum yield loss coefficient A=90 for corn and soybean yield equations.

Equation	d.f.	Coefficient estimate A	Standard error SE(A)	Asymptotic $t(H_0)$	Test statistic t(.05)
C1	16	93.1	314.7	0.01	2.12
C2	44	37.7	13.5	-3.87	2.02
C3	43	6.8E6	1.1E11	0.00	2.02
C4	89	133.2	36.9	1.17	1.99
C5	57	85.4	20.4	-0.23	2.00
C6	60	126.9	36.1	1.30	2.00
C7	64	34.3	6.8	-8.19	2.00
S1	16	5.8	12.4	-6.79	2.12
S2	24	90.7	11.9	0.06	2.06
S3	138	126.7	8.4	4.37	1.97
S4	33	2.4E11	1.1E17	0.00	2.03
S5	58	126.5	56.1	0.65	2.00
S6	28	28.1	15.7	-3.94	2.05

Note: $t(H_0) = (A - 90)/SE(A)$

In eight of the 13 equations, the hypothesis cannot be rejected with 95% confidence. The eight include all cases where the A estimate exceeds 100%. In tables 4.13 and 4.14, all 13 equations are re-estimated with A set parametrically at 90.

Table 4.13: Corn yield as a hyperbolic function of weed density setting A = 90.

Equation	Site[2]	d.f.	S.E.E.	Coefficient estimate[1] YWF	IFOX	ILAM	IPIG
C1	L	17	7.8	155.3 (35.1)**	0.05 (2.34)**		
C2	L	45	13.6	163.0 (65.5)**	0.16 (2.80)**	0.10 (0.26)	
C3	M	44	17.5	150.3 (30.7)**	0.11 (1.89)*	-0.06 (-0.11)	0.22 (0.82)
C4	W	90	24.6	171.2 (29.2)**	0.11 (5.43)**	0.96 (1.52)	-1.20 (-0.31)
C5	A	58	22.8	131.9 (13.2)**	-0.28 (-0.40)	9.91 (3.20)**	16.96 (1.66)
C6	A	61	19.5	146.7 (25.7)**		7.86 (5.38)**	
C7	M[3]	65	15.1	99.8 (34.4)**	0.18 (2.38)**	0.83 (2.11)	0.06 (0.15)

[1] The following equations contained other broadleaved weeds with I coefficient estimates as follows:
C1: Mixed broadleaves: 1.99 (0.68)
C4: Velvetleaf: 0.78 (1.38), Common ragweed: -0.97 (-1.85)*
C5: Velvetleaf: 3.42 (3.25)**, Other broadleaves: 2.28 (0.97)
C6: Velvetleaf: 3.50 (4.12)**
C7: Other weeds: 0.24 (0.63).
Equations C1 and C7 included dummy variables for low input management practices and waterlogged plots, respectively.

[2] Refers to year 1989 unless otherwise indicated. Sites are:
A - Arlington, WI R - Rosemount, MN
L - Lamberton, MN W - Waseca, MN
M - Morris, MN.

[3] Years 1985-86 in pooled sample. YWF represents 1985 yield; coefficient estimate for 1986 dummy is 42.9 (7.44)**.

Table 4.14: Soybean yield as a hyperbolic function of weed density setting A = 90.

Equa-tion	Site	d.f.	S.E.E.	Coefficient estimate[1] YWF	IFOX	ILAM	IPIG
S1	L	17	4.7	43.1	-0.00		
				(15.5)**	(-0.09)		
S2	W	25	6.9	49.2	0.17	6.78	-1.61
				(6.00)**	(1.59)	(2.32)**	(-0.30)
S3	W	139	7.2	38.3	1.67[2]	-14.02	7.18
				(14.2)**	(4.04)**	(-1.55)	(3.17)**
S4	L	34	11.5	42.8	0.49		
				(14.7)**	(2.24)**		
S5	R	59	4.5	29.8	1.91	3.69	-0.61
				(30.3)**	(3.94)**	(1.21)	(-1.68)*
S6	M[3]	29	3.6	37.8	0.23	0.10	-0.00
				(36.4)**	(1.35)	(0.38)	(-0.01)

[1] The following equations contained other broadleaved weeds with I coefficient estimates as follows:

S1: Mixed broadleaves: 30.65 (1.39)
S2: Velvetleaf: 0.22 (0.28)
S3: Velvetleaf: 15.37 (1.98)**
S5: Nightshade: 1.46 (1.15)
S6: Other weeds: 1.32 (1.64).

Equations S1 and S6 included dummy variables for low input management practices and waterlogged plots, respectively.

[2] Foxtails were measured in dry weight units (g/m^2), which are not directly comparable with density units. A regression of foxtail density on dry weight using 1989 Lamberton data found considerable unexplained variability (R^2=0.12).

[3] Years 1985-86 in pooled sample. YWF represents 1985 yield; coefficient estimate for 1986 dummy is 8.6 (3.64)**.

Setting maximum yield loss parametrically at 90% has little effect on standard errors of estimate (SEE). Only for equation S3 does the SEE increase by more than 5%.

Parameterizing A has little effect on the number of significant competition coefficients in corn. Two new foxtail coefficients become significant (C1 and C7), and one lambsquarters coefficient does as well (C7). In soybean, the results are similar. One significant lambsquarters coefficient is gained (S2) and so is one pigweed coefficient (S5). However the last of these is negative, which implausibly implies that soybean yield increases with pigweed density. Parameterizing A can have a large effect on the magnitude of competition coefficients. In equations C2, C4, C7 and S1, some I estimates change by a factor of ten or more. Except for C4, these are equations for which the hypothesis A=90 was rejected.

Equations C7 and S6 use the Morris 1985-86 data, so they are of particular interest. That the hypothesis A=90 was rejected for these equations is unfortunate, since it appears justified for most of the other yield functions. Since the A parameter influences the other coefficient estimates, the restriction was imposed anyway, to keep the C7 and S6 equations consistent. Judging from the SEE's, variability in the predicted yield is little different with A parameterized at 90. Equation S6 shows insignificant weed competition coefficients before and after the parameterization of A. Equation C7, which had no significant I coefficients before parameterization of A, gains significance on the foxtail and lambsquarters ones (although their absolute values diminish considerably).

Heteroscedasticity has been found in some yield-weed density functions in the form of decreasing variance (Roush and Radosevich). If present, it should be compensated for in order to obtain efficient parameter estimates. More important, in generating random yield variables, it needs to be modeled explicitly. In order to test the hypothesis that the yield models are homoscedastic in their competition coefficients, the hyperbolic yield function was linearized and OLS regressions run on the absolute residuals. The test was applied to equations C7 and S6. Equation (3.8) was made linear as follows:

$$Y = Y_0\left[1 - \frac{\sum_i I_i w_i}{100\left(1 + \sum_i I_i w_i / A\right)}\right] \tag{3.8}$$

Defining Q as percent yield loss due to weeds, (3.8) can be rewritten,

$$Q \equiv 100\left(1 - \frac{Y}{Y^0}\right) = \frac{\sum I_i w_i}{1 + \frac{\sum I_i w_i}{A}}$$

Multiplying through by the right-hand side denominator,

$$Q\left(1+\frac{\sum I_i w_i}{A}\right) = \sum_i I_i w_i$$

Now, subtract $Q\Sigma I_i w_i/A$ from both sides,

$$Q = \sum_i I_i w_i (1 - Q/A)$$

Dividing through by (1 - Q/A) and rearranging produces the expression,

$$\frac{QA}{A-Q} = \sum_i I_i w_i \qquad \textbf{(4.4)}$$

By setting A and YWF parametrically at 90 and the nonlinear YWF estimate, respectively, the dependent variable in equation (4.4) can be calculated, yielding a regression that is linear in weed density.

To test for heteroscedasticity, residuals from estimation of (4.4) were saved, and their absolute values regressed on the weed density independent variables. Neither the corn nor the soybean regressions gave significant evidence of heteroscedasticity. The corn residuals regression had an adjusted $R^2 = 0.01$ and $F(3,65) = 1.29$. The soybean residuals regression summary statistics were adjusted $R^2 = 0.06$ and $F(3,29) = 1.69$. The 95% confidence level test statistic for $F(3,65)$ is 2.75. Since the null hypothesis that the equations are homoscedastic cannot be rejected, there is no need for weighted estimation.

Summarizing the yield function results, the median competition coefficient estimates for corn with A=90 are:

foxtail, 0.11, common lambsquarters, 0.89, and redroot pigweed, 0.14. For soybeans, they are: foxtail, 0.36, lambsquarters, 1.88, and pigweed, -0.30. Expert opinion suggests that pigweed should be on par with lambsquarters, and that foxtails should be only half as competitive (Lybecker et al. 1991b). Generally speaking, corn is expected to compete more strongly against weeds than soybean.

Final competition coefficient estimates were chosen to reflect the information obtained from all estimated equations in light of expert opinion. The Morris 1985-86 foxtail and lambsquarters corn yield coefficient estimates fall in the middle of the pack. The pigweed value is set equal to the lambsquarters one. It remains within a 95% confidence interval of the Morris 1985-86 estimate. For soybean, competition parameters equal to the lambsquarters median were selected for both lambsquarters and pigweed. Final parameter choices are presented in Table 4.15.

Table 4.15: Final yield parameters chosen for the weed management simulation model.

Equation	Foxtail	Lambs-quarters	Redroot Pigweed
Yield loss (I_i)			
Corn	0.2	0.8	0.8
Soybean	0.2	1.9	1.9

4.2.1 Validation of corn yield equation

Validation data from the 1990 Morris data set were available for corn, but not soybean. Because 40 observations with herbicide and 40 without were available in 1990, two observations per farm were dropped to make it conform to the 72 residuals from estimation of the 1985-86 equations. Two types of residuals were generated from the 1990 data: 1) residuals by subtracting predicted 1990 yields based on 1990 weeds from actual 1990 yields, and 2) residuals by subtracting predicted 1990 yields based on predicted 1990 weeds from actual 1990 yields. The three sets of residuals permitted three hypothesis tests: 1) Residuals from regression of predicted 1990 yields from actual weeds are distributed as those from 1985-86, 2) Residuals from regression of predicted 1990 yields from predicted weeds are distributed as those from 1985-86, and 3) Residuals from regression of predicted 1990 yields from predicted weeds are distributed as those from predicted 1990 yields from actual weeds. The $\chi^2(5)$ test statistics were 16.33, 18.68 and 8.49, respectively. Since the $\chi^2(5,.05)$ critical value is 11.07, the first two hypotheses can be rejected with 95% confidence. We cannot, however, reject the hypothesis that the distributions of residuals from 1990 predicted yields based on actual and projected weed densities are the same. As shown in Table 4.7, the 1990 weed densities deviated drastically from the 1985-86 data. This fact, plus the fact that the yield coefficients were developed from a number of data sets obtained from different years and locations were interpreted as sufficient reason not to reject the validity of the estimated yield equation.

4.3 Weed control efficacy

The model incorporates the principal corn and soybean weed control treatments currently practiced in Minnesota. These are executed via calls to function Surv from procedures WSPreTrt and WSPostTrt in WEEDSIM and PRESurv and POSTTrt in WFARM. The predominant chemical treatments encountered in a 1988 survey of Minnesota farms (Gianessi and Puffer) have been updated to delete those no longer legal (chloramben) and add new arrivals of importance (e.g., sethoxydim, nicosulfuron). Mechanical control in the form of rotary hoeing has also been added.

"Kill" functions for these treatments take the form of weed control step functions based upon the efficacy ratings from available herbicide data (Durgan et al., Kidder et al.) along with new data from recent experiments with mechanical control (Gunsolus 1990b and 1991a). Herbicide treatments are

Table 4.16: Efficacy percentage and application time of weed control treatments included in the model, by crop.

Treatment	Application time[3]	Percentage Killed[1] Fox-tail	Lambs-quarter	Pig-weed	Materials cost per acre[2] PRE	POST
		- - - - - - % - - - - - - -			- - $ - - -	
Corn						
No control	0,1,2	0	0	0	0	0
Alachlor 4E	0,1	90	30	90	16.25	--
Atrazine 4F	0,1,2	90	90	90	6.78	4.07
Bromoxynil 2E	2	0	90	70	--	6.89
Cyanazine 4F	0,1,2	90	90	50	14.71	8.80
Dicamba 4S	1,2	10	90	90	6.05	6.05
Eradicane (EPTC) 6.7E	0	90	70	50	15.48	--
Nicosulfuron	2	90	30	90	--	17.98
Rotary hoe	2	30	50	50	--	--[4]
2,4-D Amine 4S	2	0	90	90	--	1.49
Soybean						
No control	0,1,2	0	0	0	0	0
Acifluorfen 2S	2	10	10	90	--	15.03
Alachlor 4 MT	0,1	90	30	90	16.99	--
Bentazon 4S	2	0	10	90	--	11.22
Imazathapyr 2L	2	90	10	90	--	18.11
Metribuzin DF	0,1	50	90	90	16.62	--
Rotary hoe	2	30	50	50	--	--[4]
Sethoxydim 1.5EC	2	90	0	0	--	16.72
Trifluralin 4E	0	90	70	90	5.25	--

[1] Efficacy percentages are a linear transformation of the qualitative ratings published in Durgan et al. where "good" efficacy is interpreted as 90% efficacious and "poor" as 10% efficacious.

[2] Applied at the average of the recommended rates in Durgan et al. Application costs per acre (Fuller et al., 1991), omitting labor, are:

PPI (sprayer & cultivator)	$4.82
PRE (sprayer)	$1.40
POST (sprayer)	$1.40
Rotary hoe	$2.04.

[3] Codes are as follows: 0=pre-plant incorporated, 1=pre-weed emergence, 2=post-weed emergence.

[4] Rotary hoe causes 3-5% stand loss (Gunsolus, personal communication), leading to an average loss of 1.5% of yield.

assumed to be applied at the manufacturer's recommended rate, so variable application rates are not considered. Chemical and mechanical treatments included in the model are listed in Table 4.16.

4.4 Weed and crop growth rates

Certain weed control treatments are not feasible beyond a given stage of weed or crop growth. For example, rotary hoeing does not effectively control weeds once their roots are well established. Atrazine efficacy drops sharply from its 90% rating on foxtails once the weedy grass exceeds 1.5 inches height. This temporal efficacy threshold requires information on plant growth rates, which are simulated using procedures CropGrowth and WeedGrowth in WFARM. The period of interest covers the first several weeks of the growing season, before the post-emergence weed control decision is taken.

Growth rates for corn, soybean, mixed green and yellow foxtails, common lambsquarters, and redroot pigweed were estimated from reported University of Minnesota weed control experimental data at the Lamberton, Morris, Rosemount and Waseca reserch stations (Eberlein et al. 1987, 1988; Buhler et al. 1989). Regression of plant height on squared days after planting (DAP^2) provided higher coefficients of determination than regression on linear DAP. Because plant size must remain non-negative, no intercept was included. Results from the quadratic regressions are presented in Table 4.17. Coefficient estimates for weed growth range from 0.0033 to 0.0051. For crops, estimates are higher, 0.0100 for corn and 0.0069 for soybean. Corn field data were analyzed separately from soybean field data. All equations based on the latter were heteroscedastic. In

Table 4.17: Estimated crop and weed seedling growth rates: OLS, heteroscedasticity test, and weighted least squares.

		Coefficient estimates				
		OLS	Abs. residuals			WLS
Plant	n	DAP^2	Constant	DAP^2	adj.R^2	DAP^2
Corn	23	0.0100	1.556	0.0011	.025	
		(14.84)[1]	(1.80)	(1.25)		
Soybean	40	0.0069	0.133	0.0024	.317	0.0069
		(14.37)	(0.28)	(4.37)		(13.47)
Foxtail (in corn)	21	0.0044	0.457	0.0009	.036	
		(9.85)	(0.79)	(1.32)		
Foxtail (in soybean)	50	0.0048	0.031	0.0020	.294	0.0050
		(13.04)	(0.08)	(4.63)		(13.39)
Lambsquarters (in corn)	20	0.0033	0.740	0.0002	-.044	
		(13.26)	(1.69)	(0.45)		
Lambsquarters (in soybean)	39	0.0047	-0.716	0.0033	.545	0.0034
		(10.02)	(-1.82)	(6.82)		(44.43)
R. pigweed (in corn)	16	0.0035	0.276	0.0006	.106	
		(12.78)	(0.64)	(1.66)		
R. pigweed (in soybean)	27	0.0051	-0.347	0.0031	.462	0.0040
		(9.84)	(-0.77)	(5.72)		(10.96)
Velvetleaf (in corn)	23	0.0033	0.345	0.0005	-.073	
		(7.49)	(0.63)	(0.67)		
Velvetleaf (in soybean)	40	0.0031	-0.037	0.0011	.212	0.0034
		(11.39)	(-0.12)	(2.83)		(11.73)

[1] t-ratios in parentheses.

general, estimates differ little between corn and bean datasets. For modeling weed growth, results from the two data sets were combined, weighted by the number of observations (n).

4.5 Input data files for stochastic simulation

The input data files for stochastic simulation contain three types of variables. The first are correlated, pseudo-random, additive error terms. These are called in procedure GetStateErrors and used to adjust predicted values in procedures CalibrateGerm, CropGrowth, and WeedGrowth, as well as the yield and weed seed production equations of WFARM. They are generated from the empirical probability distributions of residuals from the estimated equations. The second set of random variates are pseudo-random, multivariate normal deviates from estimated coefficient values. These are called in procedure GetStateBetas and used to adjust equation coefficient values in CalibrateGerm, CropGrowth and WeedGrowth. The third set of input variables are actual historical data on random natural processes such as precipitation, days when soil conditions were suitable for field work, growing degree days, and weed-free yields. These are called in procedure GetYear and used in CalibrateGerm (Forcella predicted germination) and PRETrt (weekly rainfall), as well as the weekly loops (field days) and year-end accounting loop (weed-free yield) of the main WFARM program.

4.5.1 Generation of pseudo-random disturbances

For the thirteen equations estimated from the 1985-86 and 1990 Morris, MN, data sets, correlated, pseudo-random, additive error terms were generated using the generalized multivariate process generator developed by King. The procedure creates multivariate normal variables using a method proposed by Naylor et al., and then transforms them to correlated random variables based on empirical marginal distributions. The five crop growth functions, which were estimated from data assembled from experiment station trials around Minnesota in 1987-89, were assumed to be uncorrelated with one another and with the other 13 equations.

In order to generate the correlated random variates, a correlation matrix was estimated from residuals of the retained equations, including the revised germination calibration equations. Those 13 equations include the following: two weighted SUR pre-plant emergence calibrations (WW0FOX and WW0LAM), three weighted SUR post-planting germination calibrations (WW1FOX, WW1LAM and WW1PIG), three weighted SUR late season germination calibrations (WW2FOX, WW2LAM and WW2PIG), two yield (SOYYLD, CORNYLD nonlinear maximum likelihood) and three unweighted SUR seed bank equations (FOXSEED, LAMSEED and PIGSEED). Correlation coefficients were estimated from the largest number of observations available that included both members of each pair of variables. Sample size ranged from 184 for the correlation between pre-plant emergence equations to only 24 for the correlation between soybean yields and the weed seed bank equations. Since the normal statistic generated to test for significance of the correlation coefficients is a function of sample size (Freund), coefficients of the same magnitude do not necessarily have the same significance level.

Table 4.18: Correlation of residuals from crop yield and weed population dynamics equations.[1]

WW0FOX	1.00							
WW0LAM	.14	1.00						
WW1FOX	-.12	.16*	1.00					
WW1LAM	.28***	.32***	.15	1.00				
WW1PIG	.01	.09	.45***	.21**	1.00			
WW2FOX	.01	.10	0[2]	0	0	1.00		
WW2LAM	.13	.15	0	0	0	.24***	1.00	
WW2PIG	-.09	.07	0	0	0	.53***	.15	1.00
CORNYLD	-.24**	-.06	.29**	.10	.18	.13	-.09	.10
SOYYLD	-.04	.27	-.35*	-.06	.06	-.21	-.07	-.36**
FOXSEED	.05	.01	-.00	.01	-.13	.15	.13	-.14
LAMSEED	-.05	.16	.05	-.12	-.11	-.03	.51***	.07
PIGSEED	.07	.12	-.02	.08	-.21	-.17	.21	-.08

CORNYLD	1.00				
SOYYLD	0	1.00			
FOXSEED	-.41***	.38*	1.00		
LAMSEED	-.23	.30	.10	1.00	
PIGSEED	-.17	-.05	.15	.33***	1.00

[1] Asterisks denote statistical significance at the 0.10 (*), 0.05 (**), and 0.01 (***) levels for rejection of the hypothesis that $\rho=0$ (Freund, p. 381).
[2] Single zeroes identify coefficients assumed to be zero because the data could not support their estimation.

The correlation matrix is presented in Table 4.18. most correlations are low in absolute value but have the expected signs. In particular, correlations are 1) positive across the weed seed bank equations, 2) negative between corn yields and weed seed production, 3) generally positive across weed emergence, and always across emergence at the same seasonal stage. The only striking incongruities are the significantly positive correlations between soybean yield and both foxtail seed production and pre-plant lambsquarters emergence.

A total of 1080 pseudo-random observations were generated for each of the thirteen correlated and five uncorrelated error terms above. These were needed to accommodate one for each of up to nine fields in twenty six-year simulations. Visual comparison of graphed cumulative distribution functions generated by the pseudo-random variates compared with the data used to generate them identified no obvious differences. Descriptive statistics on the variables, presented in Table 4.19, reveal that, with the exception of the seed production equations, all means are zero $\pm$ 0.3. Mean seed production errors are large, however, due to the estimation restriction of regression through the origin. Means for these are 407, 95 and 198 seeds/m^2 for foxtails, lambsquarters and pigweed, suggesting that the seed bank increases unaccountably from year to year. These large expected values were incorporated into the data used by the WeedGerm subroutine to forecast germination in the WEEDSIM recommendations module.

Variability in the pseudo-random disturbance terms is quite high. While the standard deviations and extrema for the seed equations are the most striking, standard deviations for the germination equations are also high, given that these are weighted regression results.

Table 4.19: Descriptive statistics on 1080 pseudo-random disturbance terms.

Equation	Mean	Standard deviation	Minimum	Maximum
Germination[1]				
WW0FOX	-0.17	2.62	-9.81	17.21
WW0LAM	-0.12	2.18	-6.41	15.91
WW1FOX	0.04	3.20	-16.40	11.70
WW1LAM	-0.15	2.81	-12.54	11.37
WW1PIG	0.00	1.89	-4.60	9.58
WW2FOX	-0.01	2.69	-10.64	22.16
WW2LAM	0.13	3.17	-10.45	19.97
WW2PIG	0.10	1.85	-3.42	6.92
Yield				
CORNYLD	-0.24	15.96	-46.20	32.49
SOYYLD	0.09	3.70	-11.39	6.90
Seed production				
FOXSEED	407.33	1183.28	-1520.16	6944.16
LAMSEED	95.12	157.77	-237.34	767.44
PIGSEED	197.77	368.95	-162.23	1911.52
Plant growth				
CORNGROW	-0.12	3.33	-11.77	8.94
SOYGROW	-0.04	1.19	-3.78	4.51
FOXGROW	-0.03	1.33	-3.97	4.36
LAMGROW	0.02	1.22	-4.49	3.41
PIGGROW	-0.03	1.09	-3.12	3.95

[1] All eight germination equations are weighted regressions.

4.5.2 Generation of pseudo-random coefficients

Recognizing that coefficients estimated from data are random variables, pseudo-random coefficients were generated for the eight germination calibration equations as well as the five crop and weed growth equations. Since coefficients for the two yield equations and the three weed seed production equations were chosen from aggregates of prior studies or literature citations, these were treated as if they were known values.

The pseudo-random coefficient variates for the germination equations were generated as multivariate normal deviates from the coefficient estimates. As the coefficients had been estimated by SUR, they were assumed to be distributed multivariate normal. Where heteroscedasticity was present in the original regressions, the weighted regressions were the basis for the pseudo-random coefficient deviate generation. Like the pseudo-random disturbance terms, the 1080 random deviates for each coefficient estimate in the eight germination calibration equations were generated using the multivariate normal process generator proposed by Naylor et al. and developed by King. Coefficient deviates for the five plant growth equations were generated as independent normal random variates.

The lower-triangular covariance matrices used to generate the coefficient deviates are presented in Table 4.20. Coefficients in the three different systems of estimated equations are assumed to be unrelated. The standard deviations of the quadratic days-after-planting (DAP) term coefficients in the independent growth equations for corn and soybean are 0.0007 and 0.0005. The pooled standard deviations of the quadratic DAP coefficients for foxtail, lambsquarters and pigweed are, respectively, 0.00040, 0.00040, and 0.00046. Except for the constant terms, coefficient estimate variability is quite modest.

Table 4.20: Covariance of coefficients in weighted weed germination calibration equations.

Pre-plant germination (W0)						
Constant (Fox)	3.05					
Seeds (Fox)	-4.81E-03	2.45E-05				
$Seeds^2$ (Fox)	3.80E-07	-2.01E-09	1.69E-13			
Constant (Lam)	6.15E-02	-2.74E-05	1.65E-09	1.36		
Seeds (Lam)	-1.64E-04	1.46E-06	-1.13E-10	-9.61E-04	2.71E-05	
$Seeds^2$ (Lam)	2.88E-08	-3.04E-10	2.36E-14	2.20E-07	-6.36E-09	1.59E-12
Post-plant germination (W1)						
Constant(Fox)	31.40					
Seeds (Fox)	-1.32	7.46E-05				
Constant (Lam)	0.66	8.46E-05	0.93036			
$Seeds^2$ (Lam)	-3.97E-08	1.31E-10	-6.51E-08	2.07E-12		
Constant (Pig)	3.46	-3.21E-04	0.28	-1.22E-08	2.87	
Seeds (Pig)	-1.06E-03	3.61E-06	-1.49E-05	4.71E-11	-1.21E-03	4.64E-06
Post-cultivation germination (W2)						
Constant (Fox)	1.26					
Seeds (Fox)	-3.89E-04	2.23E-06				
Constant (Lam)	4.60E-02	1.16E-08	3.96E-02			
Seeds (Lam)	-1.58E-05	1.02E-07	-5.84E-05	1.28E-06		
Constant (Pig)	1.50	-3.30E-05	5.75E-03	-1.37E-06	9.50E-02	
Seeds (Pig)	-1.36E-05	3.46E-07	1.85E-06	1.68E-08	-9.07E-05	7.83E-07

Note: Fox = foxtails, Lam = lambsquarters, and Pig = redroot pigweed.

4.5.3 Inter-year variability

Most biological relationships in the simulation model were estimated from one- or two-year data sets. Yet the inter-year variability faced by farmers typically dwarfs that within a year. Of particular interest are 1) the reliance of pre-emergent herbicides upon rainfall during the first week after application in order to be effective, 2) the availability of days suited to field work (soil dry enough to withstand tractoring), 3) weed-free crop yields, and 4) weed germination rate. In order to capture variability across years, data from the Southwest Experiment Station at Lamberton, Minnesota, were incorporated into random access data files. The data include weekly total precipitation (Table 4.21), average weed-free corn and soybean yields (Table 4.22), weekly days suited to field work (Table 4.23), and expected weed germination rates (Table 4.24). The last of these are predicted from data on cumulative growing degree days (10° C. base) in the month of April, based on the Forcella (1991) simulation model.

Table 4.21: Weekly precipitation at Lamberton, MN, for the period April 19 - July 4, 1974-1990.

	Precipitation in inches for the weed beginning										
Year	4/19	4/26	5/03	5/10	5/17	5/24	5/31	6/07	6/14	6/21	6/28
1974	0	0.12	0.71	0.73	2.37	0.84	2.31	1.31	0	0.10	0.08
1975	2.11	0.48	0.15	0.50	0.43	0	0.63	0.62	1.93	0.56	0
1976	0.48	0.08	0	0.09	0	0.27	0	0.15	0.14	0.76	0
1977	1.01	0	1.08	0.19	1.02	0.34	0.05	0.27	4.52	0.20	0.45
1978	0.62	0.03	0.74	0.31	0.12	1.42	0.69	0.04	0.84	0.07	0.72
1979	0.59	0.59	0.89	2.12	0.13	0.80	0.03	1.37	1.79	0.01	1.72
1980	0	0	0	0.16	0.58	4.41	1.82	0.74	0	0.91	0.34
1981	0.42	0.16	0.16	0.07	0.06	0.05	0.37	0.70	1.54	0.29	0.39
1982	0.34	0.02	0.37	2.04	1.46	0.42	2.22	0.56	0.77	0.02	0
1983	0	1.54	2.61	0.09	0.15	0.21	0.49	0.19	3.21	0.50	2.18
1984	0	2.49	1.68	0.37	0.09	0.50	0.17	3.61	2.70	1.42	0.05
1985	3.99	0.55	0.12	1.91	0.14	1.56	0.27	0.38	0.28	3.46	0
1986	0.61	4.09	0.45	0.44	0	1.60	0.32	0.57	0.12	1.30	1.32
1987	0.04	0.03	0.05	0.37	0.42	1.47	0	0.74	0.93	0.28	0.07
1988	0.84	0.70	0.43	0	0.91	0.16	0	0.03	0.36	0.20	0.18
1989	0.51	1.44	0.30	0	0.19	0.06	0.01	0.06	0.26	1.79	0
1990	0.05	1.29	0.28	1.52	2.14	0.59	0.30	0.25	2.58	0	0.25
Mean	0.68	0.80	0.59	0.64	0.60	0.86	0.57	0.68	1.29	0.70	0.46
Min.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00
Max.	3.99	4.09	2.61	2.12	2.37	4.41	2.31	3.61	4.52	3.46	2.18
Pr(>.5)	.47	.47	.35	.35	.35	.53	.29	.53	.59	.47	.23

Source: Seeley.

Table 4.22: Weed-free corn and soybean yields at the Southwest Experiment Station, Lamberton, MN, 1974-90.

Year	Yield in bushels/acre Corn	Soybean
1974	101	31
1975	54	34
1976	22	14
1977	146	42
1978	110	43
1979	89	50
1980	108	41
1981	84	44
1982	151	42
1983	102	39
1984	90	41
1985	109	42
1986	165	51
1987	163	48
1988	56	26
1989	155	41
1990	129	39
Mean	107.9	39.3
Standard deviation	40.8	9.0
Minimum	22	14
Maximum	165	51

Source: Ford.

Note: Regression of the two yield series on a trend variable gave insignificant $F(1,15)$ statistics, 3.81 for corn and 1.48 for soybean. This suggests no trend in yields, and hence no need to detrend the data to obtain a stationary yield distribution.

Table 4.23: Weekly days suitable for field work, Southwest Experiment Station, Lamberton, MN, April 19 - July 4, 1974-90.

	Days suitable for field work during the week beginning										
Year	4/19	4/26	5/03	5/10	5/17	5/24	5/31	6/07	6/14	6/21	6/28
1974	7	5	5	0	0	0	0	0	6	7	7
1975	0	0	6	3	6	5	4	5.5	1	4	7
1976	5	5	7	6.5	7	5	7	6.5	6	4	6
1977	1	7	3	6	1	2	6	5	1	4	5
1978	0	2	5	5	6	5	2	6	3	6	5
1979	0	0	2.5	4	7	3.5	5.5	1	2.5	6	4
1980	5	7	7	3	4	3	0	3	5	5	4
1981	1	3	3	5	5	5	4	1	3	7	5.5
1982	0	6	3	0	1	2	4	1	1	7	7
1983	0	1	1	6	4	5	3	5	0	4	0
1984	3	2	1	4	6	5	5	1	0	1	7
1985	3	0	7	3	5	6	3	6	7	7	2
1986	3	1	5	2	7	3	6	5	7	5.25	3
1987	7	7	7	6.5	5	3	7	5.5	7	6	7
1988	3.75	4	7	7	5	7	7	7	7	7	6
1989	5	1	6.5	7	5.5	7	6	7	7	5	7
1990	7	3	7	2.5	1.5	5	4	7	2	6.5	7
Mean	3.0	3.2	4.9	4.1	4.5	4.2	4.3	4.3	3.9	5.4	5.3
Min.	0	0	1	0	0	0	0	0	0	1	0
Max.	7	7	7	7	7	7	7	7	7	7	7

Source: Seeley.

Table 4.24: Predicted weed emergence rates in absence of herbicide treatment, Lamberton, MN, 1974-90 (Forcella model).

Year	April cum. GDD[1]	Predicted germination rate Foxtail	Lambsquarters	R. Pigweed
1974	41.39	0.388	0.275	0.149
1975	1.11	0.000	0.000	0.000
1976	53.06	0.441	0.297	0.145
1977	101.94	0.286	0.013	0.100
1978	11.11	0.052	0.057	0.014
1979	16.67	0.114	0.115	0.055
1980	55.00	0.445	0.298	0.144
1981	56.94	0.447	0.297	0.143
1982	26.94	0.245	0.200	0.121
1983	9.72	0.040	0.042	0.008
1984	11.11	0.052	0.057	0.014
1985	90.56	0.344	0.134	0.110
1986	30.28	0.284	0.222	0.132
1987	94.17	0.326	0.099	0.107
1988	29.44	0.275	0.217	0.130
1989	47.50	0.423	0.291	0.148
1990	76.94	0.407	0.234	0.123
Mean	44.35	0.269	0.168	0.097
Min.	1.11	0.000	0.000	0.000
Max.	101.94	0.447	0.298	0.149

[1] Cumulative growing degree days (GDD) defined as [(max T - min T)/2] - 10, where T is temperature in ^{0}C.

Source: Fuchs.

4.5.4 Coefficient input files

Best parameter estimates from estimation of the crop yield, weed germination, weed seed production, and seedling growth functions were incorporated into input data files to run the weed management decision support model. Parameter values passed to the simulation model are summarized in Table 4.25.

Other input files were obtained from published sources. Herbicide rates, average costs, and efficacy ratings come from Durgan et al. Machinery costs and operating speed data are from Fuller et al. The late planting yield loss step function data come from Hicks and Peterson and Gunsolus (1990a).

Table 4.25: Summary of biological parameter values passed to the weed management simulation model.

Equation	Foxtail	Lambs-quarters	Redroot Pigweed
Yield loss (I_i)			
Corn	0.2	0.8	0.8
Soybean	0.2	1.9	1.9
Seeds/plant (γ_i)			
Weeds surviving cultiv.	90	120	130
Weeds emerging post-cult.	9	6	13
Proportion of total emergence by stage			
Pre-plant (α_{0i})	0.18	0.40	0.00
Post-planting (α_{1i})	0.72	0.54	0.92
Post-cultivation (α_{2i})	0.10	0.06	0.08
Proportion of non-emerged seeds that die in soil	0.714	0.818	0.116
Seedling growth[1]	0.0048	0.0033	0.0038

[1] Coefficients are for the squared days-after-planting (DAP^2) term. Crop coefficients are: Corn 0.0100, Soybean 0.0069.

4.6 Model Verification and Validation

4.6.1 Model verification

Model verification answers the question, "Does it do what it's supposed to do?" Verification is an inherent part of model development. It can only be treated as an independent activity if a) the model is very simple or b) the modeler is rash enough not to test components along the way.

Law and Kelton identify five techniques for model verification: 1) write and debug the model in discrete modules, 2) have other programmers check the code, 3) trace the evolution of variable values as the simulation runs, 4) test the model under simplified assumptions, and 5) display model results at a graphics terminal as it runs. All but the last of these techniques has been applied in development of the weed management model. Most of the program modules were identified in Chapter 3. The code was reviewed by King (personal communication) and by Alessi. The QuickBasic 4.5 program editor includes a powerful debugging trace called "watchpoint" which was used routinely in program verification. In addition, the time-honored technique of running a simplified program with strategically placed PRINT statements was used repeatedly. With all that said, there remains a significant probability of erroneous code in a program as large as this. However, every effort has been made to reduce this likelihood.

The sequence of program development also provids some assurance of minimal programming error. Verification of the model proceeded in tandem with programming individual modules and procedures. The general process can be viewed as a set of concentric circles. First a core program was developed and tested. Subsequent layers were added to it, each one contributing complexity and requiring re-verification of itself and of the whole.

4.6.2 Model validation

The original version of the simulation model was validated against out-of-sample data from 1990 field trials at the North Central Soil Conservation Research Laboratory in Morris, Minnesota. Only partial validation of the model was feasible, given available data. Validation was conducted for the emergence and corn yield functions. Results were presented in sections 4.1.1.2 and 4.3.1. Statistical validation was not possible for the seed bank, plant growth and soybean yield functions.

The 1990 Morris data come from two sites. The 16 observations from the Central Farm contain very high weed seed densities for all three species modeled. The 24 observations from the North Farm generally have low weed seed densities. Descriptive statistics on the pooled sample are presented in Table 4.7. Jointly, observations from the two farms represent a wide range of weed pressures. As discussed above, the validation tests led to recalibration of the germination calibration equations and acceptance of the corn yield equation in its original form.

Statistical validation is the first step in a process which extends to sensitivity analysis and field experimentation if the model's useful life continues (France and Thornley). Since one intended purpose of this weed management model is to help identify research priorities for weed scientists, sensitivity analysis is an appropriate future application. Validation of the model by agronomic field experiments in Rosemount and Morris, Minnesota, is currently underway (Buhler 1991c).

With the model on the road to validation, it was applied to the set of model evaluation and hypothesis tests outlined in Chapter 1. The results of a set of stochastic simulation experiments are presented in the next chapter.

V. SIMULATION EXPERIMENTS

The stochastic simulation framework developed in the final section of Chapter 4 provides a tool for evaluating the recommendations module in a whole-farm context. This can be done computationally in a manner analogous to controlled scientific experimentation (see, e.g., Dent and Blackie, Law and Kelton). Experiments designed to test the hypotheses presented in Chapter 1 can be conducted in a simulation environment that mimics the unexplained variability associated with model parameters estimated from data. Stochastic simulation will be used 1) to estimate the value of weed population information, 2) to appraise different weed control decision rules, 3) to examine the effects of farm size and initial weed seed density, and 4) to predict optimal farmer response to a set of possible policy restrictions on herbicide use.

5.1 The Deterministic Model: Base Case for Simulation

Before proceeding with description of the simulation experiments, it is fitting to present deterministic model results. These take two forms. First, the recommendations module (WEEDSIM) generates weed control recommendations based upon expected weed infestations. Second, recommendations also depend upon the crop rotation, the kind of weed population information available, and expected crop prices. Due to carryover problems inherent to certain herbicides in certain climates (e.g., atrazine on soybeans after corn in the northern U.S.), the crop rotation determines which treatments will be included in the feasible set. As for information, when seed counts are available, soil-applied weed treatment recommendations can be made. When weed seedling counts are available, post-emergence control recommendations are feasible. Somewhat less reliable ones may be made from predictions based on seed counts and expected emergence rates.

As discussed in the theoretical chapter, model recommendations are developed based upon the value of yield saved by weed control relative to the cost of weed control. The model parameters developed in Chapter 4 predict yield loss, but the model user must define expected weed-free yield, crop prices, variable costs and the rate of discount. Assumptions used for the model runs presented here are listed in Table 5.1. For the deterministic case, weed-free yields are set at their 1974-90 means from the Southwest Experiment Station of the University of Minnesota at Lamberton, MN (see Table 4.22). Prices and variable costs are drawn from Fuller et al (1991). The 4% rate of discount, which is used for the two-year decision rule, is a standard value for the inflation-free time value of money in the United States. Costs of weed control are the product of average 1990 herbicide unit costs and average recommended application rates (Durgan et al.). Net returns from the model are calculated as gross revenues minus weed control costs minus allocated variable costs. Net returns are returns to land, labor, management and fixed capital.

Table 5.1: Parameter settings for deterministic runs of the weed control recommendations model.

Parameter	Unit	Level: Corn	Level: Soybean
Weed-free yield	bu/acre	108	39
Crop prices	$/bushel	2.15	5.65
Variable costs	$/acre	126.15	62.70
Discount rate	percent	4%	

Table 5.2 presents recommendations for a set of three conventionally tilled fields such as those used in the stochastic simulation. The fields grow continuous corn, corn in a corn-soybean rotation, and soybean in rotation. Three weed species are included, 1) mixed green and yellow foxtails, 2) common lambsquarters, and 3) redroot pigweed. While these are the most common annual weeds in southwestern Minnesota, they constitute but a small subset of possible weeds, and model results are likely to be sensitive to the weed species chosen. Two initial weed seed densities are assumed, one for "low" weed pressure, the other for "high" weed pressure, based upon the 1985-86 Morris data. The "low" weed pressure case has foxtails, lambsquarters, and

pigweed seeds present at 175, 25 and 50 seeds/m^2. For the "high" weed pressure case, they are present at ten times these levels. Two decision rules are considered. The "myopic" rule bases recommendations upon the expected net gain from weed control in the current year. The "foresighted" rule bases them upon the present value of expected net wealth at the end of two years.

Table 5.2: Weed control recommendations for corn and soybean under two rotations, two initial weed seed populations and two decision rules.

		Weed control recommendation		
Crop	Rotation[1]	PPI/PRE	Time[2]	POST
"Myopic" decision rule				
Low initial weed seeds				
Corn	CC	No control		Atrazine & oil
Corn	CS	Cyanazine	PPI	2,4-D
Soybean	SC	Trifluralin	PPI	Rotary hoe
High initial weed seeds				
Corn	CC	No control		Atrazine & oil
Corn	CS	Cyanazine	PPI	2,4-D
Soybean	SC	Trifluralin	PPI	Rotary hoe
"Foresighted" decision rule				
Low initial weed seeds				
Corn	CC	No control		Atrazine & oil
Corn	CS	Cyanazine	PPI	2,4-D
Soybean	SC	Trifluralin	PPI	Rotary hoe
High initial weed seeds				
Corn	CC	Cyanazine	PPI	Atrazine & oil
Corn	CS	Alachlor	PPI	Cyanazine
Soybean	SC	Trifluralin	PPI	Rotary hoe

[1] CC denotes continuous corn; CS denotes corn-soybean.
[2] PPI denotes pre-plant incorporated; PRE denotes pre-emergence.

The two rules generate identical weed control recommendations when weed pressure is low. When it is high, however, the two-year rule calls for more thorough weed control in corn, to reduce the seed population. As post-emergence weed controls in soybean are quite costly relative to their efficacy (see Table 4.16), only rotary hoeing is recommended. For the same reason, POST herbicides tend to be eschewed by soybean farmers in all but special cases (Simmonds and Brosten). Over a period of years, the result is that the two-year rule establishes a managed steady state weed seed population at a lower level than the myopic rule. Figure 5.1 illustrates this for foxtails where weed control is not constrained by available farm resources. Weed seed germination and seed production rates are held constant at 1974-90 mean values.

In a whole-farm context, of course, resources are constraining. This implies that the timeliness of operations is not always optimal. Late planting incurs yield penalties. Some weed control measures become infeasible when weeds outgrow their stage of susceptibility to post-emergence treatment. Other measures become infeasible when the crop reaches a susceptible stage. The timing of weed control operations on a farm is largely determined by the size of the cropped area, the amount and kind of machinery, the number of skilled operators available, and the suitability of weather for field work. In any given season, all of these except workable field days tend to be predetermined.

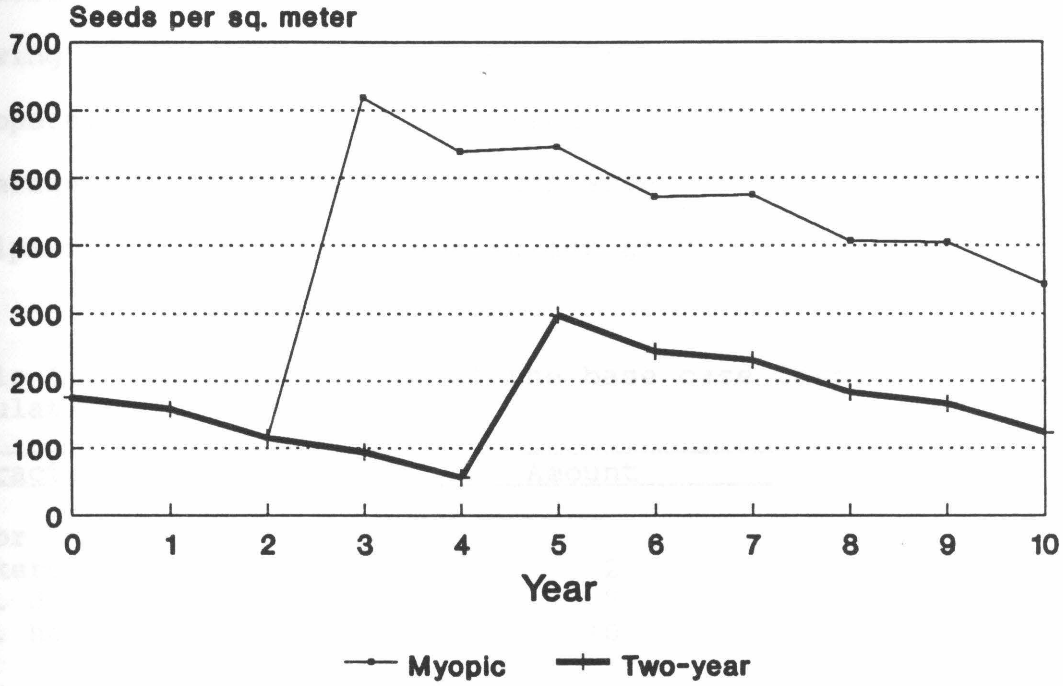

Figure 5.1: Foxtails seed bank evolution from low initial level in corn-soybean rotation: Myopic and two-year decision rules compared.

The resource endowment of the base case farm used in simulations is presented in Table 5.3. It is a 480-acre cash grain farm located in southwestern Minnesota. The farm is divided into six 80-acre fields. Two fields each are devoted to continuous corn, rotational corn and rotational soybean. During the planting and weed control season (April - June) the farm has two full time tractor operators available for field operations seven days per week, ten hours per day. The farm has two tractors capable of doing field work (160 and 120 horsepower). The machinery complement used in the simulation includes a 28-foot field cultivator, a 30-foot sprayer, an 8-row planter, an 8-row cultivator, and a

16-foot rotary hoe (Talley). Other machinery used for plowing and harvest operations is omitted, as it is not used in operations associated with weed control. Rates of field coverage and associated costs per acre for use of this equipment were obtained from Fuller et al. (1990).

Table 5.3: Characteristics of the base case farm used in simulation.

Characteristic	Unit	Amount
Labor		
Workers		2
Max. days per week		7
Max. hours/day		10
Land		
Field size	acres	80
Continuous corn	proportion	1/3
Rotation corn	proportion	1/3
Rotation soybean	proportion	1/3
Machinery		
2 tractors	horsepower	120,160
Field cultivator	feet	28
Planter (8-row)	rows	8
Sprayer	feet	30
Cultivator (8-row)	feet	30
Rotary hoe	feet	16

Table 5.4 illustrates the effect of reduced workable field days. Weed management results with the number of workable field days in 1982 are contrasted with those for 1987 using the recommendations in Table 5.2. In 1982, only 18 workable days were available at Lamberton between April 19 and June 20, whereas in 1987, 55 workable days were available during that period. Crop yields, germination

rates and precipitation were held constant at their 1974-90 means for the simulation.

Table 5.4: Impact of restricted workable field days: Simulated weed management on base farm in 1982 versus 1987 using the two-year decision rule with high initial weed seeds.

Performance criterion	Measurement unit	Workable field days 4/19 - 6/20 18 (1982)	55 (1987)
Farm net revenue	dollars	- 6,582	1,675
Herbicide load			
Cont. corn	lbs ai/acre[1]	2.7	4.2
Rotn. corn	lbs ai/acre	4.3	4.3
Rotn. soybean	lbs ai/acre	0.8	0.8
Percent max. yield			
Cont. corn	percent	71.6	76.6
Rotn. corn	percent	70.6	75.9
Rotn. soybean	percent	66.4	64.7
Weed density			
Foxtails	plants/m^2	94	107
Lambsquarters	plants/m^2	10	6
Pigweed	plants/m^2	9	10

[1] Pounds of chemical active ingredient per acre.

Weed-free yields in 1982 and 1987 were both high, 151 and 163 bushels per acre for corn and 42 and 48 bu/acre for soybean, so other things being equal, net revenue is expected to be high. Since initial weed pressure for both years is identical in the simulation, differences in percent of maximum (weed-free) yield obtained are entirely due to timeliness and infeasible weed control treatment penalties. Late planting penalties take the form of yield loss. Under 1982 conditions, late planting leads to a 7% yield loss on the corn fields. Infeasible weed control penalties increase yield loss and/or treatment cost. The lower herbicide load on continuous corn in 1982 is due to post-emergence atrazine application becoming infeasible because the foxtails had grown too large. The higher weed densities in 1987 are due to infeasibility of the recommended rotary hoeing of weeds in soybeans. In both cases, the next best alternative was not to control weeds. The interplay between yield loss and treatment cost is discussed more thoroughly in the context of herbicide bans in Swinton and King.

5.2 Design of the Simulation Experiments

5.2.1 Experimental factors

The simulation experiments are designed to examine the hypotheses presented in Chapter 1. The experimental factors examined are 1) the decision rule, 2) initial weed seed population level, 3) farm size, 4) weed seed population information available to the farm manager, and 5) herbicide restriction policy. These factors are summarized in Table 5.5.

The decision rules reviewed are the myopic, the cautious myopic, and the foresighted (or two-year) rule. The myopic decision rule chooses the weed control plan that maximizes current year expected net revenue. The "cautious myopic" rule described in Chapter 3 is computationally equivalent to the myopic one, except that it employs a lower (ergo, more cautious) threshold for weed control. In the simulation experiments here, it reduces by five percent the expected net revenue from no control against which control treatments are evaluated (ie., in equation (3.1), $\theta = 0.05$). The two-year rule applies an optimal control with a two-year time horizon to the multiple weed species management problem.

Table 5.5: Levels of experimental factors employed in stochastic simulation.

Experimental factor	Unit	Low	Medium	High
Farm size	acres	480		720
Initial weed seeds				
Foxtails	seeds/m^2	175		1750
Lambsquarters	seeds/m^2	25		250
Pigweed	seeds/m^2	50		500
Decision rule		Myopic	Cautious myopic[1]	2-year
Information on weed population	sample counts	None[2]	seedlings[3]	seeds & seedlings
Herbicide bans	policy	No ban	Atrazine ban	Triazines ban[4]

[1] Treat if expected net revenue exceeds 95% of expected return with no control (i.e, theta = 0.05).

[2] Strategies are, for corn, EPTC (plus safener) PPI and dicamba POST; for soybean, trifluralin PPI and bentazon POST.

[3] POST strategy from model; PPI/PRE same as above.

[4] Including atrazine, cyanazine and metribuzin.

Weed species and density are the crucial variables in the weed management model. Observed densities in the field vary immensely. The initial weed seed densities used in the simulations represent the bottom and top quartiles of the 1985-86 Morris data set. Relative proportions also represent those observed in that data set. For combined green and yellow foxtails, common lambsquarters and redroot pigweed, the "low" initial weed seed populations are 175, 25, and 50 seeds per square meter (m^2). The "high" initial populations are ten times that high.

In order to test the hypothesis that farmers apply liberal doses of soil-applied herbicides as insurance against untimely post-emergent control, two farm sizes are included. Farm acreage includes both owned and rented land. The 480-acre farm represents a medium-large southwest Minnesota cash grain farm (Talley). The machinery complement is fairly typical of the wide variety of equipment present on such farms. The 720-acre farm represents a large cash grain farm. The machinery complement is the same, as a means of testing the hypothesis that, with other factors constant, yield penalties due to untimely weed control operations increase with farm acreage.

Three levels of weed population information are examined. The "high information" case includes estimates of both weed seeds (prior to time of application of soil-applied herbicides) and weed seedlings (prior to application of post-emergence control measures). The model makes all weed control recommendations. The "POST information" case includes only post-emergence weed seedling density estimates. Soil applied weed control follows extension recommendations. The recommendations used in the simulation are EPTC plus safener, pre-plant incorporated (PPI) on corn, and trifluralin, PPI on soybean (Gunsolus 1991b). Finally, the "no information" case follows extension recommendations independent of weed population information for all control. The recommendations used in the simulation experiments are the PPI measures stated above, followed by dicamba POST on corn and bentazon POST on soybean (Gunsolus 1991b). The information levels applied here correspond to the flexible, mixed, and fixed weed control strategies evaluated by King et al. and Lybecker et al. (1991a).

Weed seed and seeding population information are assumed known with certainty. While on the surface this seems an unrealistic assumption, it was made in order not to exaggerate the already substantial random variability in the stochastic model. The pseudo-random errors generated for the stochastic simulation model implicitly reflect the sampling error associated with weed seed and seedling density data used to estimate model parameters. To introduce sampling error again would be to double count.

The last experiment examines the effect of three alternative policy restrictions on herbicide use. These are 1) no change from current policy, 2) ban on atrazine, and

3) ban on all triazine herbicides. Three triazines are included among the treatments used for the simulation model. Besides atrazine, they are cyanazine and metribuzin. The relatively abundant presence of atrazine in groundwater has led to growing public concern about its use.

5.2.2 Experimental methods

The unit of observation for the simulation experiments is the farm "state of nature," a six-year period of simulated weed management. Six years encompasses three complete corn-soybean rotations. While this may not be sufficient time to reach a managed steady state, it is long enough to differentiate among the dynamic tendencies of different management strategies.

Each experiment is replicated under twenty states of nature. A state of nature governs each six-year weed management period beginning from a given initial weed seed bank level. Each simulation year draws upon historical data from the Southwest Experiment Station at Lamberton, MN, covering weed-free yields, precipitation levels, available field time and April growing degree days (from which expected weed seed germination rates are calculated). The years are chosen at random from a uniform distribution of the 17 years 1974-90.

Within a year, pseudo-random error terms are added to predictions from field-level biological equations. For the germination calibration equations, these disturbances are heteroscedastic, varying with weed seed density. Multivariate normal pseudo-random deviates are also added to the statistically estimated coefficients in the weed germination and plant growth equations. The same sequence of years and random disturbances and random coefficients is applied to each simulation experiment.

Several performance criteria are used to evaluate the outcomes of the simulation experiments. The present value of accumulated net returns at the end of the period is presented in the form of the annual annuity payment which would generate that sum (Weston and Copeland, p.80). This is termed "the annualized net present value of accumulated income," or simply "annualized net income." The standard deviation of this value provides a measure of variability. The money-equivalent values of expected utility from constant absolute risk attitude (CARA) exponential utility functions are presented for decision makers with coefficients of absolute risk aversion of -.0001 (mildly risk-loving), 0 (risk-neutral), .0001 (mildly risk-averse), and .001 (strongly risk-averse). These values are typical of those reported for annual farm income in studies which elicited risk attitudes in the United States (Raskin and Cochran).

Biological performance measures include the mean percentage of yearly maximum yield attained, mean weed density (plants per square meter), and end-period weed seed density (seeds per square meter). In the absence of time series data on true maximum potential yields, maximum yield is defined as the weed-free yield observed at the Lamberton station.

Herbicide load provides a measure of the environmental impact of chemicals used. Strictly a quantitative index, it fails to capture such important qualitative aspects as toxicity to humans and to weeds of individual chemicals. Since the new post-emergence herbicides are applied at rates as low as one-half ounce per acre (e.g., nicosulfuron), versus several pounds for the older compounds, this is increasingly important. However, the new, low-dose compounds tend to be recommended rarely by the model, due to their relatively high cost. Since the older ones vary less in dose level, the herbicide load index is less misleading than might be feared. In the absence of more sophisticated indices, raw herbicide load gives a rough measure of chemicals entering the biosphere.

5.3 Results of the Simulation Experiments

Results of the stochastic simulation experiments provide the means to test the nine hypotheses set forth in Chapter 1. Other salient points are discussed less formally. The principal statistic used for hypothesis tests is the paired difference t statistic. By taking into account the fact that the variables being compared come from the same experimental block, the paired difference t-test is more discerning than tests designed to compare independent variables. It assumes that the two variables share the same distribution and that their difference follows a normal distribution with mean zero. The statistic is similar to an ordinary t statistic, except that the sample standard deviation in the denominator is divided by the square root of the number of degrees of freedom (Mendenhall et al., p. 517):

$$t = \frac{\bar{d} - \mu_d}{s_d/\sqrt{n}}$$

where $\bar{d}$ is the sample mean difference, μ_d is the population mean difference, s_d is the sample standard deviation, and n is the number of observations.

The baseline simulation results, which are presented in tables 5.6 and 5.7, are discussed in the following subsections. They cover three information levels (none, POST only, and high), two initial weed seed densities (low and high), and three decision rules (myopic, cautious myopic, and two-year).

Table 5.6: Stochastic simulation results for 480-acre farm with low initial weed seed density: 6 year simulation under 20 states of nature.

	Information level & decision rule						
	No infor-	Seedling counts			Seed & seedling counts		
	mation	Myopic	Cautious	2-year	Myopic	Cautious	2-year
Mean annualized net income ($)							
(Standard deviation)							
Farm	2,718	9,699	8,340	9,011	10,386	9,047	10,104
	7,065	(7,488)	(8,432)	(8,861)	(7,270)	(8,448)	(8,827)
Cont. corn	-2,963	-444	-915	-871	-278	-804	-325
	(3,867)	(4,393)	(4,674)	(4,410)	(3,927)	(4,577)	(4,492)
Rotn. corn	-2,178	-462	-903	-512	4	-337	-28
	(2,873)	(3,006)	(3,474)	(3,664)	(3,022)	(3,386)	(3,693)
Rotn. soy	7,859	10,604	10,158	10,394	10,660	10,188	10,458
	(3,294)	(2,990)	(3,628)	(3,128)	(2,943)	(3,596)	(3,060)
Mean herbicide load (lb ai/ac)							
Cont. corn	4.88	5.27	5.25	5.39	2.81	2.83	2.94
Rotn. corn	4.88	5.01	5.02	5.06	2.99	2.92	3.05
Rotn. soy	1.50	0.77	0.77	0.79	0.76	0.77	0.79
Mean percent of max. yield (%)							
Cont. corn	76	80	79	80	79	77	80
Rotn. corn	77	80	78	81	80	79	82
Rotn. soy	71	73	72	74	74	72	74
Mean weed density (plants/m^2)							
Continuous corn							
Foxtails	76	42	54	48	61	75	55
Lambsqtrs	3	3	3	3	3	3	3
Pigweed	20	12	12	13	10	10	10
Corn-soybean rotn.							
Foxtails	99	74	70	56	74	72	56
Lambsqtrs	5	5	4	5	5	5	5
Pigweed	20	12	15	13	11	13	12
Mean terminal weed seed density (seeds/m^2)							
Continuous corn							
Foxtails	2,273	1,240	1,448	1,396	1,412	1,792	1,432
Lambsqtrs	176	150	163	151	157	175	160
Pigweed	2,542	1,535	1,471	1,526	1,271	1,245	1,256
Corn-soybean rotn.							
Foxtails	3,929	2,650	2,161	1,936	2,616	2,231	1,915
Lambsqtrs	205	179	203	204	188	209	215
Pigweed	2,637	1,657	1,813	1,683	1,528	1,606	1,542

Table 5.7: Stochastic simulation results for 480-acre farm with high initial weed seed density: 6 year simulation under 20 states of nature.

	Information level & decision rule						
	No infor-	Seedling counts			Seed & seedling counts		
	mation	Myopic	Cautious	2-year	Myopic	Cautious	2-year
Mean annualized net income ($)							
(Standard deviation)							
Farm	-19,315	-6,489	-7,336	-5,656	-4,751	-5,610	-3,751
	(8,917)	(6,543)	(7,642)	(7,499)	(6,316)	(7,737)	(7,587)
Cont. corn	-10,090	-5,127	-5,570	-5,223	-4,255	-4,788)	-4,251
	(4,700)	(3,410)	(3,771)	(3,632)	(3,478)	(3,898)	(3,771)
Rotn. corn	-9,322	-5,898	-6,139	-5,227	-5,328	-5,460	-4,626
	(3,351)	(2,400)	(3,114)	(2,814)	(2,289)	(3,162)	(2,928)
Rotn. soy	97	4,535	4,372	4,794	4,832	4,639	5,127
	(2,996)	(3,105)	(3,494)	(3,197)	(2,938)	(3,624)	(3,125)
Mean herbicide load (lb ai/ac)							
Cont. corn	4.88	5.47	5.44	5.42	3.63	3.57	3.58
Rotn. corn	4.88	5.05	5.06	5.05	3.33	3.31	3.50
Rotn. soy	1.50	0.76	0.78	0.79	0.76	0.77	0.78
Mean percent of max. yield (%)							
Cont. corn	57	69	67	70	71	69	72
Rotn. corn	59	67	65	70	68	67	72
Rotn. soy	50	58	58	61	59	59	62
Mean weed density (plants/m^2)							
Continuous corn							
Foxtails	290	112	122	105	113	124	100
Lambsqtrs	6	4	4	4	4	4	4
Pigweed	49	23	23	23	16	17	16
Corn-soybean rotn.							
Foxtails	295	181	177	119	167	167	113
Lambsqtrs	7	7	7	7	7	7	8
Pigweed	46	23	26	22	20	23	20
Mean terminal weed seed density (seeds/m^2)							
Continuous corn							
Foxtails	5,725	1,562	1,903	1,673	1,595	1,982	1,614
Lambsqtrs	189	149	163	152	161	176	166
Pigweed	4,630	2,278	2,259	2,240	1,638	1,663	1,640
Corn-soybean rotn.							
Foxtails	7,441	3,925	3,540	2,325	3,565	3,185	2,239
Lambsqtrs	220	186	212	211	200	230	230
Pigweed	4,807	2,427	2,610	2,360	2,152	2,250	2,057

5.3.1 Experiment 1: Value of weed population information

The ranking of information from greatest (seed and seedling counts) to least (no weed information) correlates perfectly with annualized net income. This is true for both low and high initial weed seed pressures under all decision rules. This result is consistent with the proof of Chavas and Pope that costless information cannot reduce net returns.

The hypothesis that strategies using and ignoring weed population information yield equal annualized net income (Hypothesis H1), is subjected to two sets of paired difference t-tests in Table 5.8. In the first set of tests, POST-only seedling count information is compared with no information. Under all three decision rules and both initial weed pressures, the hypothesis can be rejected with 99% confidence (the one-tailed t(19;.01) test value is 3.17). In the second set of tests, the annualized net income with high information is compared to that with POST-only information. Again, the hypothesis of equal returns can be rejected with 99% confidence in all cases. As expected, the value of the two-year decision rule is greatest when seed count information is also included. The value of information is especially significant when initial weed pressure is high. The significant value of information encountered here is consistent with the findings of Bosch and Eidman, Byerlee and Anderson, King <u>et al</u>., and Regmi.

Table 5.8: Paired difference t-tests of annualized income over 20 states of nature: Gains in annualized net farm income due to high and POST information.

Initial weeds, decision rule	HIGH over POST information: Mean difference	HIGH over POST information: Standard deviation	HIGH over POST information: t statistic	POST over NO information: Mean difference	POST over NO information: Standard deviation	POST over NO information: t statistic
Low initial weeds						
Myopic	687	913	3.37	6,981	3,525	8.86
Cautious	707	996	3.18	5,622	4,046	6.21
Two-year	1,093	598	8.18	6,293	5,839	4.82
High initial weeds						
Myopic	1,738	792	9.81	12,826	6,814	8.42
Cautious	1,727	778	9.93	11,978	7,400	7.24
Two-year	1,906	876	9.73	13,658	6,702	9.11

Hypothesis H2, that the same level of herbicide is applied regardless of information level, is soundly rejected in the paired difference t-tests presented in Table 5.9. However, the results differ by information level. Compared to no information, high information leads to significantly lower herbicide load for virtually all crops, rotations and initial weed pressures. Compared to POST information, high information leads to significantly lower herbicide loads in both corn rotations. On the other hand, compared with no information, POST weed seedling counts lead to herbicide loads that are higher in corn (both rotations) and lower in soybean. The increased load in corn is due to WEEDSIM's propensity to recommend POST 2,4-D or atrazine over the "no information" default of dicamba. These dramatic results should be interpreted with some caution, however, since the base "no information" case uses a PPI treatment with a particularly high herbicide load (EPTC at 4.5 pounds of active ingredient per acre).

Table 5.9: Paired difference t-tests of herbicide load over 20 states of nature: Change in load due to high and POST weed population information.

	Change in herbicide load from HIGH information Over POST information			Over NO information			Change from POST info. Over NO information		
Initial weeds, decision rule	Mean difference	Standard deviation	t statistic	Mean difference	Standard deviation	t statistic	Mean difference	Standard deviation	t statistic
Low initial weeds	- lb ai/A -			- lb ai/acre -			- lb ai/acre -		
Cont. corn									
Myopic	-2.46	0.40	-27.22	-2.07	0.47	-19.47	0.40	0.19	9.53
Cautious	-2.42	0.37	-29.08	-2.05	0.47	-19.35	0.37	0.18	9.20
Two-year	-2.45	0.30	-36.30	-1.93	0.37	-23.11	0.52	0.17	13.87
Rotn. corn									
Myopic	-2.02	0.20	-45.73	-1.88	0.20	-41.32	0.14	0.07	9.14
Cautious	-2.10	0.29	-32.59	-1.95	0.28	-31.09	0.15	0.07	10.00
Two-year	-2.00	0.22	-41.06	-1.80	0.22	-36.63	0.18	0.07	10.98
Rotn. soybean									
Myopic	-0.01	0.01	-1.83	-0.74	0.03	-104.20	-0.73	0.04	-88.68
Cautious	0.00	0.00	0.00	-0.73	0.04	-86.04	-0.73	0.04	-86.04
Two-year	-0.00	0.02	-0.90	-0.26	0.71	-1.66	-0.71	0.04	-74.91
High initial weeds									
Cont. corn									
Myopic	-1.84	0.17	-48.55	-1.25	0.24	-23.46	0.59	0.18	15.05
Cautious	-1.87	0.22	-38.85	-1.30	0.30	-19.64	0.57	0.17	15.14
Two-year	-1.84	0.21	-39.02	-1.30	0.27	-21.14	0.55	0.19	12.89
Rotn. corn									
Myopic	-1.72	0.17	-44.89	-1.54	0.15	-45.09	0.18	0.06	13.22
Cautious	-1.75	0.16	-48.59	-1.56	0.15	-46.75	0.19	0.07	12.33
Two-year	-1.55	0.24	-28.52	-1.37	0.22	-28.07	0.17	0.10	7.69
Rotn. soybean									
Myopic	-0.00	0.00	-0.00	-0.74	0.03	-118.37	-0.74	0.03	-120.65
Cautious	-0.00	0.01	-1.17	-0.73	0.02	-142.98	-0.72	0.02	-137.55
Two-year	-0.01	0.01	-2.17	-0.72	0.02	-144.47	-0.71	0.03	-110.95

The value of information is intimately linked to the decision maker's attitude toward risk (Byerlee and Anderson). Table 5.10 suggests that the value of weed population information is highest when weed pressure is high. This runs counter to what would be expected if the key decision was whether or not to control. In that case the most valuable information would be that which implies that control is unneeded. It appears, however, that the key decision is **how** to control, rather than whether to control. When weed pressure is high, sub-optimal rules of thumb have more serious repercussions than when it is low.

Table 5.10: Value of weed population information under four expected utility functions.

Experimental factor	Coefficient of absolute risk aversion -.0001	0	.0001	.001
	- - - - - - - $ equivalent - - - - - -			
Low initial weeds				
Seed & seedling information				
Myopic	7,670	7,668	7,321	4,666
Two-year	8,590	7,387	6,054	3,756
Seedling information only				
Myopic	7,197	6,981	6,592	4,794
Two-year	7,550	6,293	4,958	2,616
High initial weeds				
Seed & seedling information				
Myopic	12,476	14,564	16,396	18,734
Two-year	14,303	15,564	16,697	20,643
Seedling information only				
Myopic	10,932	12,826	14,576	17,224
Two-year	12,420	13,658	14,930	19,262
Difference between seed & seedling and seedling information only				
Low initial weeds				
Myopic	473	687	729	- 128
Two-year	1,040	1,093	1,096	1,140
High initial weeds				
Myopic	1,544	1,738	1,821	1,510
Two-year	1,883	1,906	1,767	1,381

The value of weed population information increases monotonically with risk aversion when initial weed pressure is high and decreases with risk aversion when it is low. The estimated value of post-emergence weed seedling counts exceeds that of seed counts alone. Values for seedling counts under the two-year decision rule range from $2,616 ($5.45 per acre) for the strong risk averter facing low initial weed pressure to $19,262 ($40.13 per acre) for the strong risk averter confronting high initial weed pressure.

The difference between the value of high information and that of the POST information alone provides a rough estimate of the supplementary value of seed information on top of seedling counts. To decision makers with the specified utility functions using the two-year rule, it would be worth an additional $1,040 ($2.17 per acre) to $1,906 ($3.97 per acre) to obtain seed bank estimates. This suggests that obtaining weed population information is a viable commercial proposition. This possibility is discussed further in section 5.4.

5.3.2 Experiment 2: Evaluation of decision rules

The hypothesis that strategies using dynamic decision rules yield the same annualized net income as static ones (H3) cannot be rejected. The paired difference t-tests in Table 5.11 indicate that the two-year and cautious myopic decision rules do not yield higher annualized net incomes than the myopic rule.

Table 5.11: Paired difference t-tests of annualized net income under high information: Gains by two-year and cautious myopic decision rules over myopic decision rule.

Initial weeds, decision rule	Mean diffe-rence	Standard devia-tion	t sta-tistic
	- - - - $ - - - -		
Two-year over Myopic			
Low initial weeds	- 282	4,226	-0.30
High initial weeds	1,000	4,701	0.95
Cautious over Myopic			
Low initial weeds	-1,339	4,643	-1.29
High initial weeds	- 859	4,289	-0.90

The ranking of decision rules by certainty equivalence puts the two-year rule first when initial weed pressure is high. When initial weed seed density is low, the myopic rule ranks first for risk neutral and risk averse decision makers, while the two-year rule ranks first with the mild risk lover. The cautious myopic rule is lowest of all for the four utility functions specified under all simulation scenarios. It is also dominated under the mean-variance efficiency criterion (Anderson et al.) when initial weed pressure is high.

Table 5.12: Certainty-equivalent of annualized farm net income under four exponential expected utility functions.

Experimental factor	Coefficient of absolute risk aversion -.0001	0	.0001	.001
	- - - - - - $ equivalent - - - - - -			
Low initial weeds				
Seed & seedling information				
Myopic	12,564	10,386	7,378	- 3,110
Cautious myopic	11,981	9,047	4,744	-10,258
Two-year	13,485	10,104	6,111	- 4,021
Seedling information				
Myopic	12,091	9,699	6,649	- 2,982
Cautious myopic	11,259	8,340	4,210	- 9,548
Two-year	12,445	9,011	5,015	- 5,161
No information	4,895	2,718	57	- 7,776
High initial weeds				
Seed & seedling information				
Myopic	- 3,086	- 4,751	- 7,056	-16,641
Cautious myopic	- 3,231	- 5,610	- 9,673	-25,877
Two-year	- 1,259	- 3,751	- 6,756	-14,733
Seedling information				
Myopic	- 4,630	- 6,489	- 8,877	-18,151
Cautious myopic	- 4,930	- 7,336	-11,067	-26,211
Two-year	- 3,142	- 5,656	- 8,523	-16,113
No information	-15,562	-19,315	-23,453	-35,375

The hypothesis that herbicide load does not differ between dynamic and static decision rules (H4) can be rejected in specific cases when weed pressure is high. Herbicide loads appear virtually identical across decision rules within information levels, as indicated in tables 5.6 and 5.7. Nonetheless, the paired difference t-tests presented in Table 5.13 reveal that differences do exist. When initial weed pressure is high, the two-year decision rule leads to higher herbicide loads in rotational corn and soybean than the myopic rule. For soybean, the two-year rule calls for more herbicide than the myopic rule even when weed pressure is low (t(19;.05) = 2.43). Contrary to expectation, the cautious myopic rule does not lead to a significantly different herbicide load than the myopic one.

Table 5.13: Paired difference t-tests of herbicide load under high information: Gains by two-year and cautious myopic decision rules over myopic decision rule.

	Two-year over Myopic			Cautious over Myopic		
Cropping system, initial weeds	Mean difference	Standard deviation	t statistic	Mean difference	Standard deviation	t statistic
	- - lbs ai/acre - -			- - lbs ai/acre - -		
Continuous corn						
Low initial weeds	0.13	0.49	1.23	0.02	0.55	0.14
High initial weeds	-0.05	0.24	-0.85	-0.05	0.38	-0.65
Rotational corn						
Low initial weeds	0.06	0.26	1.00	-0.07	0.25	-1.21
High initial weeds	0.17	0.19	3.97	-0.02	0.19	-0.47
Rotational soybean						
Low initial weeds	0.02	0.04	2.43	0.01	0.05	1.25
High initial weeds	0.02	0.03	2.63	0.01	0.04	1.29

The myopic rule, preferred by risk averse decision makers when weed pressure is low, generally leads to lower herbicide loads, although the difference is significant only for the cases cited above. This apparent contradiction supports Pannell's (1990) finding that when the yield function is strictly convex, the expected utility of risk averse decision makers is maximized by reducing weed control.

Related to the lack of distinction between decision rules regarding herbicide load, end-period weed seed densities are also not uniformly lower with the dynamic two-year rule. Aggregating all weed species and weighting by the number of fields in each rotation, mean terminal seed densities are lowest under the two-year decision rule.

5.3.3 Experiment 3: Effect of farm size

An increase in farm size from 480 to 720 acres results in a sharp decline in mean annualized net farm income per unit of land. However hypothesis H5 cannot be rejected, since the decline is not generally statistically significant under the paired difference t-tests presented in Table 5.14. The exception is the myopic decision rule when weed pressure is low, in which case annualized net income is reduced at the 10% significance level (one-tailed $t(19;.10) = 2.09$). Nonetheless, Table 5.15 indicates that when weed pressure is low, mean farm net income is only marginally higher despite using 50% more land. When weed pressure is high (Table 5.16), mean annualized net income is actually lower under all decision rules on the larger farm. Untimely crop management results in yield penalties, lower herbicide load and higher weed pressure than in the 480-acre farm case. Mean percent of maximum corn yield is lower across the board due to late planting penalties and cases where weed controls become infeasible. Herbicide load is lower because treatments become infeasible. The result is higher mean weed density and higher terminal weed seed population in virtually every case.

In spite of the reduced terminal wealth per acre on the larger farm, evidence does not support the profitability of commonly practiced blind PPI/PRE control. In no instance did the mixed strategy of POST information generate higher mean annualized net farm income than high information with the same decision rule.

Table 5.14: Paired difference t-tests of annualized farm net income per acre: Change due to increasing farm size from 480 to 720 acres.

	Low initial weeds			High initial weeds		
Information level decision rule	Mean diffe-rence	Standard devia-tion	t sta-tistic	Mean diffe-rence	Standard devia-tion	t sta-tistic
	- - $/ac - -			- - $/ac - -		
Seed & seedling info.						
Myopic	-5.39	10.67	-2.26	-4.11	12.47	-1.47
Cautious myopic	-2.73	13.06	-0.93	-2.46	12.92	-0.85
Two-year	-3.38	11.65	-1.30	-2.60	10.21	-1.11
Seedling info. only						
Myopic	-6.05	11.23	-2.41	-3.50	12.28	-1.28
Cautious myopic	-3.35	13.23	-1.13	-1.86	13.01	-0.64
Two-year	-3.71	11.49	-1.45	-2.41	10.74	-0.98
No information	-9.46	15.88	-2.66	-3.99	15.40	-1.16

Table 5.15: Stochastic simulation results for 720-acre farm with low initial weed seed density: 6 year simulation under 20 states of nature.

	Information level & Decision rule						
	No information	Seedling counts			Seed & seedling counts		
		Myopic	Cautious	2-year	Myopic	Cautious	2-year
Mean annualized net income ($)							
(Standard deviation)							
Farm	-2,735	10,189	10,095	10,843	11,702	11,605	12,720
	(14,914)	(14,230)	(14,224)	(14,260)	(14,125)	(14,137)	(14,248)
Cont. corn	-6,713	-2,584	-2,590	-2,486	-1,849	-1,858	-1,575
	(6,557)	(6,825)	(6,811)	(6,783)	(6,486)	(6,472)	(6,661)
Rotn. corn	-6,568	-2,756	-2,808	-2,360	-1,961	-2,013	-1,504
	(6,368)	(5,669)	(5,672)	(5,688)	(5,790)	(5,812)	(5,762)
Rotn. soy	10,545	15,529	15,494	15,689	15,512	15,476	15,799
	(6,018)	(5,622)	(5,607)	(5,653)	(5,553)	(5,542)	(5,673)
Mean herbicide load (lb ai/ac)							
Cont. corn	4.88	5.25	5.24	5.34	2.76	2.75	2.85
Rotn. corn	4.88	5.01	5.00	5.06	2.91	2.90	3.08
Rotn. soy	1.50	0.78	0.78	0.79	0.78	0.78	0.79
Mean percent of max. yield (%)							
Cont. corn	71	76	76	77	76	76	77
Rotn. corn	71	75	75	77	76	76	77
Rotn. soy	68	73	73	74	73	73	74
Mean weed density (plants/m^2)							
Continuous corn							
Foxtail	130	72	72	63	84	85	71
Lambsqtrs	4	2	2	3	3	3	3
Pigweed	27	12	12	12	10	10	10
Corn-soybean rotn.							
Foxtail	126	75	78	62	78	82	62
Lambsqtrs	5	5	5	5	5	5	5
Pigweed	32	14	14	13	12	13	12
Mean terminal weed seed density (seeds/m^2)							
Continuous corn							
Foxtail	4,454	1,893	1,911	1,722	1,951	1,968	1,825
Lambsqtrs	205	152	152	154	164	164	163
Pigweed	3,268	1,548	1,583	1,549	1,313	1,330	1,316
Corn-soybean rotn.							
Foxtail	4,379	2,395	2,474	2,032	2,435	2,534	2,042
Lambsqtrs	308	222	228	223	232	233	232
Pigweed	3,819	1,749	1,755	1,693	1,575	1,588	1,523

Table 5.16: Stochastic simulation results for 720-acre farm with high initial weed seed density: 6 year simulation under 20 states of nature.

		Information level & Decision rule					
	No infor-	Seedling counts			Seed & seedling counts		
	mation	Myopic	Cautious	2-year	Myopic	Cautious	2-year
Mean annualized net income ($)							
(Standard deviation)							
Farm	-31,847	-12,257	-12,343	-10,205	-10,084	-10,184	- 7,553
	(13,291)	(12,043)	(12,012)	(12,499)	(12,058)	(12,078)	(12,487)
Cont. corn	-15,839	- 8,743	- 8,764	- 8,489	- 7,709	- 7,728	- 7,184
	(5,291)	(5,647)	(5,651)	(5,628)	(5,678)	(5,663)	(5,839)
Rotn. corn	-16,334	-10,549	-10,582	- 9,224	- 9,772	- 9,811	- 8,322
	(5,105)	(4,570)	(4,571)	(4,846)	(4,642)	(4,679)	(4,891)
Rotn. soy	326	7,035	7,004	7,508	7,397	7,355	7,954
	(5,733)	(5,369)	(5,351)	(5,548)	(5,307)	(5,295)	(5,490)
Mean herbicide load (lb ai/ac)							
Cont. corn	4.88	5.44	5.44	5.45	3.58	3.56	3.62
Rotn. corn	4.88	5.07	5.06	5.07	3.31	3.27	3.52
Rotn. soy	1.50	0.77	0.77	0.79	0.78	0.78	0.79
Mean percent of max. yield (%)							
Cont. corn	56	67	67	68	68	68	70
Rotn. corn	55	63	63	66	64	64	68
Rotn. soy	50	59	59	62	59	59	62
Mean weed density (plants/m^2)							
Continuous corn							
Foxtails	273	125	127	105	128	129	106
Lambsqtrs	5	3	3	4	4	4	4
Pigweed	57	22	22	22	17	17	17
Corn-soybean rotn.							
Foxtails	335	177	177	126	166	167	117
Lambsqtrs	8	7	7	7	7	7	8
Pigweed	59	25	25	22	22	22	19
Mean terminal weed seed density (seeds/m^2)							
Continuous corn							
Foxtails	6,733	2,182	2,205	1,864	2,258	2,307	1,975
Lambsqtrs	205	152	153	155	165	166	167
Pigweed	5,881	2,269	2,281	2,263	1,707	1,750	1,700
Corn-soybean rotn.							
Foxtails	8,473	3,526	3,550	2,494	3,248	3,290	2,385
Lambsqtrs	315	230	233	230	240	245	244
Pigweed	6,170	2,509	2,534	2,312	2,178	2,210	2,010

5.3.4 Experiment 4: Value of initial seed bank

The value of a low initial weed seed bank is manifest in both the medium and large farm cases. Paired difference t-tests show that mean annualized net income is significantly greater when initial weed seed banks are low than when they are high (one-tailed $t(19;.01) = 3.17$). Hypothesis H6 is rejected under every decision rule and information level, as displayed in Table 5.17. The clear value of a low initial weed seed bank provides empirical support for the principle of a dynamic decision rule.

The second point of interest concerning initial seed banks is that the standard deviation of annualized net income is lower when the seed bank starts high (tables 5.6 and 5.7). This echoes the finding of Roush and Radosevich that the variance of yield functions declines as weed competitive pressure increases. As weed pressure increases, it displaces the effect of other environmental factors on the variability of yield (and, by extension, annualized net income).

As expected, low initial weed seed density also results in reduced chemical load. For corn under both rotations, paired difference t-tests in Table 5.18 reveal that with high information, a low initial weed seed bank leads to significantly lower herbicide load than a high one.

Table 5.17: Paired difference t-tests of annualized farm net income: Gains from low initial seed bank over high one.

Information level decision rule	Mean difference	Standard deviation	t statistic
	- - - - - $ - - - - -		
Seeds & seedling info.			
Myopic	15,137	3,867	17.51
Cautious myopic	14,657	3,323	19.73
Two-year	13,855	3,723	16.64
Seedling info. only			
Myopic	16,188	4,597	15.75
Cautious myopic	15,676	3,724	18.83
Two-year	14,667	4,189	15.66
No information	22,032	8,044	12.25

Table 5.18: Paired difference t-tests of herbicide load under high information: Gains from low initial seed bank over high one by cropping system.

Cropping system, decision rule	Mean difference	Standard deviation	t statistic
	- lbs ai/acre -		
Continuous corn			
Myopic	-0.82	0.35	-10.55
Cautious myopic	-0.74	0.28	-11.99
Two-year	-0.64	0.28	-10.09
Rotational corn			
Myopic	-0.34	0.18	-8.18
Cautious myopic	-0.39	0.27	-6.38
Two-year	-0.45	0.17	-11.50
Rotational soybean			
Myopic	-0.00	0.01	-1.62
Cautious myopic	-0.00	0.03	-0.08
Two-year	0.00	0.03	0.47

In general, the low initial seed bank results in higher yields, lower weed densities and lower terminal weed seed populations. It appears that the weed seed bank levels converge to a managed equilibrium. Mean terminal weed seed densities for both initial levels were very close, despite having started an order of magnitude apart (tables 5.6 and 5.7). Under the two-year decision rule with high information, the model allows foxtail seed populations to grow from 175 to 1,432 seeds/m^2, while those starting at 1,750 drop to 1,614 seeds/m^2. Lambsquarters seed densities change from 25 and 250 seeds/m^2 to 160 and 166. Pigweed seeds multiply more dramatically (partly because of longer seed survival in the soil). From 50 and 500 seeds/m^2, they increase to 1,256 and 1,640 seeds/m^2, respectively.

5.3.5 Experiment 5: Impact of herbicide bans

Herbicide bans reduce mean annualized farm income in every case. The reduction is statistically significant (one-tailed $t(19;.05) = 2.43$) for a triazines ban under all scenarios reviewed. It is statistically significant for an atrazine ban when initial weed pressure is high. Under the two-year decision rule it is also significant when initial weed pressure is low. Hence, the hypothesis that a herbicide ban does not affect annualized net income (H8) can be rejected in every instance for a triazines ban and can be rejected when initial weed pressure is high for an atrazine ban.

The income impact of restricting weed control options is greatest when weed pressure is high. The high information case with the two-year decision rule, shown in Table 5.19, is a case in point. When weed pressure is low, the atrazine ban reduces mean annualized net farm income by $296 for a 480-acre farm. Since atrazine is an option only on the 160 acres of continuous corn, the loss on those fields is $1.85 per acre. When initial weed pressure is high, however, the atrazine ban costs $720, or $4.50 per acre of continuous corn. The ban on triazines affects the corn-soybean rotation fields as well, both via cyanazine use on corn and metribuzin on soybean. The reductions in

Table 5.19: Paired difference t-tests of changes in annualized farm net income due to bans on atrazine and all triazines.

Initial weeds, decision rule	Atrazine ban: Gain over No Ban base case — Mean difference	Standard deviation	t statistic	Triazines ban: Gain over No Ban base case — Mean difference	Standard deviation	t statistic
	- - - - $ - - - -			- - - - $ - - - -		
Low initial weeds						
Myopic	-196	975	-0.90	-613	997	-2.75
Cautious myopic	-280	606	-2.07	-741	828	-4.00
Two-year	-296	535	-2.48	-867	609	-6.37
High initial weeds						
Myopic	-1,056	619	-7.62	-1,863	1,189	-7.01
Cautious myopic	-1,235	641	-8.62	-2,213	1,186	-8.34
Two-year	-720	483	-6.67	-1,905	1,040	-8.19

annualized net farm income are $867 and $1,905 for low and high initial weed seed populations, respectively. This amounts to $1.81 and $3.97 per acre, farm-wide.

The modest farm level impact of an atrazine ban is consistent with the results of Cox, and Cox and Easter. Focusing upon average weed populations in continuous corn with expected yield of 152 bu/ac and corn at $2.43/bu, Cox estimates an atrazine ban in southeastern Minnesota to cost $7.93 per acre. Due in part to lower expected yields in southwestern Minnesota and lower assumed corn price, the comparable figures from this study are $1.85 and $4.50, at low and high initial weed pressures, respectively.

The cost per acre of a triazines ban estimated in this stack is considerably lower than the $29.76 per acre drop in returns to management and fixed resources calculated by Cashman et al. The difference is likely accounted for by the yield function in their deterministic linear programming model of an Indiana corn-soybean cash grain farm. Their model appears to be particularly sensitive to a ban on metribuzin, due perhaps to the different weed species incorporated in their model.

Results from these three studies, however, apply to partial equilibrium analysis only. The general equilibrium regional analysis of Osteen and Kuchler (1987) suggests that bans on atrazine and the entire triazine family would cause increases in corn and soybean prices that would more than offset income losses due to increased costs and/or reduced yields. The computable general equilibrium results of Hrubovcak et al. also highlight the link between input demand and output price.

In general, annualized income can be ranked such that no ban > atrazine ban > triazines ban. The same ranking holds for the certainty equivalents of all four utility functions specified, as shown in Table 5.20. Interestingly,

Table 5.20: Certainty equivalent expected utility under bans on atrazine and all triazines with high information and two-year decision rule.

Initial weeds, type of ban	Standard deviation ann. income	Coefficient of absolute risk aversion -.0001	0	.0001	.001
		- - - - - - - - - $ equivalent - - - - - - - - -			
Low initial weeds					
No ban	8,827	13,485	10,104	6,111	-4,021
Atrazine ban	8,775	13,117	9,808	5,826	-4,337
Triazines ban	8,871	12,642	9,237	5,221	-4,534
High initial weeds					
No ban	7,587	-1,259	-3,751	-6,756	-14,733
Atrazine ban	7,489	-2,050	-4,471	-7,421	-15,323
Triazines ban	7,635	-3,138	-5,656	-8,726	-16,656

the standard deviation of annualized farm income decreases under an atrazine ban. This is likely due to the fact that when field days are scarce, post-emergence atrazine becomes an infeasible treatment, so income variability is more closely tied to field days variability when atrazine is an option.

The bans also have significant impacts on herbicide loads. However, since the impact depends upon the weed control treatment that substitutes for the banned herbicide, the direction of the impacts is indeterminate. Where no control, mechanical control or low-dose herbicides are substituted, chemical load decreases. Where higher dose herbicides are substituted, on the other hand, chemical load increases.

Herbicide bans have especially marked impacts on chemical load in continuous corn. Table 5.21 shows that the hypothesis of unchanged chemical load (H9) in continuous corn can be rejected in all cases under both bans (two-tailed $t(19;.01) = 2.86$). When initial weed seed populations are low, herbicide load increases. When they are high, herbicide load dedclines. Banning atrazine results in substitution of more costly, higher dose herbicide alternatives such as alachlor and cyanazine or lower-dose 2,4-D on continuous corn. The net financial outcome is that costs are slightly higher, while the biological result, shown in Table 5.22, is that weed populations in continuous corn rise slightly, but other performance indicators are virtually unaffected. At high initial weed seed levels, Table 5.22 indicates that the effect of substituting slightly less efficacious treatments is to allow foxtail populations to rise and to reduce the mean percent of maximum crop yield attained.

Table 5.21: Paired difference t-tests of changes in herbicide load due to bans on atrazine and all triazines.

Cropping system, initial weeds, decision rule	Atrazine ban: Gain over No Ban base case — Mean difference	Standard deviation	t statistic	Triazines ban: Gain over No Ban base case — Mean difference	Standard deviation	t statistic
	- - lb ai/acre - -			- - lb ai/acre - -		
Continuous corn						
Low weeds - myopic	0.11	0.16	2.91	0.59	0.29	9.00
Low weeds - two-year	0.17	0.26	2.99	0.75	0.36	9.22
High weeds - myopic	-0.27	0.15	-8.19	-0.39	0.21	-8.37
High weeds - two-year	-0.13	0.18	-3.13	-0.16	0.21	-3.33
Rotational corn						
Low weeds - myopic	0	0	--	0.71	0.27	11.65
Low weeds - two-year	0	0	--	0.54	0.23	10.34
High weeds - myopic	0	0	--	0.00	0.21	0.03
High weeds - two-year	0	0	--	-0.16	0.13	-5.63
Rotational soybean						
Low weeds - myopic	0	0	--	-0.00	0.00	-1.45
Low weeds - two-year	0	0	--	-0.00	0.01	-0.98
High weeds - myopic	0	0	--	-0.00	0.01	-1.65
High weeds - two-year	0	0	--	0.00	0.02	0.31

In the corn-soybean rotation fields, the effect of a ban on chemical load is apparent only on corn. When initial weed pressure is low, chemical load increases. When it is high, chemical load declines (Table 5.21), at least under the two-year decision rule. As in the continuous corn case, a triazines ban leads to reduced mean yields and increased populations of foxtails and lambsquarters (Table 5.22). The substitute weed control treatments also appear to reduce pigweed populations.

Table 5.22: Impact of herbicide bans on biological performance indicators under high information using the two-year decision rule.

Experimental factor	Low initial weeds: Type of ban			High initial weeds: Type of ban		
	None	Atrazine	Triazines	None	Atrazine	Triazines
Mean herbicide load (lb ai/ac)						
Cont. corn	2.94	3.11	3.69	3.58	3.44	3.40
Rotn. corn	3.05	3.05	3.59	3.50	3.50	3.35
Rotn. soy	0.79	0.79	0.78	0.78	0.78	0.78
Mean percent of max. yield (%)						
Cont. corn	80	80	79	72	71	69
Rotn. corn	82	82	81	72	72	71
Rotn. soy	74	74	74	62	62	61
Mean weed density (plants/m^2)						
Continuous corn						
Foxtails	55	54	60	100	105	125
Lambsqtrs	3	3	3	4	5	7
Pigweed	10	10	9	16	18	16
Corn-soybean rotation						
Foxtails	56	56	60	113	113	133
Lambsqtrs	5	5	5	8	8	8
Pigweed	12	12	11	20	20	18
Mean terminal weed seed density (seeds/m^2)						
Continuous corn						
Foxtails	1,432	1,654	1,836	1,614	1,935	2,162
Lambsqtrs	160	163	174	166	174	190
Pigweed	1,256	1,273	1,202	1,640	1,730	1,622
Corn-soybean rotation						
Foxtails	1,915	1,915	1,985	2,239	2,239	2,498
Lambsqtrs	215	215	230	230	230	237
Pigweed	1,542	1,542	1,513	2,057	2,057	1,973

These results provide some guidance in designing policy to restrict groundwater contamination from triazine herbicides. First, bans on atrazine or the triazine family reduce crop yields of corn and soybean. In partial equilibrium (holding prices fixed), this translates to a reduction in farm income. Policy impacts need to be evaluated in general equilibrium to determine whether price changes will offset the reduced yields.

The income effect of the bans is greatest when weed pressure is high. The micro-level impact of a ban on farm income turns on the density and species composition of the weed infestation. A well-designed policy should recognize this. Rather than impose a ban across the board, more flexible policy alternatives are preferable (Segerson). From least to most flexible, these include 1) regional bans where groundwater threats are greatest (e.g., Cox), 2) a ban with specified exceptions, 3) government purchase of herbicide use rights (e.g., Taff and Cox), 4) marketable herbicide use permits, 5) a tax (Gianessi et al., Hrubovcak et al.), and 6) a subsidy on weed management information. General equilibrium models further suggest that chemical use can be reduced by cutting crop price supports or increasing set-asides (Hrubovcak et al.). These alternatives all deserve further study.

The chemical load effect of the bans is not necessarily to reduce the quantity of chemicals applied to the land. Of course, the objective of a ban is to prevent a specific chemical from being released into the environment. It should be recognized, however, that banning one chemical may result in greater ambient quantities of some alternative chemical or chemicals. Certain chemicals which are not now perceived as groundwater threats could become threats if used more extensively.

5.4 Discussion of the Value of Weed Information

The significant gross value of information deserves closer examination to evaluate the practical feasibility of a weed management model such as WEEDSIM. When acquiring information incurs costs, those costs determine the feasibility of using information-intensive management practices (Fohner _et al_.). The costs of information are divided between those involved in obtaining weed population estimates and those of using the predictor embodied in this model. If the model is provided free of cost by the public sector, then the value of the model to a decision maker with a specified utility function is equal to the difference between the calculated value of information and the private cost of obtaining weed population data. As the model's value is estimated as a residual, private costs must first be examined.

The cost of obtaining weed population information depends upon sampling intensity and measurement methods. Given a normal probability distribution, the sampling intensity depends on 1) the maximum tolerable error, 2) the desired likelihood that a parameter estimate falls within the associated confidence interval, and 3) $\tilde{\sigma}$, a prior estimate of the population standard deviation, σ (Snedecor and Cochran, p. 59). If 1) and 2) are held constant across weed species, multiple species sampling intensity is determined by the species with the largest $\tilde{\sigma}$.

Wilson et al. decomposed the variance of weed seed density estimates by field, field division, and soil cores within a division. Most variability occurred within soil cores within a division. For yellow foxtail, common lambsquarters and redroot pigweed, the variance component of soil cores within a division was 98, 54, and 63 percent. Of secondary importance was variability between fields, responsible for 2, 35, and 37 percent of variance, respectively. Wilson et al. calculate the number of soil cores needed to obtain seed estimates within 50% of the mean 20% of the time as four for lambsquarters. Extending their analysis, figures for yellow foxtail and redroot pigweed are 36 and 3 (by the formula in Snedecor and Cochran). The numbers of core samples required using this calculation for the 1985-86 and 1990 pooled Morris data (Table 4.7) for foxtails, lambsquarters and pigweed are 28, 46 and 18.[1] The Wilson et al. variance decomposition suggests that additional sampling would be necessary to capture the between-field variance of lambsquarters and pigweed. Adequate sampling intensity to meet the stated level of accuracy might cover one subdivision of each field with a large number of cores sampled from that area.

The principal cost of estimating seed populations is that of counting seeds. So long as soil cores are composited, this is the cost per composite sample. Buhler (1991b) estimates seed sampling and extraction costs at $14 per composite sample (net of equipment, building and travel costs). Of this, field sampling (relevant for weed seedling counts as well as seed counts) amounts to $2.50. This might rise by a factor of two to four given the numbers of soil cores calculated above. Suppose field sampling costs $10 per composite sample and travel costs $20 per farm. Then the variable cost of obtaining composite samples from six fields is approximately $150 (21.50 x 6 + 20).

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[1] The number of cores actually sampled per plot was six for conventional tillage plots and twelve for reduced tillage plots (Forcella and Lindstrom 1988b).

The fixed costs of analyzing the samples are the cost of building and equipment depreciation. Cost per sample for these is difficult to estimate.[1] However, even if total cost were triple the estimated $150 variable cost, the purchase would be worthwhile to a decision maker with any of the utility functions specified except an extreme risk averter following the myopic rule with low initial weed seeds.

Given the low sampling costs and high estimated value of post-emergent weed seedling counts, the potential welfare gains due to the model are substantial. It appears that seed counts are likely to be feasible for most decision makers. POST seedling counts should be feasible for all decision makers in the range of risk attitudes considered. This suggests that the <u>ex ante</u> value of the model as a decision aid -- net of private information acquisition costs -- is significantly positive. However, these estimates are indicative only. Much more research needs to be done on weed population sampling methods and associated costs before reliable conclusions can be drawn. For seed density, in particular, timely estimates are important. This militates in favor of seed extraction rather than germination methods

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[1]The centrifuge seed extraction process requires a centrifuge, dryer, blower and freezer at an estimated cost of $20,000. The germination method, followed by Forcella and Lindstrom, requires a germinator ($12,000) plus a freezer and greenhouse of unspecified cost (Buhler, 1991b).

(Ball and Miller), despite of the accuracy advantages ascribed to germination (Forcella 1991). Forcella's (1991) finding that sampling in spring provides more accurate seed bank estimates than sampling in autumn makes timely analysis doubly important.

VI. SUMMARY AND CONCLUSION

Weed control is at once a major contributor to and a potentially major detractor from social welfare in the United States. The high crop yields afforded by chemical weed control help farmers prosper and keep consumer food costs low. Yet herbicides and their metabolites also leach into the groundwater, posing a poorly understood threat to human health.

This thesis began by positing incomplete information as a partial explanation for heavy herbicide use. Information deficiency offers an alternative to the more common economic externality rationale for pesticide "overuse." While the externality case builds upon the assumption that decision makers successfully optimize private utility, the incomplete information case assumes that they fail to do so. From a policy design standpoint, the incomplete information argument is more appealing because it implies a technical rather than a distributional solution.

Weed growth, reproduction and competition with crops are biological processes intimately linked with stochastic environmental and ecological processes. Since farmers make weed management decisions under uncertainty about outcomes, it is insufficient to test the incomplete information hypothesis by demonstrating that a certain prediction or recommendation could have left a farmer better off. Most of us find instances in which we could have been better off had we acted on a particular piece of advice. But that knowledge will change our behavior the next time only if we believe the predictor is reliable. The predictor must be reliable enough on average to leave us more satisfied with the outcome having followed the advice at whatever cost, than having proceeded with our best prior choice (Byerlee and Anderson). For the case at hand, demonstrating that weed control decisions are systematically inadequate due to insufficient information requires constructing a predictor that outperforms ordinary weed control decisions. The improvement in performance must be great enough to overcome the associated costs. This appears to be true for the WEEDSIM model.

6.1 Summary

The WEEDSIM weed management bioeconomic model developed here identifies nearly optimal tactics for weed control in corn and soybean, based on weed population density estimates. By incorporating multiple controls and weed species into a dynamic model, it fills a gap between existing multiple species, multiple control static models and single species, single control dynamic ones. Its open design allows it to run with any suitable set of input parameter data.

Within a limited economic optimization framework, WEEDSIM links several simple submodels of weed germination, reproduction, susceptibility to controls, and competition with crops. Simulation of weed biology and crop yield response allows the model to predict crop yield loss under different weed control tactics. Balancing the value of yield loss against the cost of a given weed control, the model generates recommended control tactics. Two mechanisms for striking that balance are evaluated. A two-year optimal control rule chooses the current year tactics consistent with maximizing discounted expected net returns over a two year planning horizon. A one-year "myopic" rule limits its perspective to maximization of expected net returns in the current year.

The thesis devotes considerable attention to statistical estimation and validation of biological functions, since they constitute a key part of the predictor whose informational value is being evaluated. The short available time series of weed population dynamics data is a deficiency that required re-estimation of weed germination equations after unsatisfactory validation results. As in other bioeconomic modeling studies (Briggs, Regmi, Zacharias and Grube), the existing base of biological data was found to be less than desired. Developing the input parameter set required stretching the use of biological data beyond the purposes for which it was originally gathered. Remaining gaps were bridged with assumptions. Even this much information was available only for three species of weeds[1], whose choice may have an important effect on the simulation results.

In addition to addressing the question: "Is the current weed control information typically used by farm managers complete?", the model seeks to identify how much information is desirable. It does so by comparing two levels of supplemental information to the base practice of following general extension recommendations abstracted from information on the specifics of the weed problem. Sample counts of emerged weed seedlings constitute one form of information; sample counts of weed seeds in the soil the other.

A whole-farm stochastic simulation model is developed and employed to evaluate WEEDSIM. Called WFARM, it provides a means to capture the labor, equipment and field time constraints faced by corn and soybean farmers when choosing and implementing weed control treatments. Like WEEDSIM, WFARM is a dynamic model that allows strategies to be evaluated on the basis of multi-year simulations. The stochastic factors are 1) randomly selected historical environmental parameters (e.g., rain, field time, weed-free crop yields) and 2) random disturbances in the estimated biological functions. Repeated model runs under identical sets of stochastic

[1]Mixed green and yellow foxtails, common lambsquarters, and redroot pigweed.

exogenous production factors permit comparison of differing management strategies under uncertainty. Strategies are compared on the basis of several performance criteria over the simulation period: mean and standard deviation of annualized net farm income, three additional utility functions over annualized net income, mean herbicide load, mean percent of maximum crop yield, mean weed density, and mean terminal weed seed density.

Hypothesis tests of results from the six-year simulation experiments yield several clear conclusions: First, strategies using weed population information increase annualized net farm income. Mean annualized net farm income can be ranked from highest to lowest by information level such that mean income with weed seed and seedling counts (high information) exceeds mean income with weed seedling counts alone (POST information) which, in turn, exceeds mean income with no weed population information. The same ranking obtains for expected utility under all four specified utility functions. Second, strategies using "high" weed population information tend to use less chemical over the long term than those that do not. Third, compared with a high initial weed seed bank, a low one raises mean annualized net income and expected utility. Fourth, compared with a high initial weed seed bank, a low one reduces herbicide load in corn. Fifth, bans on atrazine and on all triazine herbicides reduce mean annualized net farm income. Sixth, bans on atrazine and triazines change herbicide load levels, but the changes may result in either an increase or a decrease.

Equally instructive were the hypothesis tests that did not yield statistically clear results: 1) The two-year and myopic decision rules do not generate significantly different mean terminal wealth levels. Moreover, the cautious myopic rule fails to outperform the myopic rule by any performance criterion. 2) Apart from heavier herbicide use on soybean under the two-year rule, herbicide load does not differ by decision rule. Although terminal weed seed densities are generally lower under the two-year decision rule than under the two myopic rules, they are not lower across the board. 3) While increasing farm size reduces mean annualized net farm income, the reduction is only statistically significant when initial weed pressure is low and even then only under the myopic and "no information" scenarios. 4) Despite income-reducing field time constraints on the 720-acre farm, rule-based pre-emptory PPI/PRE weed control followed by an information-based POST control fails to generate higher mean annualized net farm income than using weed population information for both controls.

Rejection of the hypothesis that net farm income is the same with and without weed population information confirms the thesis that weed management decisions made without weed population information tend to be sub-optimal. However, it begs the question, "Is the value of that information worth the cost?" Based on certainty equivalent money metrics of utility for four utility functions, the calculated value of weed population information far exceeds the likely cost of acquiring it. This is true of both emerged weed seedling counts and weed seed counts from soil samples. The excess value of the former is dramatic.

The importance of dynamic modeling is highlighted by rejection of the null hypothesis that initial seed density levels do not influence mean terminal wealth. In particular, this suggests that foresighted decision rules are likely to perform better than myopic ones, even though that could not be demonstrated with statistical significance.

The financial and expected utility advantage of utilizing weed population information in weed control decisions is sufficient reason to adopt such a practice. Weed population information provides a valuable supplementary input which increases the technical efficiency of weed management. Research results presented here suggest that it may also reduce herbicide load.

The herbicide ban impact analysis brings out three points. First, the farm-level impact of a ban depends upon the severity and composition of the weed problem on that farm. Second, the private, firm-level cost of a ban on atrazine alone is not very high, due to the availability of substitutes which are only slightly more expensive or less efficacious at controlling weeds. Banning all triazines would be two to five times more costly due to reduced substitution options and effects on rotational corn and soybean. Third, total chemical load will not necessarily decrease just because a single herbicide or family of herbicides is banned. Alternative policies offering greater flexibility in weed management and/or aimed at reducing total herbicide load may be preferable to across-the-board bans. Alternatives that deserve further study include marketable use permits, taxes, purchase of usage rights, and subsidies on weed management information (e.g., computerized decision aids, weed seed soil analyses).

6.2 Potential uses for model

The WEEDSIM recommendations module gave very promising results in the stochastic simulation evaluation. Its high value, net of imputed costs of information acquisition, suggests that it can provide farmers and crop consultants with a beneficial decision. Clearly, before it can go into service in such a capacity, the model will require further validation. Validation field trials for 1991 have been established at Rosemount and Morris, Minnesota (Buhler 1991c).

Because it synthesizes information on weed population dynamics, control treatment efficacy and weed-crop competition, the whole-farm stochastic model offers a comprehensive framework for identifying research needs in weed management. Sensitivity analysis of key parameters influencing recommendations could help to chart a course for future applied research based on explicit estimates of expected returns to research.

Finally, the potential of the whole-farm stochastic model for policy analysis can be extended much further than the indicative analysis presented in this thesis. The strengths of this model for firm-level herbicide policy analysis are three: 1) its modeling of weed biology allows it to capture biological dynamic effects, 2) its expandable range of herbicide treatments captures substitution effects missed by such models as that of Knutson et al., and 3) its expandable set of weed species allows it to quantify policy impacts by severity and type of weed infestation.

6.3 Directions for future research

The potential uses of the model point to desirable directions for future research, particularly for setting research priorities and analyzing potential public policies.

Returns to weed management research can be examined in two ways. The distribution of annualized net farm incomes can be examined for potential gains in certainty equivalents of expected utility from reducing overall income variance. Sensitivity analysis of specific parameters and groups of related parameters can suggest gains from specific research projects (e.g., Bosch and Shabman). The seed production parameters would be a good group to start with, as unexplained variation in their statistical estimation for this thesis was especially high.

As noted in Chapter 3, biological process simulation offers a promising alternative to the statistical methods used to model plant growth and population dynamics in this thesis. Differences between observed and simulated behavior tend to be much lower in process models than statistical ones, since the former make endogenous many of the environmental factors that remain exogenous to statistical models. The Forcella (1991) model used here provides a first step in that direction for weed germination. The recent work of Williams et al. points to possibilities for process modeling of weed-crop competition, although the challenge of accommodating of multiple weeds remains to be tackled.

Simply substituting more realistic functional forms would improve the WEEDSIM and WFARM models. The step functions used for weed control efficacy and yield penalties are strong candidates for replacement. Eradat Oskoui and Voorhees are developing a quadratic yield penalty function for late planting in corn and soybean that would be one option.

Better statistical estimates of model parameters can be developed from field experiments designed with that purpose in mind. Sounder weed seed population parameters are particularly needed. The time series experiments required for their estimation are rare and difficult to conduct. Uniform measurement standards are also needed in order to make model operation consistent across input data sets. Competing methods of counting seeds (e.g., Forcella, 1991, Ball and Miller), counting emerged weeds (in the crop row versus both in the row and in between), and determining sampling intensity all demand further study. New investigations should include cost and timeliness, along with accuracy, as performance criteria.

In spite of its weak showing in stochastic simulation, the cautious myopic decision rule deserves further examination. From theory, the principle of reducing the static economic threshold for weed control is sound. A range of levels for the percent reduction in the no control threshold should be attempted to determine whether and under what conditions values exist that make that rule preferable to the myopic one.

Further policy analysis should examine a wider range of policy scenarios than the two bans reviewed here. In particular, herbicide taxes should be examined in a search for ban-equivalent tax levels under specified levels of weed pressure. Such alternatives as marketable herbicide use permits, government purchase of herbicide use rights, and weed population information subsidies also deserve formal review.

APPENDICES

A.1 Miscellaneous Figures and Tables

Table A1.1: Data sets used for estimation of yield and weed population dynamics equations.

Equation	Data set name	Description	Principal Investigator
C1,S1	VICMS	Variable Input Crop Management Study	J. Gunsolus[1]
C2	LAMCULT	Cultivation/rotary hoe study	J. Gunsolus
C3	MORCULT	Cultivation/rotary hoe study	J. Gunsolus
C4	WASCULT	Cultivation/rotary hoe study	J. Gunsolus
C5	NTCULT	Cultivation effects on no-till corn	D. Buhler[2]
C6	CHICULT	Cultivation effects on chisel-plowed corn	D. Buhler
C7,S6	FORC8586	Tillage/rotary hoe study	F. Forcella[3]
S2	ROHOYD	Rotary hoe study	J. Gunsolus
S3	RRWASDW	Reduced herbicide rate study	J. Gunsolus
S4	DRYWTRR	Reduced herbicide rate study	J. Gunsolus
S5	PDMECH	Planting date effect on mechanical weed control	D. Buhler

[1]Department of Agronomy and Plant Genetics, University of Minnesota, St. Paul, MN.

[2]Agricultural Research Service, U.S. Department of Agriculture, University of Minnesota, St. Paul, MN.

[3]Agricultural Research Service, U.S. Department of Agriculture, North Central Soil Conservation Research Laboratory, Morris, MN.

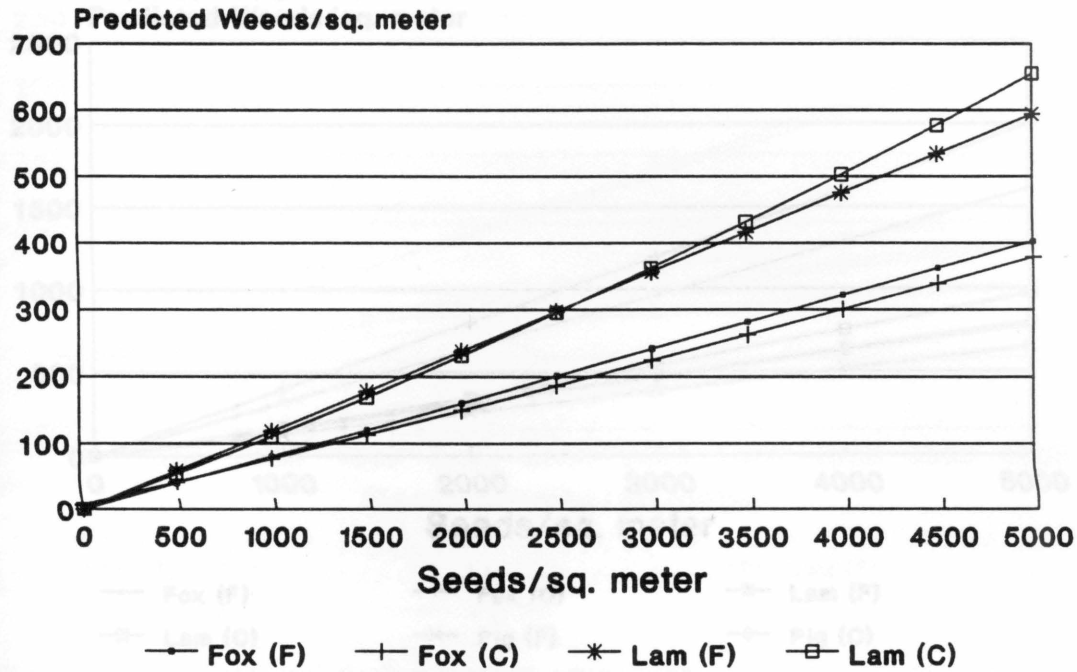

Figure A1.1: Pre-plant weed densities for 1985: Forcella predictions (F) versus recalibrated predictions (C).

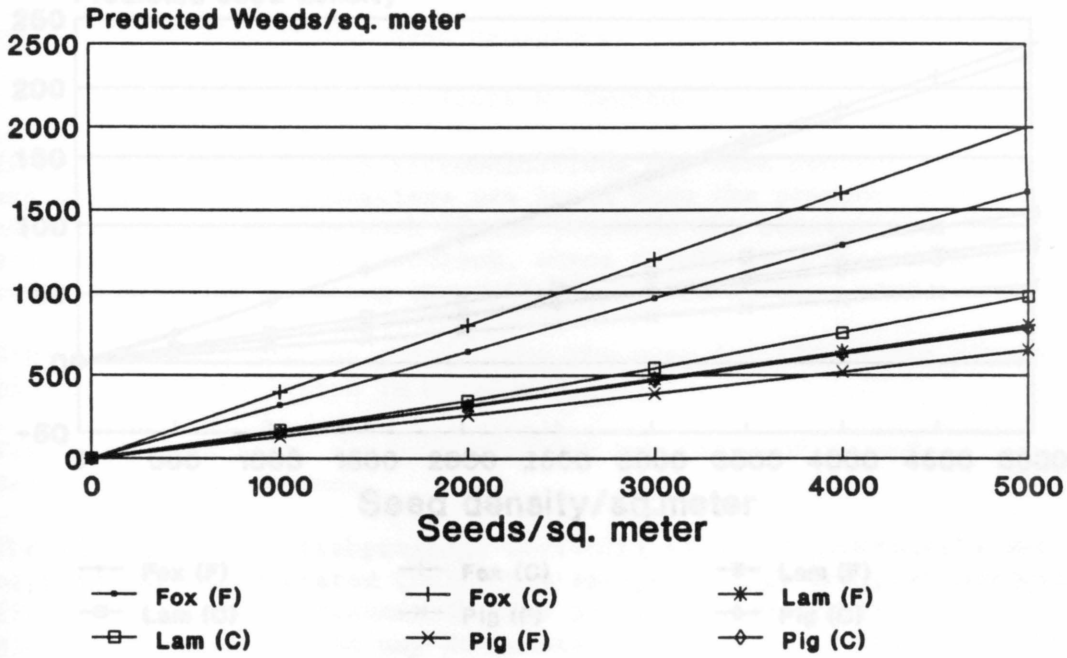

Figure A1.2: Post-crop emergence weed density in 1985: Forcella predictions (F) versus recalibrated predictions (C).

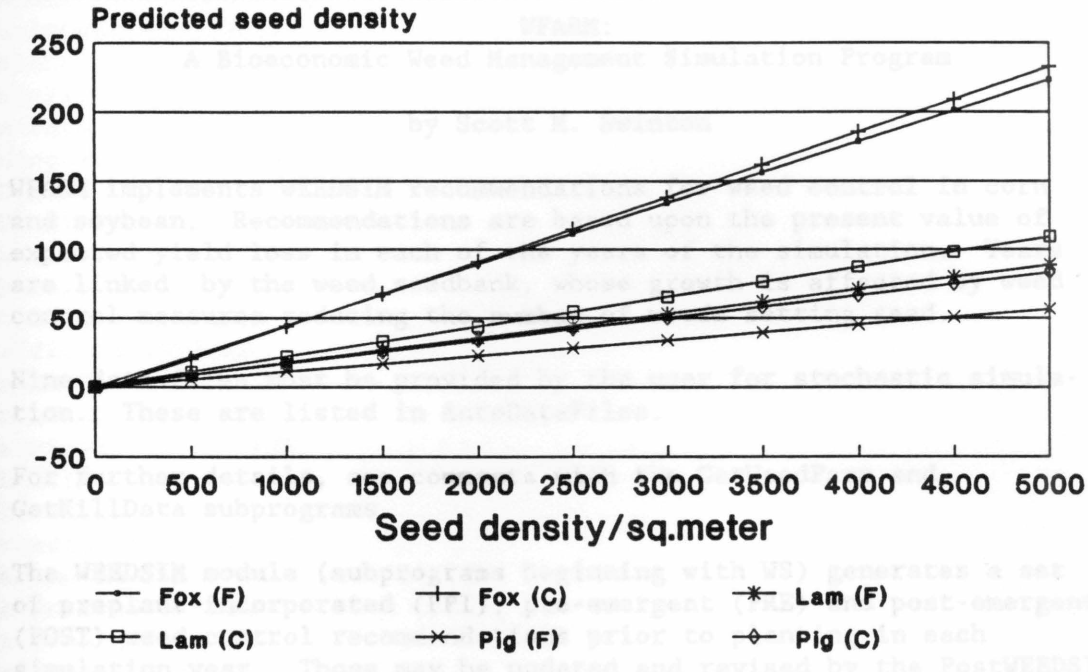

Figure A1.3: Post-cultivation weed emergence for 1985: Forcella predictions (F) versus recalibrated predictions (C).

A.2 Listing of the **WFARM** and **WEEDSIM** program code

```
'                                          Last update: 06/10/91
'
' WFARM6 version stochastic w/ random coefs. & 2-year decision rule.
'**********************************************************************
'*                               WFARM:                               *
'*      A Bioeconomic Weed Management Simulation Program              *
'*                                                                    *
'*                          by Scott M. Swinton                       *
'*                                                                    *
'* WFARM implements WEEDSIM recommendations for weed control in corn  *
'* and soybean.  Recommendations are based upon the present value of  *
'* expected yield loss in each of the years of the simulation.  Years *
'* are linked  by the weed seedbank, whose growth is affected by weed *
'* control measures reducing the number of weeds setting seed.        *
'*                                                                    *
'* Nine data files must be provided by the user for stochastic simula- *
'* tion.  These are listed in AutoDataFiles.                          *
'*                                                                    *
'* For further details, see comments with the GetWeedParm and         *
'* GetKillData subprograms.                                           *
'*                                                                    *
'* The WEEDSIM module (subprograms beginning with WS) generates a set *
'* of preplant-incorporated (PPI), pre-emergent (PRE) and post-emergent*
'* (POST) weed control recommendations prior to planting in each      *
'* simulation year.  Those may be updated and revised by the PostWEEDSIM
'* module according to conditions prior to the POST application.      *
'**********************************************************************
'
' ******************************
' *  Functions and Subprograms  *
' ******************************
TYPE cropfile
  cropId AS INTEGER
  cname AS STRING * 8
  maxyld AS SINGLE
  expMaxY AS SINGLE
  growrate AS SINGLE
  sigcint AS SINGLE
  sigcdap2 AS SINGLE
  a AS SINGLE
  seedRate AS SINGLE
  seedPric AS SINGLE
  price AS SINGLE
  vc AS SINGLE
END TYPE
```

```
TYPE hfile
  cropId AS INTEGER
  aptimeId AS INTEGER
  herbId AS INTEGER
  hname AS STRING * 16
  unitCost AS SINGLE
  minrate AS SINGLE
  maxrate AS SINGLE
  avrate AS SINGLE
  droptrt AS INTEGER
END TYPE
TYPE kfile
  aptimeId AS INTEGER
  herbId AS INTEGER
  weedId AS INTEGER
  effic AS INTEGER
  maxWdHt AS SINGLE
  maxCrnHt AS INTEGER
  maxSoyHt AS INTEGER
END TYPE
TYPE wfile
  weedId AS INTEGER
  wname AS STRING * 8
  avgerm AS SINGLE
  s0propn AS SINGLE
  s1propn AS SINGLE
  s2propn AS SINGLE
  s3mortpn AS SINGLE
  w1propag AS SINGLE
  w2propag AS SINGLE
  growrate AS SINGLE
  w0int AS SINGLE
  w0s AS SINGLE
  w0s2 AS SINGLE
  w1int AS SINGLE
  w1s AS SINGLE
  w1s2 AS SINGLE
  w2int AS SINGLE
  w2s AS SINGLE
  sig0int AS SINGLE
  sig0s AS SINGLE
  sig0s2 AS SINGLE
  sig1int AS SINGLE
  sig1s AS SINGLE
  sig1s2 AS SINGLE
  sig2int AS SINGLE
  sig2s AS SINGLE
  sig2s2 AS SINGLE
  sigwint AS SINGLE
```

```
  sigwdap2 AS SINGLE
END TYPE
TYPE cfile
  cropId AS INTEGER
  weedId AS INTEGER
  i AS SINGLE
END TYPE
TYPE mfile
  machcode AS INTEGER
  machname AS STRING * 15
  AcHr AS SINGLE
  CostAc AS SINGLE
END TYPE
TYPE ftype
  fnum AS INTEGER
  cropId AS INTEGER
  prevCrop AS INTEGER
  fsize AS INTEGER
  hflag AS INTEGER
  preApTim AS INTEGER
  precode AS INTEGER
  postcode AS INTEGER
  prename AS STRING * 16
  postname AS STRING * 16
  precost AS SINGLE
  postcost AS SINGLE
  ywf AS SINGLE
  rotation AS INTEGER
  cost AS SINGLE
  plweek AS INTEGER
  ppiweek AS INTEGER
  preweek AS INTEGER
  postweek AS INTEGER
  cropHt AS SINGLE
  preload AS SINGLE
  postload AS SINGLE
END TYPE
TYPE efile
  epsw01 AS SINGLE
  epsw02 AS SINGLE
  epsw11 AS SINGLE
  epsw12 AS SINGLE
  epsw13 AS SINGLE
  epsw21 AS SINGLE
  epsw22 AS SINGLE
  epsw23 AS SINGLE
  epsyldc AS SINGLE
  epsylds AS SINGLE
  epsseed1 AS SINGLE
```

```
  epsseed2 AS SINGLE
  epsseed3 AS SINGLE
  epsgrowc AS SINGLE
  epsgrows AS SINGLE
  epsgrowl AS SINGLE
  epsgrow2 AS SINGLE
  epsgrow3 AS SINGLE
END TYPE
TYPE bfile
  betaw010 AS SINGLE
  betaw011 AS SINGLE
  betaw012 AS SINGLE
  betaw020 AS SINGLE
  betaw021 AS SINGLE
  betaw022 AS SINGLE
  betaw110 AS SINGLE
  betaw111 AS SINGLE
  betaw120 AS SINGLE
  betaw122 AS SINGLE
  betaw130 AS SINGLE
  betaw131 AS SINGLE
  betaw210 AS SINGLE
  betaw211 AS SINGLE
  betaw220 AS SINGLE
  betaw221 AS SINGLE
  betaw230 AS SINGLE
  betaw231 AS SINGLE
  betagroc AS SINGLE
  betagros AS SINGLE
  betagrol AS SINGLE
  betagro2 AS SINGLE
  betagro3 AS SINGLE
END TYPE
TYPE yfile
  year AS INTEGER
  fd1 AS SINGLE
  fd2 AS SINGLE
  fd3 AS SINGLE
  fd4 AS SINGLE
  fd5 AS SINGLE
  fd6 AS SINGLE
  fd7 AS SINGLE
  fd8 AS SINGLE
  fd9 AS SINGLE
  fd10 AS SINGLE
  fd11 AS SINGLE
  rain1 AS SINGLE
  rain2 AS SINGLE
  rain3 AS SINGLE
```

```
  rain4 AS SINGLE
  rain5 AS SINGLE
  rain6 AS SINGLE
  rain7 AS SINGLE
  rain8 AS SINGLE
  rain9 AS SINGLE
  rain10 AS SINGLE
  rain11 AS SINGLE
  cymax AS INTEGER
  symax AS INTEGER
  foxgerm AS SINGLE
  lamgerm AS SINGLE
  piggerm AS SINGLE
END TYPE
TYPE stype
  nr AS SINGLE
  sdnr AS SINGLE
  load AS SINGLE
  ypct AS SINGLE
END TYPE
'
' Make all arrays dynamic - Use with QB/AH option (see pp. 347-348)
'$DYNAMIC
' (Command disabled if " 'x$DYNAMIC " written.)

DECLARE FUNCTION ypen! (cropId%, ywf, plwk%)
DECLARE FUNCTION yield2! (wnum%, ywf!, cropnum%, compmax%, comp() AS
  cfile, crop() AS cropfile, d!())
DECLARE FUNCTION surv! (x%)
'DECLARE SUB ScreenHeader2 ()
DECLARE SUB PrinterHeader ()
'DECLARE SUB UserParameters ()
DECLARE SUB AutoDataFiles (cropparm$, parmfile$, compfile$, herbfile$,
  killfile$, fdayfile$, machfile$, seedfile$, epsfile$, yearfile$,
  betafile$)
DECLARE SUB AutoParameters (fld() AS ftype, cropmax%, crop() AS
  cropfile, nyears%, r, hrsday, tractors%, nfields%, theta, maxCwk%,
  minSwk%, decrule%, nweeks%, nstates%)
DECLARE SUB GetCropParm (cropparm$, cropdata AS cropfile, crop() AS
  cropfile)
DECLARE SUB GetWeedParm3 (wnum%, parmfile$, wf AS wfile, weedparm() AS
  wfile)
DECLARE SUB GetKillData2 (killfile$, eff AS kfile, efftemp() AS kfile,
  killparm() AS kfile, kmax%)
DECLARE SUB GetHerbData (cropnum%, aptime%, herbfile$, herb AS hfile,
  herbtemp() AS hfile)
'DECLARE SUB UserDropTrts2 (aptime%, trtmax%, herb() AS hfile, cropnum%,
  crop() AS cropfile)
```

```
DECLARE SUB MakeKillArray (kmax%, aptime%, h%, wnum%, eff() AS kfile,
  herb() AS hfile, k%())
DECLARE SUB MakeHerbArray (cropnum%, aptime%, herbfile$, herb AS hfile,
  kmax%, wnum%, eff() AS kfile, crop() AS cropfile, cppi() AS hfile,
  cpre() AS hfile, cpost() AS hfile, sppi() AS hfile, spre() AS hfile,
  spost() AS hfile, k1c%(), k2c%(), k3c%(), k1s%(), k2s%(), k3s%())
DECLARE SUB GetWeedCompData (compfile$, comptemp() AS cfile)
DECLARE SUB GetMachData (machfile$, machtemp() AS mfile)
'DECLARE SUB ChooseMachinery (machnum%, machtemp() AS mfile, mt%, mp%,
  ms%, mc%, mr%, mf%)
DECLARE SUB AutoChooseMach (mt%, mp%, ms%, mc%, mr%, mf%)
DECLARE SUB AutoWeedSeeds (nfields%, wnum%, lamseeds%, s0wf())
'DECLARE SUB UserWeedSeeds (nfields%, wnum%, weedtemp() AS wfile)
'DECLARE SUB GetSeedData (nfields%, wnum%, seedfile$, s0wf!())
DECLARE SUB ScreenNotice ()
DECLARE SUB PrintInitWeedSeeds (nfields%, wnum%, state%, yr%, weedparm()
  AS wfile, s0wf())
DECLARE SUB InitializeScenario (wnum%, sumst() AS stype, farmstnr!,
  farmstsd!, cswst!(), ccwst!(), cssst!(), ccsst!(), urp0001#, ura0001#,
  ura001#)
DECLARE SUB InitializeState (wnum%, farmnr, sum() AS stype, csweed(),
  ccweed(), csseed(), ccseed())
DECLARE SUB GetYear (yearfile$, year AS yfile, flddays!(), rain!(),
  crop() AS cropfile, germtot!(), randnum(), newscen%)
DECLARE SUB GetStateErrors (nfields%, wnum%, newscen%, epsfile$, epsilon
  AS efile, epsw0!(), epsw1!(), epsw2!(), epsseed!(), epsyld!(),
  epscgrow(), epswgrow())
DECLARE SUB GetStateBetaErrors (nfields%, wnum%, newscen%, betafile$,
  betaeps AS bfile, betacgro!(), betawgro!(), betaw0(), betaw1(),
  betaw2())
DECLARE SUB InitializeYear (nfields%, wnum%, fld() AS ftype, crop() AS
  cropfile, sw!(), s0wf!(), diskflag%(), infeas%(), endflag%(), wk%, t%,
  yr%, grmlflag%(), load(), OTsum, maxCwk%, dropostc%(), droposts%(),
  h3c%, h3s%)
DECLARE SUB CalibrateGerm (nfields%, wnum%, wf() AS wfile, s0wf!(),
  w0germ!(), w1germ!(), w2germ!(), epsw0(), epsw1(), epsw2(), germtot(),
  betaw0(), betaw1(), betaw2())
DECLARE SUB ChooseCrop (f%, fld() AS ftype, maxCwk%, wk%)
DECLARE SUB WSWeedGerm (wnum%, weed() AS wfile, s0w(), s1w(), s2w(),
  d1w(), w0(), w1())
DECLARE SUB WSPreTrt (wnum%, h1%, h2%, mf%, ms%, k1%(), k2%(), d1w(),
  ywf, ppiherb() AS hfile, preherb() AS hfile, mach() AS mfile,
  fldSize%, plcost, h12%, d2w(), precost(), precode%(), preAvRat())
DECLARE SUB WSPostTrt (cropnum%, wnum%, h12%, h3%, ywf!, rot%, k3%(),
  d2w!(), s0w!(), s2w!(), weedparm() AS wfile, crop() AS cropfile,
  precode%(), preAvRat!(), postherb() AS hfile, compmax%, compparm() AS
  cfile, mach() AS mfile, ms%, mr%, fldSize%, d3w(), d3wij(), s3w(),
  yldpost(), postcost(), w2())
```

```
DECLARE SUB WSSeedBank (wnum%, h12%, h3%, d3w!(), s3w!(), weed() AS
  wfile, s0wl(), w2())
DECLARE SUB WSPostRev (h12%, h3%, p!, yldpost!(), postcost!(),
  precost!(), t%, r!, fldSize%, vc, netpost())
DECLARE SUB WSTopRevMyopic (h12%, h3%, netpost(), theta, kimax%, kjmax%,
  topnet)
DECLARE SUB WSNextYear (f%, wnum%, cropnum%, compmax%, h1%, h2%, h12%,
  h3%, t%, r, mf%, ms%, mr%, mp%, k1%(), k2%(), k3%(), fld() AS ftype,
  weed() AS wfile, mach() AS mfile, comp() AS cfile, crop() AS cropfile,
  ppiherb() AS hfile, preherb() AS hfile, postherb() AS hfile, s0w(),
  s0wl(), s1w(), s2w(), s3w(), d1w(), d2w(), d3w(), yldpost(),
  precost(), netpost0(), netpost1(), plcost, theta, netpost(),
  postcost(), precode%(), preAvRat(), h12o%, h3o%)
DECLARE SUB WSTopRev (h12o%, h3o%, h12%, h3%, theta, netpost1(), kimax%,
  kjmax%, topnet)
DECLARE SUB WEEDSIM (f%, wnum%, h1%, h2%, h3%, mf%, ms%, mr%, mp%, t%,
  r, s0w(), fld() AS ftype, cropnum%, crop() AS cropfile, weed() AS
  wfile, k1%(), k2%(), k3%(), ppiherb() AS hfile, preherb() AS hfile,
  postherb() AS hfile, mach() AS mfile, compmax%, comp() AS cfile,
  theta, nyears%, netpost(), h1n%, h2n%, h3n%, k1n%(), k2n%(), k3n%(),
  ppinext() AS hfile, prenext() AS hfile, postnext() AS hfile, decrule%)
DECLARE SUB PrintRecoms (f%, cropname$, fld() AS ftype, topnet!)
DECLARE SUB PPITrt (f%, nfields%, wk%, fld() AS ftype, newcost!(),
  newload(), hrs!, maxhrs, machine() AS mfile, ms%, mf%, preflag%)
DECLARE SUB FieldWeedGerm (f%, nfields%, wnum%, swlost(), grmlflag%(),
  w0germ(), w1germ())
DECLARE SUB DiskField (f%, mf%, diskflag%(), fld() AS ftype, mach() AS
  mfile, newcost(), hrs!)
DECLARE SUB PlantCrop (f%, wk%, fld() AS ftype, maxCwk%, minSwk%,
  newcost(), hrs, maxhrs, machine() AS mfile, mp%, crop() AS cropfile,
  sw(), weed() AS wfile, wnum%)
DECLARE SUB PreTrt (f%, nfields%, wk%, fld() AS ftype, newcost!(),
  newload(), hrs!, maxhrs!, machine() AS mfile, ms%, preflag%)
DECLARE SUB PRESurv (f%, nfields%, wnum%, fld() AS ftype, kmax%, eff()
  AS kfile, w1germ!(), d2wf!(), rain!())
DECLARE SUB CropGrowth (f%, wk%, crop() AS cropfile, fld() AS ftype,
  epscgrow(), betacgro())
DECLARE SUB WeedGrowth (f%, wk%, wnum%, weed() AS wfile, fld() AS ftype,
  weedHt!(), epswgrow(), betawgro())
'DECLARE SUB RotaryHoe (f%, wnum%, wk%, fld() AS ftype, kmax%, eff() AS
  kfile, weedHt!(), newcost!(), newload!(), hrs!, maxhrs!, mach() AS
  mfile, mr%, infeas%(), weed() AS wfile, rotflagl%())
DECLARE SUB PostTrt (f%, nfields%, wnum%, wk%, fld() AS ftype, kmax%,
  eff() AS kfile, weedHt(), newcost(), newload(), hrs, maxhrs, machine()
  AS mfile, ms%, mr%, infeas%(), endflag%(), d2wf(), d3wf(), sw(),
  swlost(), w2germ())
'DECLARE SUB ModifyHerbArray (h3%, f%, fld() AS ftype, post() AS hfile,
  kmax%, wnum%, eff() AS kfile, crop() AS cropfile, k3%(), dropcode%)
```

```
DECLARE SUB PostWEEDSIM (f%, wnum%, h3%, mf%, ms%, mr%, mp%, t%, r,
  s0wf(), sw(), d2wf(), fld() AS ftype, cropnum%, crop() AS cropfile,
  weed() AS wfile, k3%(), postherb() AS hfile, mach() AS mfile,
  compmax%, comp() AS cfile, costnow, theta, nyears%, netpost(), hln%,
  h2n%, h3n%, kln%(), k2n%(), k3n%(), ppinext() AS hfile, prenext() AS
  hfile, postnext() AS hfile, decrule%, dropcode%, dropost%())
DECLARE SUB WSPostReviseTrt (cropnum%, wnum%, hl%, h3%, ywf, rot%,
  k3%(), d2w(), s0w(), s2w(), weedparm() AS wfile, crop() AS cropfile,
  precode%(), preAvRat(), postherb() AS hfile, compmax%, compparm() AS
  cfile, sprayCst, fldSize%, d3w(), d3wij(), s3w(), yldpost(),
  postcost(), w2(), dropcode%, dropost%())
'DECLARE SUB PrintResults (yr%, nfields%, wnum%, weed() AS wfile, sw!(),
  netrev!(), load(), yldpct(), OTsum)
DECLARE SUB SummaryAnnual (wnum%, nfields%, fld() AS ftype, crop() AS
  cropfile, netrev(), load(), yldpct(), d3wf(), s0wf(), csweed(),
  ccweed(), csseed(), ccseed(), farmnr, sum() AS stype)
DECLARE SUB SummaryState (wnum%, nyears%, r, sum() AS stype, farmnr,
  csweed(), ccweed(), csseed(), ccseed(), sumst() AS stype, farmstnr,
  farmstsd, cswst(), ccwst(), cssst(), ccsst(), urp0001#, ura0001#,
  ura001#, stateout$)
DECLARE SUB SummaryScenario (scenout$, decrule%, theta!, lamseeds%,
  wnum%, nstates%, sumst() AS stype, farmstnr!, farmstsd!, cswst!(),
  ccwst!(), cssst!(), ccsst!(), urp0001#, ura0001#, ura001#)
'
CONST false% = 0, true% = NOT false%
'ON ERROR GOTO Chkerror
'
'***********************************
'* Array Parameters & Definitions *
'***********************************
' *************
' * Constants *
' *************
  wmax% = 3: 'Maximum number of weed species in model
  hlmax% = 7: 'Maximum number of PPI weed treatments in model
  h2max% = 7: 'Maximum number of PRE weed treatments in model
  h3max% = 8: 'Maximum number of POST weed treatments in model
  hl2max% = hlmax% + h2max% - 1
  hmax% = hl2max% + h3max% * 2
  killmax% = hmax% * wmax%
  weeksmax% = 11: 'Number of weeks starting 4/19
  statemax% = 20: 'Maximum number of states of nature
  fldsmax% = 9
  machmax% = 12
  cropmax% = 2
  compmax% = cropmax% * wmax%
  '
```

```
'*********************
' * Array Definitions *
'*********************
 DIM cropdata AS cropfile
 DIM crop(cropmax%) AS cropfile
 DIM herbarray(hmax%) AS hfile
 DIM cppi(h1max%) AS hfile
 DIM cpre(h2max%) AS hfile
 DIM cpost(h3max%) AS hfile
 DIM sppi(h1max%) AS hfile
 DIM spre(h2max%) AS hfile
 DIM spost(h3max%) AS hfile
 DIM herb AS hfile
 DIM weedfile AS wfile
 DIM weedparm(wmax%) AS wfile
 DIM compparm(compmax%) AS cfile
 DIM killparm(killmax%) AS kfile
 DIM efftemp(killmax%) AS kfile
 DIM eff AS kfile
 DIM machine(machmax%) AS mfile
 DIM fld(fldsmax%) AS ftype
 DIM epsilon AS efile
 DIM year AS yfile
 DIM sum(3) AS stype
 DIM sumst(3) AS stype
 DIM betaeps AS bfile
'
' Arrays for GetErrorTerms
 REDIM epsw0(fldsmax%, wmax%), epsw1(fldsmax%, wmax%), epsw2(fldsmax%,
   wmax%)
 REDIM epsseed(flsmax%, wmax%), epsyld(fldsmax%, cropmax%)
'
' Arrays for WEEDSIM
 REDIM netpost(h12max%, h3max%)
'
' Arrays for MakeHerbArray
 REDIM k1c%(wmax%, h1max%), k2c%(wmax%, h2max%), k3c%(wmax%, h3max%)
 REDIM k1s%(wmax%, h1max%), k2s%(wmax%, h2max%), k3s%(wmax%, h3max%)
'
'****************
'* Global values *
'****************
'
' *****************
' * Screen setting *
' *****************
 SCREEN 0
 COLOR 14, 1, 8
 CLS
```

```
'CALL ScreenHeader2
' *************
' * Constants *
' *************
CALL AutoDataFiles(cropparm$, parmfile$, compfile$, herbfile$,
  killfile$, fdayfile$, machfile$, seedfile$, epsfile$, yearfile$,
  betafile$)
CALL GetCropParm(cropparm$, cropdata, crop())
' CALL UserParameters
CALL AutoParameters(fld(), cropmax%, crop(), nyears%, r, hrsday,
  tractors%, nfields%, theta, maxCwk%, minSwk%, decrule%, nweeks%,
  nstates%)
ranyears% = nstates% * nyears%
dropcode% = -1
CALL GetWeedParm3(wnum%, parmfile$, weedfile, weedparm())
CALL GetWeedCompData(compfile$, compparm())
CALL GetKillData2(killfile$, eff, efftemp(), killparm(), kmax%)
FOR cropnum% = 1 TO cnum%
  FOR aptime% = 1 TO 3
    CALL MakeHerbArray(cropnum%, aptime%, herbfile$, herb, kmax%,
      wnum%, killparm(), crop(), cppi(), cpre(), cpost(), sppi(),
      spre(), spost(), k1c%(), k2c%(), k3c%(), k1s%(), k2s%(), k3s%())
  NEXT aptime%
NEXT cropnum%
CALL GetMachData(machfile$, machine())
' CALL ChooseMachinery(machnum%, machine(),mt%, mp%, ms%, mc%, mr%, mf%)
CALL AutoChooseMach(mt%, mp%, ms%, mc%, mr%, mf%)
IF quit% = true% THEN END
'
'Allocate dynamic arrays:
'
' Arrays for GetStateErrors
REDIM epsw0(nfields%, wnum%), epsw1(nfields%, wnum%), epsw2(nfields%,
  wnum%)
'REDIM epsseed(nfields%, wnum%), epsyld(nfields%, wnum%),
  epscgrow(cnum%)
'REDIM epswgrow(wnum%)

'Arrays for GetBetaStateErrors
REDIM betacgro(cnum%), betawgro(wnum%), betaw0(nfields%, wnum%, 3)
REDIM betaw1(nfields%, wnum%, 3), betaw2(nfields%, wnum%, 2)
'
'Arrays for GetYear
REDIM flddays(weeksmax%), rain(weeksmax%), germtot(wmax%),
  randnum(ranyears%)
'
```

```
'Arrays for CalibrateGerm
  REDIM w0germ(nfields%, wnum%), w1germ(nfields%, wnum%),
    w2germ(nfields%, wnum%)
'
'Arrays for FieldWeedGerm
  REDIM s0wf(fldsmax%, wnum%), swlost(nfields%, wnum%)
  REDIM grmlflag%(nfields%)
'
' Arrays for DiskField
  REDIM diskflag%(nfields%)
'
'Arrays for WeedGrowth
  REDIM weedHt(nfields%, wnum%)
'
'Arrays for PRETrt
  REDIM d2wf(nfields%, wnum%)
'
'Arrays for POSTTrt
  REDIM infeas%(nfields%), d3wf(nfields%, wnum%)
'
' Arrays for PostWEEDSIM
  REDIM dropostc%(h3c%), droposts%(h3s%)
'*************************
' Arrays for Main program
  REDIM cost(nfields%), newcost(nfields%), maxhrs(weeksmax%),
    sw(nfields%, wnum%)
  REDIM load(nfields%), newload(nfields%), yldpct(nfields%),
    endflag%(nfields%)
  REDIM postrec%(nfields%), cyield(nfields%), netrev(nfields%)
'
'Arrays for Summaries
  REDIM csweed(wnum%), ccweed(wnum%), csseed(wnum%), ccseed(wnum%)
  REDIM cswst(wnum%), ccwst(wnum%), cssst(wnum%), ccsst(wnum%)
'
'**********************
'* Execution Section *
'**********************
'time0 = TIMER
INPUT "Name of state data output file: ", stateout$
INPUT "Name of summary statistics output file: ", scenout$
FOR ry% = 1 TO ranyears%
  randnum(ry%) = RND
NEXT ry%
'CALL UserWeedSeeds(nfields%, wnum%,weedfile())
'CALL GetSeedData(nfields%, wnum%, seedfile$, s0wf())
```

```
'*****************
'* Scenarios loop *
'*****************
FOR lamseeds% = 25 TO 250 STEP 225
FOR decrule% = 1 TO 2
FOR gam% = 0 TO 1
IF decrule% = 2 THEN
  gam% = 1
  theta = 0
  ELSE
  theta = -.05 * gam%
END IF
CALL InitializeScenario(wnum%, sumst(), farmstnr, farmstsd, cswst(),
  ccwst(), cssst(), ccsst(), urp0001#, ura0001#, ura001#)
'************************
'* State of nature loop *
'************************
newscen% = true%
FOR state% = 1 TO nstates%
  CALL AutoWeedSeeds(nfields%, wnum%, lamseeds%, s0wf())
  CALL InitializeState(wnum%, farmnr, sum(), csweed(), ccweed(),
    csseed(), ccseed())
' **************************
' * Yearly activities loop *
' **************************
  FOR yr% = 1 TO nyears%
    CALL GetYear(yearfile$, year, flddays(), rain(), crop(), germtot(),
      randnum(), newscen%)
    CALL GetStateErrors(nfields%, wnum%, newscen%, epsfile$, epsilon,
      epsw0(), epsw1(), epsw2(), epsseed(), epsyld(), epscgrow(),
      epswgrow())
    CALL GetStateBetaErrors(nfields%, wnum%, newscen%, betafile$,
      betaeps, betacgro(), betawgro(), betaw0(), betaw1(), betaw2())
    CALL InitializeYear(nfields%, wnum%, fld(), crop(), sw(), s0wf(),
      diskflag%(), infeas%(), endflag%(), wk%, t%, yr%, grm1flag%(),
      load(), OTsum, maxCwk%, dropostc%(), droposts%(), h3c%, h3s%)
    'CALL PrintInitWeedSeeds(nfields%, wnum%, state%, yr%, weedparm(),
      s0wf())
    CALL CalibrateGerm(nfields%, wnum%, weedparm(), s0wf(), w0germ(),
      w1germ(), w2germ(), epsw0(), epsw1(), epsw2(), germtot(),
      betaw0(), betaw1(), betaw2())
    'PRINT
    'PRINT "Pre-season recommendations are:"
    'PRINT
"--------------------------------------------------------------------"
    'PRINT "Field  Crop  Rotation   PRE/PPI Trt.    Time   POST Trt.
    E(NR)"
    'PRINT
"--------------------------------------------------------------------"
```

```
FOR f% = 1 TO nfields%
  cropnum% = fld(f%).cropId
  SELECT CASE cropnum%
    CASE 1
      IF fld(f%).rotation = 1 THEN
        CALL WEEDSIM(f%, wnum%, h1c%, h2c%, h3c%, mf%, ms%, mr%,
          mp%, t%, r, s0wf(), fld(), cropnum%, crop(), weedparm(),
          k1c%(), k2c%(), k3c%(), cppi(), cpre(), cpost(),
          machine(), compmax%, compparm(), theta, nyears%,
          netpost(), h1s%, h2s%, h3s%, k1s%(), k2s%(), k3s%(),
          sppi(), spre(), spost(), decrule%)
      ELSE
        CALL WEEDSIM(f%, wnum%, h1c%, h2c%, h3c%, mf%, ms%, mr%,
          mp%, t%, r, s0wf(), fld(), cropnum%, crop(), weedparm(),
          k1c%(), k2c%(), k3c%(), cppi(), cpre(), cpost(),
          machine(), compmax%, compparm(), theta, nyears%,
          netpost(), h1c%, h2c%, h3c%, k1c%(), k2c%(), k3c%(),
          cppi(), cpre(), cpost(), decrule%)
      END IF
    CASE 2
      CALL WEEDSIM(f%, wnum%, h1s%, h2s%, h3s%, mf%, ms%, mr%, mp%,
        t%, r, s0wf(), fld(), cropnum%, crop(), weedparm(), k1s%(),
        k2s%(), k3s%(), sppi(), spre(), spost(), machine(),
        compmax%, compparm(), theta, nyears%, netpost(), h1c%, h2c%,
        h3c%, k1c%(), k2c%(), k3c%(), cppi(), cpre(), cpost(),
        decrule%)
  END SELECT
  'CALL PrintRecoms(f%, cropname$, fld(), topnet)
  postrec%(f%) = fld(f%).postcode
NEXT f%
'PRINT
"-------------------------------------------------------------------"
'PRINT "Press any key to continue."
'resume$ = INPUT$(1)
'cls
'  **************************
'  * Weekly activities loop *
'  **************************
  FOR wk% = 1 TO nweeks%
    hrs = overtime
    overtime = 0
    maxhrs(wk%) = hrsday * tractors% * flddays(wk%)
    FOR f% = 1 TO nfields%
      newcost(f%) = 0
      newload(f%) = 0
      FOR w% = 1 TO wnum%
        swlost(f%, w%) = 0
      NEXT w%
    NEXT f%
```

```
FOR f% = 1 TO nfields%
  IF hrs >= maxhrs(wk%) THEN
    overtime = hrs - maxhrs(wk%)
    EXIT FOR
  END IF
  preflag% = false%
  IF (grmlflag%(f%) = false%) THEN CALL FieldWeedGerm(f%,
     nfields%, wnum%, swlost(), grmlflag%(), w0germ(), w1germ())
  IF (fld(f%).preApTim = 1 AND fld(f%).ppiweek = 0) AND hrs <
     maxhrs(wk%) THEN CALL PPITrt(f%, nfields%, wk%, fld(),
     newcost(), newload(), hrs, maxhrs(wk%), machine(), ms%, mf%,
     preflag%)
  IF (fld(f%).preApTim <> 1 AND diskflag%(f%) = false%) AND hrs <
     maxhrs(wk%) THEN CALL DiskField(f%, mf%, diskflag%(), fld(),
     machine(), newcost(), hrs)
  IF (fld(f%).plweek = 0 AND hrs < maxhrs(wk%)) AND
     (diskflag%(f%) = true% OR fld(f%).ppiweek > 0) THEN CALL
     PlantCrop(f%, wk%, fld(), maxCwk%, minSwk%, newcost(), hrs,
     maxhrs(wk%), machine(), mp%, crop(), sw(), weedparm(),
     wnum%)
  IF (fld(f%).preApTim = 2 AND fld(f%).preweek = 0) AND hrs <
     maxhrs(wk%) THEN CALL PreTrt(f%, nfields%, wk%, fld(),
     newcost(), newload(), hrs, maxhrs(wk%), machine(), ms%,
     preflag%)
  IF (preflag% = true%) THEN CALL PRESurv(f%, nfields%, wnum%,
     fld(), kmax%, killparm(), w1germ(), d2wf(), rain())
NEXT f%

FOR f% = 1 TO nfields%
  IF hrs >= maxhrs(wk%) THEN
    overtime = hrs - maxhrs(wk%)
    EXIT FOR
  END IF
  IF fld(f%).postweek = 0 THEN
    CALL CropGrowth(f%, wk%, crop(), fld(), epscgrow(),
       betacgro())
    CALL WeedGrowth(f%, wk%, wnum%, weedparm(), fld(), weedHt(),
       epswgrow(), betawgro())
    cropnum% = fld(f%).cropId
    costnow = fld(f%).cost + newcost(f%)
RevisedPost:
    SELECT CASE cropnum%
      CASE 1
       'CALL ModifyHerbArray(h3c%, f%, fld(), cpost(), kmax%,
          wnum%, killparm(), crop(), k3c%(), dropcode%)
```

```
        IF fld(f%).rotation = 1 THEN
          CALL PostWEEDSIM(f%, wnum%, h3c%, mf%, ms%, mr%, mp%, t%,
              r, s0wf(), sw(), d2wf(), fld(), cropnum%, crop(),
              weedparm(), k3c%(), cpost(), machine(), compmax%,
              compparm(), costnow, theta, nyears%, netpost(), h1s%,
              h2s%, h3s%, k1s%(), k2s%(), k3s%(), sppi(), spre(),
              spost(), decrule%, dropcode%, dropostc%())
        ELSE
          CALL PostWEEDSIM(f%, wnum%, h3c%, mf%, ms%, mr%, mp%, t%,
              r, s0wf(), sw(), d2wf(), fld(), cropnum%, crop(),
              weedparm(), k3c%(), cpost(), machine(), compmax%,
              compparm(), costnow, theta, nyears%, netpost(), h1c%,
              h2c%, h3c%, k1c%(), k2c%(), k3c%(), cppi(), cpre(),
              cpost(), decrule%, dropcode%, dropostc%())
        END IF
        CASE 2
         'CALL ModifyHerbArray(h3s%, f%, fld(), spost(), kmax%,
              wnum%, killparm(), crop(), k3s%(), dropcode%)
          CALL PostWEEDSIM(f%, wnum%, h3s%, mf%, ms%, mr%, mp%, t%,
              r, s0wf(), sw(), d2wf(), fld(), cropnum%, crop(),
              weedparm(), k3s%(), spost(), machine(), compmax%,
              compparm(), costnow, theta, nyears%, netpost(), h1c%,
              h2c%, h3c%, k1c%(), k2c%(), k3c%(), cppi(), cpre(),
              cpost(), decrule%, dropcode%, droposts%())
      END SELECT
      infeas%(f%) = false%
      IF (fld(f%).postweek = 0) AND hrs < maxhrs(wk%) THEN CALL
        PostTrt(f%, nfields%, wnum%, wk%, fld(), kmax%,
        killparm(), weedHt(), newcost(), newload(), hrs,
        maxhrs(wk%), machine(), ms%, mr%, infeas%(), endflag%(),
        d2wf(), d3wf(), sw(), swlost(), w2germ())
      IF infeas%(f%) = true% THEN
        dropcode% = fld(f%).postcode
        GOTO RevisedPost:
      END IF
    END IF
  NEXT f%

'   ******************************************
'   * Weekly accumulation & update of states *
'   ******************************************
    endyear% = true%
    FOR f% = 1 TO nfields%
      IF endflag%(f%) = false% THEN endyear% = false%
      fld(f%).cost = fld(f%).cost + newcost(f%)
      load(f%) = load(f%) + newload(f%)
      FOR w% = 1 TO wnum%
        sw(f%, w%) = sw(f%, w%) - swlost(f%, w%)
      NEXT w%
```

```
      NEXT f%
      'OTsum = OTsum + overtime
      IF endyear% = true% THEN EXIT FOR
    NEXT wk%
'   *******************************************
'   * Yearly accumulation and update of states *
'   *******************************************
    FOR f% = 1 TO nfields%
      FOR w% = 1 TO wnum%
        sw(f%, w%) = sw(f%, w%) - weedparm(w%).s3mortpn * (1 -
          germtot(w%)) * s0wf(f%, w%)
        IF sw(f%, w%)< 0 THEN sw(f%, w%) = 0
        s0wf(f%, w%) = sw(f%, w%) + weedparm(w%).w1propag * .2 *
          (d3wf(f%, w%) - w2germ(f%, w%)) + weedparm(w%).w2propag *
          w2germ(f%, w%) + epsseed(f%, w%)
        IF s0wf(f%, w%) < 0 THEN s0wf(f%, w%) = 0
        d3wff(w%) = d3wf(f%, w%)
      NEXT w%
      maxyld = crop(fld(f%).cropId).maxyld
      fld(f%).ywf = maxyld * (1 - ypen(fld(f%).cropId, maxyld,
        fld(f%).plweek))
      cyield(f%) = yield2(wnum%, fld(f%).ywf, fld(f%).cropId, compmax%,
        compparm(), crop(), d3wff()) + epsyld(f%, fld(f%).cropId)
      IF fld(f%).postcode = 10 AND fld(f%).cropId = 1 THEN cyield(f%) =
        cyield(f%) * .985
      IF cyield(f%) < 0 THEN cyield(f%) = 0
      yldpct(f%) = 100 * (cyield(f%) / maxyld)
      netrev(f%) = ((crop(fld(f%).cropId).price * cyield(f%) -
        crop(fld(f%).cropId).vc) * fld(f%).fsize - fld(f%).cost) / (1 +
        r) ^ t%
      fld(f%).prevCrop = fld(f%).cropId

    NEXT f%
    'CALL PrintResults(yr%, nfields%, wnum%, weedparm(), s0wf(),
      netrev(), load(), yldpct(), OTsum)
    CALL SummaryAnnual(wnum%, nfields%, fld(), crop(), netrev(), load(),
      yldpct(), d3wf(), s0wf(), csweed(), ccweed(), csseed(), ccseed(),
      farmnr, sum())

  NEXT yr%
  CALL SummaryState(wnum%, nyears%, r, sum(), farmnr, csweed(),
    ccweed(), csseed(), ccseed(), sumst(), farmstnr, farmstsd, cswst(),
    ccwst(), cssst(), ccsst(), urp0001#, ura0001#, ura001#, stateout$)

NEXT state%
CALL SummaryScenario(scenout$, decrule%, theta, lamseeds%, wnum%,
  nstates%, sumst(), farmstnr, farmstsd, cswst(), ccwst(), cssst(),
  ccsst(), urp0001#, ura0001#, ura001#)
```

```
NEXT gam%
NEXT decrule%
NEXT lamseeds%
'
'time1 = TIMER
'minutes% = INT((time1 - time0) / 60)
PRINT
PRINT
'PRINT "Execution time: ";
'PRINT minutes%;
'PRINT " minutes."
endjob$ = TIME$
PRINT "Simulation complete at "
PRINT endjob$
SCREEN 0
COLOR 7, 0, 0
END

Chkerror:
ON ERROR GOTO 0

REM $STATIC
```

```
SUB AutoChooseMach (mt%, mp%, ms%, mc%, mr%, mf%)
'                               'Last update: 04-27-91
'*****************************************************************
'*                           AutoChooseMach                     *
'*    Pre-sets machinery selections.                             *
'*                                                               *
'* Parameters passed to (and returned from) AutoChooseMach are:  *
'*       mt%               Tractor machinery code selected       *
'*                            1=100 hp                           *
'*                            2=120 hp                           *
'*                            3=160 hp                           *
'*       mp%               Planter machinery code selected       *
'*                            4=6 row, 30" planter               *
'*                            5=8 row, 30" planter               *
'*       ms%               Sprayer machinery code selected       *
'*                            6=30 foot                          *
'*       mc%               Cultivator machinery code selected    *
'*                            7=6 row, 30" cultivator            *
'*                            8=8 row, 30" cultivator            *
'*       mr%               Rotary hoe machinery code selected    *
'*                            9=16 foot rotary hoe               *
'*       mf%               Field cultivator machinery code selecte*
'*                            10=18 foot field cultivator        *
'*                            11=28 foot field cultivator        *
'*                            12=30 foot springtooth harrow      *
'*****************************************************************
'
mt% = 1
mp% = 5
ms% = 6
mc% = 8
mr% = 9
mf% = 11
END SUB
```

```
SUB AutoDataFiles (cropparm$, parmfile$, compfile$, herbfile$,
 killfile$, fdayfile$, machfile$, seedfile$, epsfile$, yearfile$,
 betafile$)
'                                        Last update: 06-10-91
'**********************************************************************
'*                          AutoDataFiles                             *
'*  Subprogram AutoDataFiles supplies the names of text files         *
'* containing data used by the main module.                           *
'*                                                                    *
'* Arguments returned by AutoDataFiles are:                           *
'*     cropparm$            String variable with name of crop parameter *
'*                          file                                      *
'*     parmfile$            String variable with name of weed parameter *
'*                          file                                      *
'*     compfile$            String variable with name of weed-crop com- *
'*                          petition parameter file                   *
'*     herbfile$            String variable with name of weed treatment *
'*                          file                                      *
'*     killfile$            String variable with name of weed treatment *
'*                          efficacy file                             *
'*     fdayfile$            String variable with name of field days   *
'*                          datafile (omitted for stochastic sim.)    *
'*     machfile$            String variable with name of machinery    *
'*                          parameter file                            *
'*     epsfile$             String variable with name of additive errors *
'*                          file                                      *
'*     yearfile$            String variable with name of year data file *
'*     betafile$            String variable with name of coefficient  *
'*                          errors file                               *
'**********************************************************************

cropparm$ = "crop2.dat"
parmfile$ = "weed5.dat"
compfile$ = "comp2.dat"
'herbfile$ = "herb.dat"
INPUT "Please type name of treatment file: ", herbfile$
killfile$ = "kill.dat"
'fdayfile$ = "fday1990.dat"
machfile$ = "machine2.dat"
'seedfile$ = "seed1990.dat"
INPUT "Name of state-of-nature additive errors input file: ", epsfile$
INPUT "Name of state-of-nature random coefficients input file: ",
 betafile$
INPUT "Name of yearly data input file: ", yearfile$
'betafile$ = "d:betarv.rnd"
'epsfile$ = "d:stat1080.rnd"
'yearfile$ = "d:inpt7490.rnd"
END SUB
```

```
SUB AutoParameters (fld() AS ftype, cropmax%, crop() AS cropfile,
  nyears%, r, hrsday, tractors%, nfields%, theta, maxCwk%, minSwk%,
  decrule%, nweeks%, nstates%)
'                                        Last update: 05/02/91
'**********************************************************************
'*                               AutoParameters                       *
'* Subprogram UserParameters automatically specifies typical agronomic *
'* and economic parameters.  It also prints a summary to the screen.  *
'* It is used primarily for testing the model and making repeated runs.*
'*                                                                    *
'* Parameters passed to AutoParameters are:                           *
'*     fld()                   Record array of field characteristics  *
'*     crop()                  Record array of crop parameters        *
'*     cropmax%                Total number of crops in model         *
'* Default parameter values returned are:                             *
'*     cropId                  Crop identification code: 1=corn, 2=soy*
'*     nweeks%                 Number of weeks in weed control season *
'*     nyears%                 Number of years to model               *
'*     nstates%                Number of random states of nature      *
'*     crop(c%).price          Expected price of crop c%              *
'*     crop(c%).maxyld         Maximum expected crop yield with no    *
'*                             weeds and optimal planting date        *
'*     crop(c%).vc             Variable cost/acre apart from weed trt.*
'*     r                       Discount rate on future income         *
'*     hrsday                  Hours per day worked per tractor       *
'*     tractors%               Number of tractors                     *
'*     nfields%                Number of fields in farm               *
'*     theta                   Proportion by which weed treatment     *
'*                             threshold net revenue to exceed no     *
'*                             control net revenue level.             *
'*     fld(f%).fsize           Field size of field f%                 *
'*     fld(f%).prevCrop        Previous crop in field f%              *
'*     fld(f%).rotation        Preferred crop rotation                *
'*                               1 = Corn-soy,  2 = Continuous corn   *
'*     maxCwk%                 Last week for planting corn            *
'*     minSwk%                 Earliest week for planting soybean     *
'*     decrule%                Decision rule for weed control infor-  *
'*                             mation                                 *
'*                               1 = Current year info. only          *
'*                               2 = Current year & expectations of   *
'*                                   next                             *
'**********************************************************************
nyears% = 6
nweeks% = 11
nstates% = 20
r = .04
hrsday = 10
tractors% = 2
fsize% = 80
```

```
PRINT "Total farm acreage (divisible by ";
PRINT USING "##"; fsize%;
INPUT "-acre fields): ", acreage%
nfields% = acreage% \ fsize%
'INPUT "How many years would you like to model? ", nyears%
'PRINT
'PRINT "The WFARM base case includes two rotations: continuous corn and
  a corn-soy"
'PRINT "rotation.  To include both in the analysis, choose a multiple of
  3 fields."
'PRINT
'INPUT "Number of 40-acre fields: ", nfields%
'PRINT
'PRINT "The weed control decision rule used depends upon the time
  horizon chosen:"
'PRINT "    '1' for a 1-year (myopic) horizon, or"
'PRINT "    '2' for a 2-year horizon"
'INPUT "Please type your choice: ", decrule%
'CLS
'INPUT "Proportion (theta) by which N.R. should exceed no treatment
  N.R.: ", theta
REDIM fld(nfields%) AS ftype
maxCwk% = 6
minSwk% = 3
FOR c% = 1 TO cropmax%
  SELECT CASE c%
    CASE 1
      crop(c%).price = 2.15
      crop(c%).expMaxY = 108
      crop(c%).vc = 126.15
    CASE 2
      crop(c%).price = 5.65
      crop(c%).expMaxY = 39
      crop(c%).vc = 62.7
  END SELECT
NEXT c%
FOR f% = 1 TO nfields%
  fld(f%).fsize = fsize%
  rotat% = f% MOD 3
  SELECT CASE rotat%
    CASE 1, 2
      fld(f%).rotation = 1
    CASE 0
      fld(f%).rotation = 2
  END SELECT
  rot% = fld(f%).rotation
  SELECT CASE rot%
    CASE 1
      fld(f%).prevCrop = 1 + (rotat% MOD 2)
```

```
 CASE 2
   fld(f%).prevCrop = 1
 END SELECT
NEXT f%
'PRINT
'PRINT
'PRINT "This model examines the economics of weed control in two
' rotations:"
'PRINT "          1. Corn-soybean rotation."
'PRINT "          2. Continuous corn"
'PRINT
'FOR c% = 1 TO cropmax%
'*  PRINT "Expected price of ";
'*  PRINT RTRIM$(crop(c%).cname);
'*  PRINT " is:"; TAB(51);
'** PRINT USING "$$###.##"; crop(c%).price;
'   PRINT " /bushel."
'NEXT c%
'FOR c% = 1 TO cropmax%
'  PRINT "Expected maximum weed-free yield of ";
'  PRINT RTRIM$(crop(c%).cname);
'  PRINT " is: "; TAB(56);
'  PRINT USING "###"; crop(c%).maxyld;
'  PRINT "  bu/acre."
'NEXT c%
'FOR c% = 1 TO cropmax%
'  PRINT "Average variable crop costs for ";
'  PRINT RTRIM$(crop(c%).cname);
'  PRINT " amount to:"; TAB(51);
'  PRINT USING "$$###.##"; crop(c%).vc;
'  PRINT " /acre."
'NEXT c%
'PRINT "Discount rate is assumed to be: "; TAB(56);
'PRINT USING "###"; 100 * r;
'PRINT " %"
'PRINT
'PRINT "The decision rule is based upon a ";
'SELECT CASE decrule%
'  CASE 1
'    PRINT "1";
'  CASE 2
'    PRINT "2";
'END SELECT
'PRINT "-year time horizon."
'PRINT
'PRINT "Press any key to continue."
'resume$ = INPUT$(1)
'CLS
END SUB
```

```
SUB AutoWeedSeeds (nfields%, wnum%, lamseeds%, s0wf())
'                                       Last update: 04-25-91
'***********************************************************************
'*                            AutoWeedSeeds                              *
'*  Subprogram AutoWeedSeeds generates an initial weed seed density     *
'* per square meter for each weed sp[ecies in each field.  Relative     *
'* proportions from Forcella 1985-86 study at Morris, MN.               *
'*                                                                       *
'* Parameters passed to AutoWeedSeeds are:                               *
'*     nfields%          Number of fields on farm                        *
'*     wnum%             Number of weeds in model                        *
'*     lamseeds%         Number of lambsquarters seeds chosen            *
'*                                                                       *
'* Arguments returned by AutoWeedSeeds are:                              *
'*     s0wf(f%,w%)       Array of weed seed densities in each field
'***********************************************************************
'
'PRINT
'PRINT "Base case numbers of weed seeds in the soil are proportional to
 the number"
'PRINT "of common lambsquarters seeds."
'INPUT "Please type the initial seed density/m2 of common lambsquarters:
 ", lam
'PRINT
fox = 7 * lamseeds%
pig = 2 * lamseeds%
FOR f% = 1 TO nfields%
 mult% = 1
' + INT((f% - 1) / 2)
 FOR w% = 1 TO wnum%
   IF w% = 1 THEN
     s0wf(f%, w%) = mult% * fox
   ELSEIF w% = 2 THEN
     s0wf(f%, w%) = mult% * lamseeds%
   ELSEIF w% = 3 THEN
     s0wf(f%, w%) = mult% * pig
   ELSE
     PRINT "Too many weed species for AutoWeedSeeds subprogram."
   END IF
 NEXT w%
NEXT f%
END SUB
```

```
SUB CalibrateGerm (nfields%, wnum%, wf() AS wfile, s0wf(), w0germ(),
  w1germ(), w2germ(), epsw0(), epsw1(), epsw2(), germtot(), betaw0(),
  betaw1(), betaw2())
'                                        Last update: 06-07-91
'************************************************************************
'*                              CalibrateGerm                           *
'*    This sub-program calculates germination levels from total germi-
'* nation rates, seed counts, proportions of germination by stage of the
'* season, and calibration equation coefficients relating germination to
'* seed numbers.  First expected germination densities are calculated  *
'* from predicted germination rates, initial seed counts and calibration
'* equations.  Then (possibly) heteroscedastic errors are added to      *
'* create stochastic weed densities.                                    *
'*                                                                      *
'*  The sub-program accepts the following parameters:                   *
'*    nfields%               Number of fields                           *
'*    wnum%                  Number of weed species                     *
'*    wf(w)                  Array of weed parameters                   *
'*    s0wf(f,w)              Array of weed seed densities by field      *
'*    epswX(f,w)             Array of weed germination error terms      *
'*                           for germination stage X (0,1,2)            *
'*    germtot()              Total germination for year (from GetYear
'*    betawX(f,w,b)          Array of weed germination coef. errors     *
'*                           for germination stage X                    *
'*                                                                      *
'*  The sub-program calculates the following values:                    *
'*    Ew0germ(f,w)           Array of expected pre-plant weed           *
'*                           densities                                  *
'*    Ew1germ(f,w)           Array of expected post-plant weed          *
'*                           densities                                  *
'*    Ew2germ(f,w)           Array of expected post-cult. weed          *
'*                           densities                                  *
'*    sigw0(f,w)             Array of pre-plant weed std. errors        *
'*    sigw1(f,w)             Array of post-plant weed std. errors       *
'*    sigw2(f,w)             Array of post-cult weed std. errors        *
'* For Forcella eqn., sigw1(f,1) is logarithmic eqn, so exponential     *
'* transform is made.                                                   *
'*                                                                      *
'*  The sub-program returns the following values:                       *
'*    w0germ(f,w)            Array of pre-plant weed densities          *
'*    w1germ(f,w)            Array of post-plant weed densities         *
'*    w2germ(f,w)            Array of post-cult. weed densities         *
'************************************************************************

REDIM Ew0germ(nfields%, wnum%), Ew1germ(nfields%, wnum%),
  Ew2germ(nfields%, wnum%)
REDIM sigw0(nfields%, wnum%), sigw1(nfields%, wnum%), sigw2(nfields%,
  wnum%)
FOR f% = 1 TO nfields%
```

```
 FOR w% = 1 TO wnum%
   Ew0germ(f%, w%) = (germtot(w%) * wf(w%).s0propn * s0wf(f%, w%)) +
     ((wf(w%).w0int + betaw0(f%, w%, 1)) + (wf(w%).w0s + betaw0(f%, w%,
     2)) * s0wf(f%, w%) + (wf(w%).w0s2 + betaw0(f%, w%, 3)) * s0wf(f%,
     w%) ^ 2)
   Ew1germ(f%, w%) = (germtot(w%) * wf(w%).s1propn * s0wf(f%, w%)) +
     ((wf(w%).w1int + betaw1(f%, w%, 1)) + (wf(w%).w1s + betaw1(f%, w%,
     2)) * s0wf(f%, w%) + (wf(w%).w1s2 + betaw1(f%, w%, 3)) * s0wf(f%,
     w%) ^ 2)
   Ew2germ(f%, w%) = (germtot(w%) * wf(w%).s2propn * s0wf(f%, w%)) +
     ((wf(w%).w2int + betaw2(f%, w%, 1)) + (wf(w%).w2s + betaw2(f%, w%,
     2)) * s0wf(f%, w%))
   sigw0(f%, w%) = EXP(wf(w%).sig0int + wf(w%).sig0s * s0wf(f%, w%) +
     wf(w%).sig0s2 * s0wf(f%, w%) ^ 2)
   sigw1(f%, w%) = EXP(wf(w%).sig1int + wf(w%).sig1s * s0wf(f%, w%) +
     wf(w%).sig1s2 * s0wf(f%, w%) ^ 2)
   sigw2(f%, w%) = EXP(wf(w%).sig2int + wf(w%).sig2s * s0wf(f%, w%) +
     wf(w%).sig2s2 * s0wf(f%, w%) ^ 2)
   w0germ(f%, w%) = Ew0germ(f%, w%) + epsw0(f%, w%) * sigw0(f%, w%)
   w1germ(f%, w%) = Ew1germ(f%, w%) + epsw1(f%, w%) * sigw1(f%, w%)
   w2germ(f%, w%) = Ew2germ(f%, w%) + epsw2(f%, w%) * sigw2(f%, w%)
   IF w0germ(f%, w%) < 0 THEN w0germ(f%, w%) = 0
   IF w1germ(f%, w%) < 0 THEN w1germ(f%, w%) = 0
   IF w2germ(f%, w%) < 0 THEN w2germ(f%, w%) = 0
 NEXT w%
 PRINT ;
NEXT f%
END SUB
```

```
SUB ChooseCrop (f%, fld() AS ftype, maxCwk%, wk%)
'                                  Last update: 12-05-90
'**********************************************************************
'*                          ChooseCrop                                *
'*  Subprogram ChooseCrop chooses the crop to plant in a given field  *
'* based upon the preferred rotation (continuous corn or corn-soy),   *
'* the previous crop, and current date.  For a corn-soy rotation, the *
'* rotation crop is chosen unless that would be corn and the last     *
'* planting date for corn is past.  For continuous corn, corn is planted
'* unless the last planting date for corn is past, in which case soy  *
'* is planted.                                                        *
'*                                                                    *
'* Parameters passed to ChooseCrop are:                               *
'*      fld()               Array of field info (including previous   *
'*                          crop)                                     *
'*      maxCwk%             Last feasible week for planting corn      *
'*      wk%                 Current week                              *
'*      f%                  Current field number                      *
'*                                                                    *
'* Value returned by the subprogram is:                               *
'*      fld(f%).cropId      Crop to plant in field f%                 *
'**********************************************************************
'
prevCrop% = fld(f%).prevCrop
rot% = fld(f%).rotation
SELECT CASE rot%
 CASE 1: 'Corn-soy rotation
   SELECT CASE prevCrop%
     CASE 1
       fld(f%).cropId = 2
     CASE 2
       IF wk% <= maxCwk% THEN
         fld(f%).cropId = 1
       ELSE
         fld(f%).cropId = 2
       END IF
     CASE ELSE
       PRINT "Error in fld().prevCrop array from ChooseCrop sub."
   END SELECT
 CASE 2: 'Continuous corn
   IF wk% <= maxCwk% THEN
     fld(f%).cropId = 1
   ELSE
     fld(f%).cropId = 2
   END IF
END SELECT
END SUB
```

```
SUB CropGrowth (f%, wk%, crop() AS cropfile, fld() AS ftype, epscgrow(),
 betacgro())
'                                        Last update 06-06-91
'***********************************************************************
'*                           CropGrowth                                *
'*  This subprogram "grows" the crop in each field as a function of the*
'* number of days since planting (dap%).                               *
'*                                                                     *
'* Parameters passed to CropGrowth are:                                *
'*      f%                         Current field number                *
'*      wk%                        Current week number                 *
'*      crop()                     Record file of crop parameters ( " )  *
'*      fld()                      Record file of field parameters     *
'*      epscgrow(c)                Array of crop growth errors         *
'*      betacgro(c)                Array of growth coefficient errors  *
'*                                                                     *
'* Arguments returned by CropGrowth are:                               *
'*      fld(f%).cropHt             Height (inches) of crop growing in field
'*                                  f%                                 *
'***********************************************************************
dap% = (wk% - fld(f%).plweek) * 7
IF dap% > 0 THEN
 sigmagro = crop(fld(f%).cropId).sigcint + sigcdap2 * dap% ^ 2
 fld(f%).cropHt = (crop(fld(f%).cropId).growrate +
  betacgro(fld(f%).cropId)) * dap% ^ 2 + sigmagro *
  epscgrow(fld(f%).cropId)
END IF
END SUB

SUB DiskField (f%, mf%, diskflag%(), fld() AS ftype, mach() AS mfile,
 newcost(), hrs)
'                                    Last update: 01-06-91
'***********************************************************************
'*                                 DiskField                           *
'*    Subprogram DiskField disks conventional tillage fields that have *
'* not been disked during PPI herbicide application.                   *
'*      f%                       Current field                         *
'*      mf%                      Field cultivator code                 *
'*      fld()                    Record array of field data            *
'*      mach()                   Record array of machinery data        *
'* Arguments returned by DiskField are:                                *
'*      diskflag%(f%)            Flag for completion of disk operation *
'*      hrs                      Current number of hours worked in week *
'*      newcost()                Array of new costs                    *
'***********************************************************************
newcost(f%) = newcost(f%) + mach(mf%).CostAc
hrs = hrs + fld(f%).fsize / mach(mf%).AcHr
diskflag%(f%) = true%
END SUB
```

```
SUB FieldWeedGerm (f%, nfields%, wnum%, swlost(), grmlflag%(), w0germ(),
 w1germ())
'**                                          Last update: 04/18/91
'************************************************************************
'*                           FieldWeedGerm                              *
'* This subprogram calculates weed seedling germination as a function *
'* of seeds from previous season.                                       *
'*                                                                      *
'* Parameters passed to subprogram WeedGerm are:                        *
'*     f%                      Current field                            *
'*     nfields%                Number of fields                         *
'*     wnum%                   Number of weed species                   *
'*     s0wf(f%,w%)             Array of initial seedbank densities for*
'*                             species w% (seeds/m2) in field f%        *
'*     w0germ(f%,w%)           Array of pre-plant weed densities    .   *
'*     w1germ(f%,w%)           Array of post-plant weed densities       *
'*                                                                      *
'* Variables returned by subprogram WeedGerm are:                       *
'*   '  d1wf(f%,w%)             Array of germinating weed densities     *
'*                              after crop planting (but before POST    *
'*                              trt.) in field f%                       *
'*     swlost(f%,w%)           Array of seed numbers lost to germina- *
'*                             tion prior to PRE treatment in field f%*
'*     grmlflag%(f%)           Array of flags signaling completion of *
'*                             pre-plant weed germination               *
'************************************************************************
'
FOR w% = 1 TO wnum%
'd1wf(f%, w%) = weed(w%).s1germ * (1 - weed(w%).s0germ) * s0wf(f%, w%)
'd0wf(f%, w%) = weed(w%).s0germ * s0wf(f%, w%)
  swlost(f%, w%) = w0germ(f%, w%) + w1germ(f%, w%)
NEXT w%
grmlflag%(f%) = true%
END SUB
```

```
SUB GetCropParm (cropparm$, cropdata AS cropfile, crop() AS cropfile)
'                                         Last update: 04/28/91
'***********************************************************************
'*                               GetCropParm                           *
'* Subprogram GetCropParm reads the names of crops to be included in the
'* model, along with related parameters.                               *
'*                                                                     *
'* Parameter passed to GetWeedParm is:                                 *
'*      cropparm$                Name of the crop parameter file       *
'*      cropdata                 Record form for crop parameter file   *
'*      crop()                   Record array for crop parameter file  *
'*                                                                     *
'* The crop() records returned by GetWeedParm include                  *
'*      cropId(c%)               Crop identification code              *
'*      cname$(c%)               Crop common names                     *
'*      growrate(c%)             Quadratic growth rate (function of days*
'*                               after planting, DAP)                  *
'*      sigcint                  Standard error equation intercept     *
'*      sigcdap2                 Std. error eqn. coef. on DAP          *
'*      a(c%)                    Maximum percent yield loss as weed    *
'*                               density approaches infinity           *
'*      seedPric(c%)             Crop seed price                       *
'*      seedRate(c%)             Crop seeding rate                     *
'***********************************************************************
'
SHARED cnum%
Filenuml = FREEFILE
c% = 0
OPEN cropparm$ FOR INPUT AS #Filenuml
DO UNTIL EOF(Filenuml)
  c% = c% + 1
  INPUT #Filenuml, cropdata.cropId, cropdata.cname, cropdata.growrate,
    cropdata.sigcint, cropdata.sigcdap2, cropdata.a, cropdata.seedRate,
    cropdata.seedPric
  crop(c%) = cropdata
LOOP
CLOSE #Filenuml
cnum% = c%
END SUB
```

```
SUB GetHerbData (cropnum%, aptime%, herbfile$, herb AS hfile, herbtemp()
 AS hfile)
'                                     Last update: 02/05/91
'**********************************************************************
'*                                  GetHerbData                        *
'* This subprogram reads a file of weed treatment costs & rates, and  *
'* selects the records required for a particular crop and application  *
'* time.  Herbicide treatment data comes from "Cultural and Chemical   *
'* Weed Control in Field Crops" (Minn. Extension Service).             *
'*                                                                     *
'* Parameters passed to GetHerbData are:                               *
'*      cropnum%                    Crop code                          *
'*      aptime%                     Application time code (1=PPI,2=PRE, *
'*                                  3=POST)                            *
'*      herbfile$                   Name of weed treatment rate & price file
'*      herb                        Treatment record form              *
'*      herbtemp()                  Treatment record array             *
'*                                                                     *
'* The herbtemp() records returned by GetHerbData include:             *
'*      cropId                      Crop code                          *
'*      aptimeId                    Application time code              *
'*      herbId                      Treatment code                     *
'*      hname                       Treatment name                     *
'*      unitCost                    Treatment cost                     *
'*      minrate                     Minimum application rate           *
'*      maxrate                     Maximum application rate           *
'*      avrate                      Average application rate           *
'*      droptrt                     0/1 indicator for whether treatment to *
'*                                  be dropped (1) or not (0)          *
'**********************************************************************
'
Filenum1 = FREEFILE
SHARED htemp%
  OPEN herbfile$ FOR INPUT AS #Filenum1
  i% = 0
 DO UNTIL EOF(Filenum1)
   INPUT #Filenum1, herb.cropId, herb.aptimeId, herb.herbId,
     herb.hname, herb.unitCost, herb.minrate, herb.maxrate,
     herb.droptrt
   herb.avrate = (herb.minrate + herb.maxrate) / 2
   IF cropnum% = herb.cropId AND aptime% = herb.aptimeId THEN
     i% = i% + 1
     herbtemp(i%) = herb
   END IF
  LOOP
  htemp% = i%
  CLOSE #Filenum1
END SUB
```

```
SUB GetKillData2 (killfile$, eff AS kfile, efftemp() AS kfile,
 killparm() AS kfile, kmax%)
'                                         Last update: 02/12/91
'**********************************************************************
'*                                GetKillData2                        *
'* This subprogram reads a file of weed treatment efficacy ratings.   *
'* Herbicide treatment data come from "Cultural and Chemical Weed     *
'* Control in Field Crops" (Minn. Extension Service).                 *
'*                                                                    *
'* Parameters passed to GetKillData2 are:                             *
'*      killfile$                 Name of treatment efficacy file     *
'*      eff                       Treatment record form               *
'*      efftemp()                 Treatment record array              *
'*      killparm()                Treatment record array              *
'*      kmax%                     Maximum number of treatments        *
'*                                                                    *
'* The efftemp() record array returned by GetKillData2 contains:      *
'*      aptimeId                  Application time code               *
'*      herbId                    Treatment code                      *
'*      weedId                    Weed code                           *
'*      effic                     Treatment efficacy rating           *
'*      maxWdHt                   Maximum weed height for rated efficacy *
'*      maxCrnHt                  Maximum corn height for safe use on corn
'*      maxSoyHt                  Maximum soybean height for safe use *
'**********************************************************************
'

Filenum1 = FREEFILE
OPEN killfile$ FOR INPUT AS #Filenum1
i% = 0
DO UNTIL EOF(Filenum1)
  i% = i% + 1
  INPUT #Filenum1, eff.aptimeId, eff.herbId, eff.weedId, eff.effic,
    eff.maxWdHt, eff.maxCrnHt, eff.maxSoyHt
  efftemp(i%) = eff
LOOP
CLOSE #Filenum1
kmax% = i%
REDIM killparm(kmax%) AS kfile
FOR i% = 1 TO kmax%
  killparm(i%) = efftemp(i%)
NEXT i%
ERASE efftemp

END SUB
```

```
SUB GetMachData (machfile$, machtemp() AS mfile)
'                                   Last update: 11/02/90
'*********************************************************************
'*                              GetMachData                          *
'* This subprogram reads a data file on farm machinery available in the*
'* model.                                                            *
'*                                                                   *
'* Parameters read in by GetMachData are:                            *
'*     machfile$            Name of farm machinery data file.        *
'*     machtemp()           Indexed record file for data.            *
'*                                                                   *
'* Variables returned by GetMachData (as machtemp() records) are:    *
'*     machcode             Machinery code (see AutoChooseMach)      *
'*     machname$            Name of piece of machinery               *
'*     AcHr                 Acres per hour covered (speed).          *
'*     CostAc               Cost per acre (dollars/acre).            *
'*********************************************************************
'
SHARED machnum%
Filenum1 = FREEFILE
OPEN machfile$ FOR INPUT AS #Filenum1
i% = 0
DO WHILE NOT EOF(Filenum1)
 i% = i% + 1
 INPUT #Filenum1, machtemp(i%).machcode, machtemp(i%).machname,
   machtemp(i%).AcHr, machtemp(i%).CostAc
LOOP
machnum% = i%
CLOSE #Filenum1
END SUB
```

```
SUB GetStateBetaErrors (nfields%, wnum%, newscen%, betafile$, betaeps AS
  bfile, betacgro(), betawgro(), betaw0(), betaw1(), betaw2()) STATIC
'                                   Last update: 06-07-91
'************************************************************************
'*                          GetStateBetaErrors                          *
'*    Subprogram GetStateErrors reads correlated random errors corres-  *
'* ponding to equations in the model, from an input data file.         *
'*                                                                      *
'* Parameters passed to GetStateBetaErrors are:                         *
'*      nfields%               Number of fields on farm                 *
'*      wnum%                  Number of weeds in model                 *
'*      newscen%               New scenario flag                        *
'*      statenum%              Number of states of nature               *
'*      betafile$              File containing synthetic error terms    *
'*      betaeps                Record array of synthetic eror terms     *
'*                                                                      *
'* Arguments returned by GetStateBetaErrors are:                        *
'*      betaw0(f,w,b)          Array of pre-plant weed emergence coef.  *
'*                             errors by field, weed and coefficient (b)*
'*      betaw1(f,w,b)          Array of post-plant weed emergence coef. *
'*                             errors by field, weed and coefficient (b)*
'*                             NB: betaw1(f%,2,2) is coef on quadratic  *
'*                             term.                                    *
'*      betaw2(f,w,b)          Array of post-cult. weed emergence coef. *
'*                             errors by field, weed and coefficient (b)*
'*      betacgro(c)            Array of crop growth coef. errors        *
'*      betawgro(w)            Array of weed growth coef. errors        *
'************************************************************************
'
Filenum1 = FREEFILE
OPEN betafile$ FOR RANDOM AS #Filenum1 LEN = LEN(betaeps)
statenum% = LOF(Filenum1) \ LEN(betaeps)
IF betstate% >= statenum% THEN newscen% = true%
IF newscen% = true% THEN
  betstate% = 0
  newscen% = false%
END IF
FOR f% = 1 TO nfields%
  betstate% = betstate% + 1
  GET #Filenum1, betstate%, betaeps
  betaw0(f%, 1, 1) = betaeps.betaw010
  betaw0(f%, 1, 2) = betaeps.betaw011
  betaw0(f%, 1, 3) = betaeps.betaw012
  betaw0(f%, 2, 1) = betaeps.betaw020
  betaw0(f%, 2, 2) = betaeps.betaw021
  betaw0(f%, 2, 3) = betaeps.betaw022
  betaw0(f%, 3, 1) = 0
  betaw0(f%, 3, 2) = 0
  betaw0(f%, 3, 3) = 0
```

```
  betawl(f%, 1, 1) = betaeps.betawl10
  betawl(f%, 1, 2) = betaeps.betawl11
  betawl(f%, 1, 3) = 0
  betawl(f%, 2, 1) = betaeps.betawl20
  betawl(f%, 2, 2) = 0
  betawl(f%, 2, 3) = betaeps.betawl22
  betawl(f%, 3, 1) = betaeps.betawl30
  betawl(f%, 3, 2) = betaeps.betawl31
  betawl(f%, 3, 3) = 0
  betaw2(f%, 1, 1) = betaeps.betaw210
  betaw2(f%, 1, 2) = betaeps.betaw211
  betaw2(f%, 2, 1) = betaeps.betaw220
  betaw2(f%, 2, 2) = betaeps.betaw221
  betaw2(f%, 3, 1) = betaeps.betaw230
  betaw2(f%, 3, 2) = betaeps.betaw231
  betacgro(1) = betaeps.betagroc
  betacgro(2) = betaeps.betagros
  betawgro(1) = betaeps.betagro1
  betawgro(2) = betaeps.betagro2
  betawgro(3) = betaeps.betagro3
NEXT f%
CLOSE #Filenum1

END SUB
```

```
SUB GetStateErrors (nfields%, wnum%, newscen%, epsfile$, epsilon AS
  efile, epsw0(), epswl(), epsw2(), epsseed(), epsyld(), epscgrow(),
  epswgrow()) STATIC
'                               Last update: 04-29-91
'**********************************************************************
'*                           GetStateErrors                           *
'*   Subprogram GetStateErrors reads correlated random errors corres- *
'* ponding to equations in the model, from an input data file.       *
'*                                                                    *
'* Parameters passed to GetStateErrors are:                          *
'*    nfields%              Number of fields on farm                  *
'*    wnum%                 Number of weeds in model                  *
'*      statenum%           Number of states of nature                *
'*      newscen%            New scenario flag                         *
'*      epsfile$            File containing synthetic error terms     *
'*      epsilon             Record array of synthetic eror terms      *
'*                                                                    *
'* Arguments returned by GetStateErrors are:                         *
'*      epsw0(f,w)          Array of pre-plant weed emergence errors *
'*      epswl(f,w)          Array of post-plant weed emergence errors*
'*      epsw2(f,w)          Array of post-cult. weed emergence errors*
'*      epsseed(f,w)        Array of weed seed production errors     *
'*      epsyld(f,c)         Array of crop yield errors               *
'*      epscgrow(c)         Array of crop growth errors              *
'*      epswgrow(w)         Array of weed growth errors              *
'**********************************************************************
'
Filenuml = FREEFILE
OPEN epsfile$ FOR RANDOM AS #Filenuml LEN = LEN(epsilon)
statenum% = LOF(Filenuml) \ LEN(epsilon)
IF errstate% >= statenum% THEN newscen% = true%
IF newscen% = true% THEN
  errstate% = 0
  newscen% = false%
END IF
FOR f% = 1 TO nfields%
  errstate% = errstate% + 1
  GET #Filenuml, errstate%, epsilon
  epsw0(f%, 1) = epsilon.epsw01
  epsw0(f%, 2) = epsilon.epsw02
  epsw0(f%, 3) = 0
  epswl(f%, 1) = epsilon.epswll
  epswl(f%, 2) = epsilon.epswl2
  epswl(f%, 3)= epsilon.epswl3
  epsw2(f%, 1) = epsilon.epsw21
  epsw2(f%, 2) = epsilon.epsw22
  epsw2(f%, 3) = epsilon.epsw23
  epsseed(f%, 1) = epsilon.epsseedl
  epsseed(f%, 2) = epsilon.epsseed2
```

```
 epsseed(f%, 3) = epsilon.epsseed3
 epsyld(f%, 1) = epsilon.epsyldc
 epsyld(f%, 2) = epsilon.epsylds
 epscgrow(1) = epsilon.epsgrowc
 epscgrow(2) = epsilon.epsgrows
 epswgrow(1) = epsilon.epsgrow1
 epswgrow(2) = epsilon.epsgrow2
 epswgrow(3) = epsilon.epsgrow3
NEXT f%
CLOSE #Filenum1
'resume$ = INPUT$(1)
END SUB

SUB GetWeedCompData (compfile$, comptemp() AS cfile)
'                               Last update: 11/02/90
'*********************************************************************
'*                      GetWeedCompData                              *
'* This subprogram reads a file of weed-crop competition indices.    *
'* Herbicide treatment data come from "Cultural and Chemical Weed    *
'* Control in Field Crops" (Minn. Extension Service).                *
'*                                                                   *
'* Parameters passed to GetWeedCompData are:                         *
'*      compfile$               Name of weed competition file        *
'*      comptemp()              Competition record array             *
'*                                                                   *
'* The efftemp() array returned by GetWeedCompData contains:         *
'*      cropId                  Crop code                            *
'*      weedId                  Weed code                            *
'*      i                       Competition index                    *
'*********************************************************************
'
SHARED compmax%
Filenum1 = FREEFILE
OPEN compfile$ FOR INPUT AS #Filenum1
i% = 0
DO UNTIL EOF(Filenum1)
 i% = i% + 1
 INPUT #Filenum1, comptemp(i%).cropId, comptemp(i%).weedId,
   comptemp(i%).i
LOOP
compmax% = i%
CLOSE #Filenum1
END SUB
```

```
SUB GetWeedParm3 (wnum%, parmfile$, wf AS wfile, weedparm() AS wfile)
'                                              Last update: 04/28/91
'**********************************************************************
'*                              GetWeedParm3                          *
'* Subprogram GetWeedParm3 reads the names of weeds to be included in *
'* the model, along with related parameters.                          *
'*                                                                    *
'* Parameter passed to GetWeedParm3 is:                               *
'*      parmfile$               Name of the weed parameter file       *
'*      wf                      Record form for weed parameter file   *
'*      weedparm()              Record array for weed parameters      *
'*                                                                    *
'* Values returned by GetWeedParm3 are:                               *
'*      wnum%                   Number of weeds                       *
'* Weedparm() record array includes                                   *
'*      weedId(w)               Weed identification code              *
'*      wname$(w)               Array of weed species common names    *
'*      avgerm(w)               Average total weed germination (based *
'*                              on Forcella model w/Lamberton GDD data)*
'*      s0propn(w)              Array of pre-planting weed germ. propns*
'*      s1propn                 Array of post-plant weed germ. propns. *
'*      s2propn                 Array of post-cult. weed germ. propns. *
'*      s3mortpn                Array of weed seed death as propn of  *
'*                              combined seed death and carryover     *
'*      w1propag                Array of viable seeds produced per post*
'*                              plant weed                            *
'*      w2propag                Array of viable seeds produced per post*
'*                              cultivation weed                      *
'*      wXint                   Array of germination calibration eqn. *
'*                              intercept terms for season stage X    *
'*                              (0,1,2)                               *
'*      wXs                     Array of germination calibration eqn. *
'*                              seed coefs. for season stage X (0,1,2) *
'*      wXs2                    Array of germination calibration eqn. *
'*                              squared seed coefs.in season stage X  *
'*                              (0,1,2)                               *
'*      sigXint                 Array of germ. calib. std. error eqn. *
'*                              intercept terms for season stage X    *
'*                              (0,1,2)                               *
'*      sigXs                   Array of germ. calib. std. error eqn. *
'*                              seed coefs. for season stage X (0,1,2)*
'*      sigXs2                  Array of germ. calib. std. error eqn. *
'*                              squared seed coefs.in season stage X  *
'*                              (0,1,2)                               *
'*      s3mortpn                Array of proportion of non-germinated *
'*                              seeds that die                        *
'*      sigwint                 Intercept for std. error of weed growth*
'*      sigwdap2                Days after planting^2 coef. in std.error
'*                              of weed growth equation.              *
```

```
'***********************************************************************
'
Filenuml = FREEFILE
i% = 0
OPEN parmfile$ FOR INPUT AS #Filenuml
DO UNTIL EOF(Filenuml)
  i% = i% + 1
  INPUT #Filenuml, wf.weedId, wf.wname, wf.avgerm, wf.s0propn,
    wf.slpropn, wf.s2propn, wf.s3mortpn, wf.wlpropag, wf.w2propag,
    wf.growrate, wf.w0int, wf.w0s, wf.w0s2, wf.wlint, wf.wls, wf.wls2,
    wf.w2int, wf.w2s, wf.sig0int, wf.sig0s, wf.sig0s2, wf.siglint,
    wf.sigls, wf.sigls2, wf.sig2int, wf.sig2s, wf.sig2s2, wf.sigwint,
    wf.sigwdap2
  weedparm(i%) = wf
LOOP
wnum% = i%
CLOSE #Filenuml
END SUB


SUB GetYear (yearfile$, yr AS yfile, flddays(), rain(), crop() AS
  cropfile, germtot(), randnum(), newscen%) STATIC
'                               Last update: 05-17-91
'***********************************************************************
'*                            GetYear                                  *
'*   Subprogram GetYear reads annual state of nature data from an      *
'* input file.                                                         *
'*                                                                     *
'* Parameters passed to GetYear are:                                   *
'*     yearnum%               Number of years                          *
'*     epsfile$               File containing synthetic error terms    *
'*     newscen%               New scenario flag                        *
'*     randnum()              Array of [0,1] random numbers            *
'*                                                                     *
'* Arguments returned by GetYear are:                                  *
'*     yr                     Record array of year data uniform randomly
'*                            selected.                                *
'*     flddays(wk%)           Weekly workable field days from 4/19     *
'*                            (11wks) in current year                  *
'*     rain(wk%)              Weekly precipitation from 4/19 (11 weeks)*
'*     crop(c%).maxyld        Maximum yield for year                   *
'*     germtot(w%)            Total weed germination for current year  *
'***********************************************************************
'
IF newscen% = true% THEN
  ry% = 0
  newscen% = false%
END IF
```

```
ry% = ry% + 1
Filenum1 = FREEFILE
OPEN yearfile$ FOR RANDOM AS #Filenum1 LEN = LEN(yr)
  yearnum% = LOF(Filenum1) \ LEN(yr)
  y% = INT(randnum(ry%) * yearnum%) + 1
  GET #Filenum1, y%, yr
CLOSE #Filenum1
  flddays(1) = yr.fd1
  flddays(2) = yr.fd2
  flddays(3) = yr.fd3
  flddays(4) = yr.fd4
  flddays(5) = yr.fd5
  flddays(6) = yr.fd6
  flddays(7) = yr.fd7
  flddays(8) = yr.fd8
  flddays(9) = yr.fd9
  flddays(10) = yr.fd10
  flddays(11) = yr.fd11
  rain(1) = yr.rain1
  rain(2) = yr.rain2
  rain(3) = yr.rain3
  rain(4) = yr.rain4
  rain(5) = yr.rain5
  rain(6) = yr.rain6
  rain(7) = yr.rain7
  rain(8) = yr.rain8
  rain(9) = yr.rain9
  rain(10) = yr.rain10
  rain(11) = yr.rain11
  crop(1).maxyld = yr.cymax
  crop(2).maxyld = yr.symax
  germtot(1) = yr.foxgerm
  germtot(2) = yr.lamgerm
  germtot(3) = yr.piggerm
END SUB
```

```
SUB InitializeScenario (wnum%, sumst() AS stype, farmstnr, farmstsd,
 cswst(), ccwst(), cssst(), ccsst(), urp0001#, ura0001#, ura001#)
'                          Last update: 05-03-91
'*********************************************************************
'*                      InitializeScenario                           *
'* This subprogram initializes end-state summary values for each new *
'* scenario.                                                         *
'*                                                                   *
'* Parameters passed to InitializeScenario are:                      *
'*     sumst()              Record array of end-state summary stats. *
'*     farmstnr             Cumulative end-state mean farm income    *
'*     farmstsd             Cumulative end-state mean income st. dev. *
'*     urp0001#             Utility of risk preferrer with r(x)=-.0001 *
'*     ura0001#             Utility of risk averter with r(x)=.0001  *
'*     ura001#              Utility of risk averter with r(x)=.001   *
'*     cssst(w),ccsst(w)    Cum end-state mean seeds at harvest in CS, *
'*                          CC rotations                             *
'*     cswst(w),ccwst(w)    Cum end-state mean weeds at harvest in CS, *
'*                          CC rotations                             *
'*********************************************************************

REDIM sumst(3) AS stype
REDIM cswst(wnum%), ccwst(wnum%), cssst(wnum%), ccsst(wnum%)
farmstnr = 0
farmstsd = 0
urp0001# = 0
ura0001# = 0
ura001# = 0
END SUB
```

```
SUB InitializeYear (nfields%, wnum%, fld() AS ftype, crop() AS cropfile,
 sw(), s0wf(), diskflag%(), infeas%(), endflag%(), wk%, t%, yr%,
 grmlflag%(), load(), OTsum, maxCwk%, dropostc%(), droposts%(), h3c%,
 h3s%)
'                                 Last update: 04-27-91
'*********************************************************************
'*                                InitializeYear                     *
'*   Subprogram InitializeYear sets initial values for cost, seedbank,*
'* and computational flags for eachy iteration of the Year loop.     *
'*                                                                   *
'* Parameters passed to InitializeYear are:                          *
'*     nfields%                   Number of fields on farm           *
'*     wnum%                      Number of weeds in model           *
'*     fld()                      Record array of field data         *
'*     crop()                     Record array of crop data          *
'*     sw(f%,w%)                  Array of current seedbank values by field, *
'*                                weed                               *
'*     s0wf(f%,w%)                Array of initial seedbank values   *
'*     infeas%()                  Array of POST infeasibility indicators *
'*     diskflag%(f)               Array of flags for completion of disking *
'*     endflag%()                 Array of flags indicating end of field *
'*                                activities                         *
'*     wk%                        Current week                       *
'*     t%                         Time setting for present value calculations*
'*     yr%                        Current year                       *
'*     grmlflag%()                Flag for completion of FieldWeedGerm *
'*                                subprogram                         *
'*     load()                     Array for cumulative herbicide load on field
'*     OTsum                      Total hours overtime worked during season *
'*     maxCwk%                    Last weed for corn planting        *
'*     dropostc%()                Array of infeasible POST trt. flags for corn
'*     droposts%()                Array of infeasible POST trt. flags for *
'*                                soybean                            *
'*     h3c%                       Number of POST corn trts.          *
'*     h3s%                       Number of POST soybean trts.       *
'*********************************************************************

wk% = 0
t% = yr% - 1
OTsum = 0

FOR f% = 1 TO nfields%
  CALL ChooseCrop(f%, fld(), maxCwk%, wk%)
  fld(f%).hflag = 0
  fld(f%).cost = 0
  fld(f%).cropHt = 0
  fld(f%).ppiweek = 0
  fld(f%).plweek = 0
  fld(f%).preweek = 0
```

```
  fld(f%).postweek = 0
  fld(f%).precost = 0
  fld(f%).postcost = 0
  fld(f%).precode = 0
  fld(f%).postcode = 0
  fld(f%).preApTim = 0
  fld(f%).ywf = crop(fld(f%).cropId).maxyld
  diskflag%(f%) = false%
  infeas%(f%) = false%
  endflag%(f%) = false%
  grmlflag%(f%) = false%
  load(f%) = 0
  FOR w% = 1 TO wnum%
    sw(f%, w%) = s0wf(f%, w%)
  NEXT w%
NEXT f%
FOR dc% = 1 TO h3c%
  dropostc%(dc%) = false%
NEXT dc%
FOR ds% = 1 TO h3s%
  droposts%(ds%) = false%
NEXT ds%
END SUB

SUB InitializeState (wnum%, farmnr, sum() AS stype, csweed(), ccweed(),
  csseed(), ccseed())
'                                   Last update: 05-05-91
'***********************************************************************
'*                             InitializeState                          *
'*  This subprogram initializes cumulative variables for a new state of*
'* nature.                                                             *
'*                                                                     *
'*  Parameters passed to InitializeState are:                          *
'*      farmnr              Cumulative discounted farm net revenue     *
'*      cXseed(w)           Cum seeds at harvest in CS and CC rotations*
'*      cXweed(w)           Cum weeds at harvest in CS and CC rotations*
'*      sum(s).nr           Mean net revenue from 1. Corn in CS rotatn.*
'*                          2. Soy in CS rot., and 3. Corn in CC rot.  *
'*      sum(s).sdnr         St.dev. net rev. from 1. Corn in CS rotatn.*
'*                          2. Soy in CS rot., and 3. Corn in CC rot.  *
'*      sum(s).load         Mean herb. load  from 1. Corn in CS rotatn.*
'*                          2. Soy in CS rot., and 3. Corn in CC rot.  *
'*      sum(s).ypct         Mean yield pct.  from 1. Corn in CS rotatn.*
'*                          2. Soy in CS rot., and 3. Corn in CC rot.  *
'***********************************************************************
REDIM sum(3) AS stype
REDIM csweed(wnum%), ccweed(wnum%), csseed(wnum%), ccseed(wnum%)
farmnr = 0
END SUB
```

```
SUB MakeHerbArray (cropnum%, aptime%, herbfile$, herb AS hfile, kmax%,
   wnum%, eff() AS kfile, crop() AS cropfile, cppi() AS hfile, cpre()
   AS hfile, cpost() AS hfile, sppi() AS hfile, spre() AS hfile,
   spost() AS hfile, k1c%(), k2c%(), k3c%(), k1s%(), k2s%(), k3s%())
'                                Last update: 02-05-91
'**********************************************************************
'*                          MakeHerbArray                            *
'*    For each crop and weed control application time in the model,  *
'* Subprogram MakeHerbArray creates 1) arrays of feasible weed control *
'* treatments and 2) arrays of corresponding efficacy ratings.  To    *
'* identify feasible treatments, it chains to Subprogram  GetHerbData *
'* and then allows treatments to be dropped by chaining to Subprogram *
'* UserDropTrts2.  For the feasible treatments so identified, it chains*
'* to MakeKillArray to construct an array of treatment efficacies.    *
'*                                                                    *
'*    Parameters passed to MakeHerbArray are:                         *
'*      cropnum%           Crop identification code (corn or soy)     *
'*      aptime%            Application time code (PPI, PRE, POST)     *
'*      herbfile$          Weed treatment file name                   *
'*      herb               Record form for weed treatments            *
'*      herbtemp()         Temporary record array for weed treatment*
'*                         parameters                                 *
'*      kmax%              Number of records in weed treatment effi-*
'*                         cacy array (from GetKillData2)             *
'*      wnum%              Number of weed species                     *
'*      eff()              Record array of weed trt. efficacy data    *
'*                                                                    *
'*    Arguments returned by MakeKillArray are:                        *
'*      h1c%, h2c%, h3c%   Number of weed treatments (PPI,PRE,POST):*
'*                         corn                                       *
'*      h1s%, h2s%, h3s%   Number of weed treatments (PPI,PRE,POST):*
'*                         soy                                        *
'*      k%()               Temporary array of efficacy data           *
'*      k1c%(),k2c%(),k3c%() Efficacy arrays (PPI,PRE,POST) for corn  *
'*      k1s%(),k2s%(),k3s%() Efficacy arrays (PPI,PRE,POST) for soybean
'*      cppi(),cpre(),cpost() Treatment record arrays (PPI,PRE,POST)  *
'*                         for corn                                   *
'*      sppi(),spre(),spost() Treatment record arrays (PPI,PRE,POST)  *
'*                         for soy                                    *
'**********************************************************************
'
SHARED h1c%, h2c%, h3c%, h1s%, h2s%, h3s%, htemp%
REDIM herbtemp(10) AS hfile
SELECT CASE cropnum%
  CASE 1
    SELECT CASE aptime%
      CASE 1
        CALL GetHerbData(cropnum%, aptime%, herbfile$, herb, herbtemp())
        REDIM k1c%(wnum%, htemp%), k%(wnum%, htemp%)
```

```
        REDIM cppi(htemp%) AS hfile
        ' CALL UserDropTrts2(aptime%, htemp%, herbtemp(), cropnum%,
          crop())
        CALL MakeKillArray(kmax%, aptime%, htemp%, wnum%, eff(),
         herbtemp(), k%())
        h1c% = htemp%
        FOR i% = 1 TO h1c%
         cppi(i%) = herbtemp(i%)
         FOR w% = 1 TO wnum%
          k1c%(w%, i%) = k%(w%, i%)
         NEXT w%
        NEXT i%
      CASE 2
        CALL GetHerbData(cropnum%, aptime%, herbfile$, herb, herbtemp())
        REDIM cpre(htemp%) AS hfile
        REDIM k2c%(wnum%, htemp%), k%(wnum%, htemp%)
       ' CALL UserDropTrts2(aptime%, htemp%, herbtemp(), cropnum%,
         crop())
        CALL MakeKillArray(kmax%, aptime%, htemp%, wnum%, eff(),
         herbtemp(), k%())
        h2c% = htemp%
        FOR i% = 1 TO h2c%
         cpre(i%) = herbtemp(i%)
         FOR w% = 1 TO wnum%
          k2c%(w%, i%) = k%(w%, i%)
         NEXT w%
        NEXT i%
      CASE 3
        CALL GetHerbData(cropnum%, aptime%, herbfile$, herb, herbtemp())
        REDIM cpost(htemp%) AS hfile
        REDIM k3c%(wnum%, htemp%), k%(wnum%, htemp%)
'        CALL UserDropTrts2(aptime%, htemp%, herbtemp(), cropnum%,
         crop())
        CALL MakeKillArray(kmax%, aptime%, htemp%, wnum%, eff(),
         herbtemp(), k%())
        h3c% = htemp%
        FOR i% = 1 TO h3c%
         cpost(i%) = herbtemp(i%)
         FOR w% = 1 TO wnum%
          k3c%(w%, i%) = k%(w%, i%)
         NEXT w%
        NEXT i%
    END SELECT
  CASE 2
    SELECT CASE aptime%
      CASE 1
        CALL GetHerbData(cropnum%, aptime%, herbfile$, herb, herbtemp())
        REDIM sppi(htemp%) AS hfile
        REDIM k1s%(wnum%, htemp%), k%(wnum%, htemp%)
```

```
        ' CALL UserDropTrts2(aptime%, htemp%, herbtemp(), cropnum%,
            crop())
          CALL MakeKillArray(kmax%, aptime%, htemp%, wnum%, eff(),
            herbtemp(), k%())
          h1s% = htemp%
          FOR i% = 1 TO h1s%
            sppi(i%) = herbtemp(i%)
            FOR w% = 1 TO wnum%
              k1s%(w%, i%) = k%(w%, i%)
            NEXT w%
          NEXT i%
        CASE 2
          CALL GetHerbData(cropnum%, aptime%, herbfile$, herb, herbtemp())
          REDIM spre(htemp%) AS hfile
          REDIM k2s%(wnum%, htemp%), k%(wnum%, htemp%)
        ' CALL UserDropTrts2(aptime%, htemp%, herbtemp(), cropnum%,
            crop())
          CALL MakeKillArray(kmax%, aptime%, htemp%, wnum%, eff(),
            herbtemp(), k%())
          h2s% = htemp%
          FOR i% = 1 TO h2s%
            spre(i%) = herbtemp(i%)
            FOR w% = 1 TO wnum%
              k2s%(w%, i%) = k%(w%, i%)
            NEXT w%
          NEXT i%
        CASE 3
          CALL GetHerbData(cropnum%, aptime%, herbfile$, herb, herbtemp())
          REDIM spost(htemp%) AS hfile
          REDIM k3s%(wnum%, htemp%), k%(wnum%, htemp%)
'         CALL UserDropTrts2(aptime%, htemp%, herbtemp(), cropnum%,
            crop())
          CALL MakeKillArray(kmax%, aptime%, htemp%, wnum%, eff(),
            herbtemp(), k%())
          h3s% = htemp%
          FOR i% = 1 TO h3s%
            spost(i%) = herbtemp(i%)
            FOR w% = 1 TO wnum%
              k3s%(w%, i%) = k%(w%, i%)
            NEXT w%
          NEXT i%
      END SELECT
END SELECT
END SUB
```

```
SUB MakeKillArray (kmax%, aptime%, h%, wnum%, eff() AS kfile, herb() AS
 hfile, k%())
'                                   Last update: 02/05/91
'*************************************************************************
'*                             MakeKillArray                             *
'*  Subprogram MakeKillArray creates an array of weed treatment efficacy
'* ratings corresponding to the weed control treatments selected by     *
'* subprograms GetHerbData and UserDropTrts2. For those treatments that
'* correspond to crop and application time parameters of MakeHerbArray,*
'* it creates an efficacy array using data from GetKillData2.  For      *
'* treatments dropped in UserDropTrts2, it sets the efficacy rating at 0
'*                                                                       *
'* Parameters passed to the subprogram are:                              *
'*      kmax%                    Number of efficacy ratings in array eff()*
'*      aptime%                  Application time code                   *
'*      h%                       Number of treatments in array herb()    *
'*      wnum%                    Number of weed species in model         *
'*      eff()                    Array of efficacy ratings (killfile$)   *
'*      herb()                   Array of suitable treatments for this   *
'*                               crop and application time               *
'*                                                                       *
'* Values returned by this subprogram are:                               *
'*      k%(w%,i%)                Array of efficacy ratings for this crop *
'*                               and application time (for permitted trts.)
'*                               giving efficacy of trt. i% on weed w%.  *
'*************************************************************************
'
FOR i% = 1 TO h%
 FOR j% = 1 TO kmax%
   IF herb(i%).herbId = eff(j%).herbId AND aptime% = eff(j%).aptimeId
     THEN
     droptrt% = herb(i%).droptrt
     SELECT CASE droptrt%
       CASE 0
         FOR w% = 1 TO wnum%
           IF eff(j%).weedId = w% THEN k%(w%, i%) = eff(j%).effic
         NEXT w%
       CASE 1
         FOR w% = 1 TO wnum%
           IF eff(j%).weedId = w% THEN
              k%(w%, i%) = 0
           END IF
         NEXT w%
     END SELECT
   END IF
 NEXT j%
NEXT i%
END SUB
```

```
SUB PlantCrop (f%, wk%, fld() AS ftype, maxCwk%, minSwk%, newcost(),
 hrs, maxhrs, machine() AS mfile, mp%, crop() AS cropfile, sw(), weed()
 AS wfile, wnum%)
'                                  Last update: 05-02-91
'**********************************************************************
'*                            PlantCrop                               *
'*    Subprogram PlantCrop determines whether a field can be planted,  *
'* based upon whether the time of the season is appropriate for planting
'* If it is too early for soybeans, then the field is skipped until the*
'* next week.  If it is too late for corn, then the crop choice must be*
'* changed by calling ChooseCrop.                                      *
'*                                                                     *
'* Parameters passed to PlantCrop are:                                 *
'*      f%                     Current field number                    *
'*      wk%                    Current weed code                       *
'*      fld()                  Array of field information              *
'*      maxCwk%                Last week for planting corn             *
'*      minSwk%                First week for planting soybean         *
'*      newcost()              Array of current week costs             *
'*      hrs                    Current week cumulative hours works     *
'*      machine()              Array of machinery parameters           *
'*      mp%                    Planter machinery code                  *
'*      crop()                 Record array including crop seed price *
'*                             & planting rate                         *
'*                                                                     *
'* Value returned is:                                                  *
'*      fld(f%).plweek         Planting week for field f%              *
'**********************************************************************
ChangeCrop:
cropId% = fld(f%).cropId
SELECT CASE cropId%
  CASE 1
    IF (wk% <= maxCwk%) THEN
        fld(f%).plweek = wk%
        newcost(f%) = newcost(f%) + ((machine(mp%).CostAc +
          crop(cropId%).seedRate * crop(cropId%).seedPric) *
          fld(f%).fsize)
        hrs = hrs + fld(f%).fsize / machine(mp%).AcHr
    ELSE
      CALL ChooseCrop(f%, fld(), maxCwk%, wk%)
      GOTO ChangeCrop:
    END IF
  CASE 2
    IF (wk% >= minSwk%) THEN
      fld(f%).plweek = wk%
      newcost(f%) = newcost(f%) + ((machine(mp%).CostAc +
        crop(cropId%).seedRate * crop(cropId%).seedPric) *
        fld(f%).fsize)
      hrs = hrs + fld(f%).fsize / machine(mp%).AcHr
```

```
    END IF
END SELECT
END SUB
```

```
SUB PostTrt (f%, nfields%, wnum%, wk%, fld() AS ftype, kmax%, eff() AS
 kfile, weedHt(), newcost(), newload(), hrs, maxhrs, machine() AS
 mfile, ms%, mr%, infeas%(), endflag%(), d2wf(), d3wf(), sw(),
 swlost(), w2germ())
'                                  Last update: 04-28-91
'*********************************************************************
'*                              POSTTrt                              *
'*  Subprogram POSTTrt evaluates the recommended post-emergent weed  *
'* treatment in light of weed growth since crop planting.  It executes *
'* an appropriate POST treatment and calculates associated costs and  *
'* labor use.  It also calculates seed germination in the period      *
'* following POST treatment.  It returns csots, labor use, the week of *
'* POST treatment,and resulting weed densities & seed losses to       *
'* germination to the main program.  POST treatment may not occur less *
'* than 2 weeks after PRE/PPI.                                        *
'*                                                                    *
'* Parameters passed to POSTTrt are:                                  *
'*      f%                      Field number                          *
'*      nfields%                Number of fields                      *
'*      wnum%                   Number of weeds in model              *
'*      wk%                     Current weed code                     *
'*      fld()                   Record array of field information     *
'*      kmax%                   Number of records in efficacy file    *
'*      weedHt()                Array of weed heights by species      *
'*      eff()                   Record array of weed control efficacy *
'*      newcost()               Array of current week costs           *
'*      newload()               Array of current week herbicide loads *
'*      hrs                     Current week cumulative hours works   *
'*      machine()               Record array of machinery parameters  *
'*      ms%                     Sprayer machinery code                *
'*      mr%                     Rotary hoe machinery code             *
'*      weed()                  Record array of weed parameters       *
'*      d2wf(f%,w%)             Array of weed seedling densities per m2*
'*                              after PRE/PPI treatment               *
'*      sw(f%,w%)               Current seedbank for weed w% in field f%
'*      w2germ(w)               Post-cult. weed densities (CalibrateGerm
'*                                                                    *
'* Arguments returned are:                                            *
'*      fld(f%).postweek        Post-emergent weed control week for   *
'*                              field f%                              *
'*      d3wf(f%,w%)             Array of weed seedling density at     *
'*                              harvest after PRE/PPI and POST treat- *
'*                              ments. Assumes cultivation kills      *
'*                              inter-row 80% of d2wf().              *
'*      swlost(f%,w%)           Seedbank losses to emergence, by species
'*      infeas%(f%)             Array of flags for infeasible         *
'*                              recommended POST treatments (0=not    *
'*                              infeasible)                           *
'*********************************************************************
```

```
IF (fld(f%).plweek = 0) THEN EXIT SUB
IF (fld(f%).postcode <> 10) THEN
  IF (wk% - fld(f%).preweek) < 2 OR (wk% - fld(f%).plweek) < 2 THEN EXIT
    SUB
  ELSEIF (wk% - fld(f%).plweek < 1) THEN EXIT SUB
END IF
IF fld(f%).postcode <> 0 THEN
  cropnum% = fld(f%).cropId
  count% = 0
  FOR k% = 1 TO kmax%
    IF (eff(k%).aptimeId = 3 AND eff(k%).herbId = fld(f%).postcode) THEN
      FOR w% = 1 TO wnum%
        IF eff(k%).weedId = w% THEN
          SELECT CASE cropnum%
            CASE 1
              IF (fld(f%).cropHt > eff(k%).maxCrnHt OR weedHt(f%, w%) >
                eff(k%).maxWdHt) THEN infeas%(f%) = true%
            CASE 2
              IF (fld(f%).cropHt > eff(k%).maxSoyHt OR weedHt(f%, w%) >
                eff(k%).maxWdHt) THEN infeas%(f%) = true%
          END SELECT
          IF infeas%(f%) = true% THEN EXIT SUB
'           d3wf(f%, w%) = surv(eff(k%).effic) * d2wf(f%, w%) +
              weed(w%).s2germ * sw(f%, w%)
          d3wf(f%, w%) = d2wf(f%, w%) * surv(eff(k%).effic) + w2germ(f%,
            w%)
'          swlost(f%, w%) = swlost(f%, w%) + weed(w%).s2germ * sw(f%,
            w%)
          swlost(f%, w%) = swlost(f%, w%) + w2germ(f%, w%)
          count% = count% + 1
        END IF
      NEXT w%
    END IF
    IF count% = wnum% THEN EXIT FOR
  NEXT k%
  IF fld(f%).postcode = 10 THEN
    equip% = mr%
    ELSE
    equip% = ms%
  END IF
  newcost(f%) = newcost(f%) + ((machine(equip%).CostAc +
    fld(f%).postcost) * fld(f%).fsize)
  newload(f%) = fld(f%).postload
  hrs = hrs + fld(f%).fsize / machine(equip%).AcHr
ELSE
  FOR w% = 1 TO wnum%
'     d3wf(f%, w%) = d2wf(f%, w%) + weed(w%).s2germ * sw(f%, w%)
    d3wf(f%, w%) = d2wf(f%, w%) + w2germ(f%, w%)
'     swlost(f%, w%) = swlost(f%, w%) + weed(w%).s2germ * sw(f%, w%)
```

```
swlost(f%, w%) = swlost(f%, w%) + w2germ(f%, w%)
NEXT w%
END IF
fld(f%).postweek = wk%
endflag%(f%) = true%
END SUB
```

```
SUB PostWEEDSIM (f%, wnum%, h3%, mf%, ms%, mr%, mp%, t%, r, s0wf(),
  sw(), d2wf(), fld() AS ftype, cropnum%, crop() AS cropfile, weed() AS
  wfile, k3%(), postherb() AS hfile, mach() AS mfile, compmax%, comp()
  AS cfile, costnow, theta, nyears%, netpost(), h1n%, h2n%, h3n%,
  k1n%(), k2n%(), k3n%(), ppinext() AS hfile, prenext() AS hfile,
  postnext() AS hfile, decrule%, dropcode%, dropost%()) STATIC
'                                              Last update: 05/05/91
'**********************************************************************
'*                               PostWEEDSIM                          *
'* Subprogram PostWEEDSIM recommends the net-revenue-maximizing weed  *
'* treatment POST strategy for the current year, ignoring             *
'* future ramifications of current action.                            *
'*                                                                    *
'* Parameters passed to PostWEEDSIM are:                              *
'*    f%                         Field number                         *
'*    wnum%                      Number of weed species               *
'*    nyears%                    Number of years in model             *
'*    h1%                        Number of PPI treatments (set at 1)  *
'*    h2%                        Number of PRE treatments (set at 1)  *
'*    h3%                        Number of POST treatments            *
'*    mf%, ms%, mr%, mp%         Field cultivator, sprayer, rotary hoe,*
'*                               and planter machinery codes          *
'*    t%                         Year                                 *
'*    r                          Discount rate                        *
'*    s0wf(w%)                   Array of initial seedbank densities in*
'*                               this field                           *
'*    sw(f,w)                    Array of seed densities in actual fld *
'*    fld()                      Record array of field data           *
'*    cropnum%                   Crop code for current field          *
'*    crop()                     Record array of crop parameters      *
'*    weed()                     Record array of weed parameters      *
'*    k1%(),k2%(),k3%()          Arrays of efficacy ratings (PPI,PRE, *
'*                               POST)                                *
'*    postherb()                 Record array of POST treatment params
'*    ppinext()                  Record array of PPI next yr trt params
'*    prenext()                  Record array of PRE next yr trt params
'*    postnext()                 Record array of POST next yr trt params
'*    mach()                     Record array of machinery parameters *
'*    compmax%                   Number of observations in competition *
'*                               array                                *
'*    comp()                     Record array of weed-crop competition *
'*                               data                                 *
'*    costnow                    Current cost
'*    theta                      Proportion by which weed treatment     *
'*                               threshold net revenue to exceed no     *
'*                               control net revenue level.             *
'*    d2wf()                     Arrays for actual current weed den.  *
'*    d1w(),d2w()                Arrays of emerged weed densities in fld
'*    dropcode%                  Code for infeasible recom'd POST trt. *
```

```
'*     dropost%(j)            Array of infeasible POST treatments    *
'*                                                                   *
'* Arguments revised by PostWEEDSIM are:                             *
'*     fld(f%).postcode       Recommended POST treatment code        *
'*     fld(f%).postname       Recommended POST treatment name        *
'*     fld(f%).postcost       Cost per acre of recommended POST trt.*
'*     fld(f%).postload       Quantity of active chem. ingredient/ac*
'*********************************************************************
'
cropnum% = fld(f%).cropId
hl% = 1
hl2n% = hln% + h2n% - 1

REDIM precode%(hl%), preAvRat(hl%)
REDIM s0w(wnum%), slw(wnum%), s2w(wnum%), w2(wnum%)
REDIM dlw(wnum%), d2w(wnum%, hl%), precost(hl%)
REDIM d3w(wnum%, hl%, h3%), d3wij(wnum%), s3w(wnum%), postcost(hl%, h3%)
REDIM s0wl(wnum%, hl%, h3%)
REDIM yldpost(hl%, h3%)
REDIM netpost(hl%, h3%), netpost0(hl%, h3%)
REDIM netpostl(hl%, h3%, hl2n%, h3n%)

FOR w% = 1 TO wnum%
  s0w(w%) = s0wf(f%, w%)
  s2w(w%) = sw(f%, w%)
  w2(w%) = (weed(w%).avgerm * weed(w%).s2propn * s0wf(f%, w%)) +
    (weed(w%).w2int + weed(w%).w2s * s0wf(f%, w%))
NEXT w%
FOR i% = 1 TO hl%
  precost(i%) = costnow
  precode%(i%) = fld(f%).precode
  preAvRat(i%) = fld(f%).preload
  FOR w% = 1 TO wnum%
   d2w(w%, i%) = d2wf(f%, w%)
  NEXT w%
NEXT i%
CALL WSPostReviseTrt(cropnum%, wnum%, hl%, h3%,
  crop(fld(f%).cropId).expMaxY, fld(f%).rotation, k3%(), d2w(), s0w(),
  s2w(), weed(), crop(), precode%(), preAvRat(), postherb(), compmax%,
 comp(), mach(ms%).CostAc, fld(f%).fsize, d3w(), d3wij(), s3w(),
  yldpost(), postcost(), w2(), dropcode%, dropost%())
CALL WSSeedBank(wnum%, hl%, h3%, d3w(), s3w(), weed(), s0wl(), w2())
CALL WSPostRev(hl%, h3%, crop(cropnum%).price, yldpost(), postcost(),
  precost(), t%, r, fld(f%).fsize, crop(cropnum%).vc, netpost())
IF (t% + 1) < nyears% AND decrule% = 2 THEN

'Foresighted decision rule (2-year horizon)
  FOR i% = 1 TO hl%
    FOR j% = 1 TO h3%
```

```
  netpost0(i%, j%) = netpost(i%, j%)
 NEXT j%
NEXT i%
REDIM precode%(h12n%), preAvRat(h12n%)
REDIM d2w(wnum%, h12n%), precost(h12n%)
REDIM d3w(wnum%, h12n%, h3n%), postcost(h12n%, h3n%)
REDIM yldpost(h12n%, h3n%), netpost(h12n%, h3n%)
REDIM netpostl(hl%, h3%, h12n%, h3n%)
IF fld(f%).rotation = 1 THEN
 nextcrop% = 1 + cropnum% MOD 2
 plcost = crop(nextcrop%).seedRate * crop(nextcrop%).seedPric +
   mach(mp%).CostAc
 CALL WSNextYear(f%, wnum%, nextcrop%, compmax%, hln%, h2n%, h12n%,
   h3n%, t%, r, mf%, ms%, mr%, mp%, kln%(), k2n%(), k3n%(), fld(),
   weed(), mach(), comp(), crop(), ppinext(), prenext(), postnext(),
   s0w(), s0wl(), slw(), s2w(), s3w(), dlw(), d2w(), d3w(),
   yldpost(), precost(), netpost0(), netpostl(), plcost, theta,
   netpost(), postcost(), precode%(), preAvRat(), hl%, h3%)
 CALL WSTopRev(hl%, h3%, h12n%, h3n%, theta, netpostl(), kimax%,
   kjmax%, topnet)
 ELSE
 nextcrop% = cropnum%
 plcost = crop(nextcrop%).seedRate * crop(nextcrop%).seedPric +
   mach(mp%).CostAc
 CALL WSNextYear(f%, wnum%, nextcrop%, compmax%, hln%, h2n%, h12n%,
   h3n%, t%, r, mf%, ms%, mr%, mp%, kln%(), k2n%(), k3n%(), fld(),
   weed(), mach(), comp(), crop(), ppinext(), prenext(), postnext(),
   s0w(), s0wl(), slw(), s2w(), s3w(), dlw(), d2w(), d3w(),
   yldpost(), precost(), netpost0(), netpostl(), plcost, theta,
   netpost(), postcost(), precode%(), preAvRat(), hl%, h3%)
 CALL WSTopRev(hl%, h3%, h12n%, h3n%, theta, netpostl(), kimax%,
   kjmax%, topnet)
END IF
topnet = topnet / 2

' Myopic decision rule
ELSE
 CALL WSTopRevMyopic(hl%, h3%, netpost(), theta, kimax%, kjmax%,
   topnet)
END IF

fld(f%).postname = postherb(kjmax%).hname
fld(f%).postcode = postherb(kjmax%).herbId
fld(f%).postcost = postherb(kjmax%).unitCost * postherb(kjmax%).avrate
fld(f%).postload = postherb(kjmax%).avrate

END SUB
```

```
SUB PPITrt (f%, nfields%, wk%, fld() AS ftype, newcost(), newload(),
 hrs, maxhrs, machine() AS mfile, ms%, mf%, preflag%)
'                                           Last update: 01-05-91
'**********************************************************************
'*                                    PPITrt                           *
'*                                                                     *
'* Parameters passed to PPITrt are:                                    *
'*      f%                        Current field number                 *
'*      nfields%                  Number of fields                     *
'*      wk%                       Current weed code                    *
'*      fld()                     Record array of field information    *
'*      newcost()                 Array of current week costs          *
'*      hrs                       Current week cumulative hours works  *
'*      maxhrs                    Number of workable hours in week     *
'*      machine()                 Record array of machinery parameters *
'*      ms%                       Sprayer machinery code               *
'*      mf%                       Field cultivator machinery code      *
'*                                                                     *
'* Value returned is:                                                  *
'*      fld(f%).ppiweek           Pre-plant incorporated weed trt. week *
'*                                for field f%                         *
'*      preflag%                  Flag for completion of PPI/PRE trt.  *
'**********************************************************************
'
IF (fld(f%).preApTim <> 1) OR (fld(f%).ppiweek <> 0) THEN EXIT SUB

IF fld(f%).precode <> 0 THEN
  newcost(f%) = newcost(f%) + ((machine(ms%).CostAc +
    machine(mf%).CostAc + fld(f%).precost) * fld(f%).fsize)
  newload(f%) = fld(f%).preload
  hrs = hrs + (fld(f%).fsize / machine(mf%).AcHr) + (fld(f%).fsize /
    machine(ms%).AcHr)
ELSE
  newcost(f%) = newcost(f%) + machine(mf%).CostAc * fld(f%).fsize
  hrs = hrs + fld(f%).fsize / machine(mf%).AcHr
END IF
fld(f%).ppiweek = wk%
preflag% = true%

END SUB
```

```
SUB PRESurv (f%, nfields%, wnum%, fld() AS ftype, kmax%, eff() AS kfile,
  wlgerm(), d2wf(), rain())
'                                       Last Update: 04-22-91
'*********************************************************************
'*                                PRESurv                            *
'*    Subprogram PRESurv returns the density of surviving weeds after *
'* implementation of the PPI or PRE weed control treatment.  If less *
'* than 0.5 inches of rain falls within a week after PRE treatment,then*
'* herbicide treatment fails.                                        *
'*                                                                   *
'* Parameters passed to PRESurv are:                                 *
'*      f%                     Current field                         *
'*      nfields%               Number of fields on farm              *
'*      wnum%                  Number of weeds in model              *
'*      fld()                  Record array of field data            *
'*      rain(wk)               Array of weekly cumulative precipitation *
'*      kmax%                  Total number of records in efficacy file *
'*      eff()                  Record array of efficacy ratings by crop,*
'*                             weed                                  *
'*      wlgerm(f%,w%)          Array of weed seedling densities per m2 *
'*                             germinating after planting            *
'*      rain()                 Current year rain (from GetYear)      *
'*                                                                   *
'* Arguments returned by PRESurv are:                                *
'*      d2wf(f%,w%)            Array of weed densities surviving PPI *
'*                             or PRE weed control treatment         *
'*********************************************************************
'
count% = 0
IF fld(f%).preApTim = 2 AND rain(fld(f%).preweek + 1) < .5 THEN
  FOR w% = 1 TO wnum%
    d2wf(f%, w%) = wlgerm(f%, w%)
  NEXT w%
  EXIT SUB
END IF
FOR k% = 1 TO kmax%
  IF (fld(f%).precode = eff(k%).herbId AND fld(f%).preApTim =
    eff(k%).aptimeId) THEN
    FOR w% = 1 TO wnum%
      IF eff(k%).weedId = w% THEN
        d2wf(f%, w%) = surv(eff(k%).effic) * wlgerm(f%, w%)
        count% = count% + 1
      END IF
    NEXT w%
  END IF
  IF count% = wnum% THEN EXIT FOR
NEXT k%

END SUB
```

```
SUB PreTrt (f%, nfields%, wk%, fld() AS ftype, newcost(), newload(),
 hrs, maxhrs, machine() AS mfile, ms%, preflag%)
'                                    Last update: 01-05-91
'**********************************************************************
'*                            PRETrt                                  *
'*    Subprogram PRETrt executes the recommended PRE treatment and    *
'* calculates associated costs and labor use.  It returns these and the*
'* week of PRE treatment to the main program.                         *
'*                                                                    *
'*                                                                    *
'* Parameters passed to PRETrt are:                                   *
'*      f%                       Current field                        *
'*      nfields%                 Number of fields                     *
'*      wk%                      Current weed code                    *
'*      fld()                    Record array of field information    *
'*      newcost()                Array of current week costs          *
'*      newload()                Array of current weed herb. load     *
'*      hrs                      Current week cumulative hours works  *
'*      machine()                Record array of machinery parameters *
'*      ms%                      Sprayer machinery code               *
'*                                                                    *
'* Arguments returned are:                                            *
'*      fld(f%).preweek          Pre-emergent weed control trt. week for*
'*                               field f%                             *
'*      preflag%                 Flag for completion of PPI/PRE trt.  *
'**********************************************************************
'
IF (fld(f%).preApTim <> 2) OR (fld(f%).plweek = 0) THEN EXIT SUB
fld(f%).preweek = wk%
IF fld(f%).precode <> 0 THEN
 newcost(f%) = newcost(f%) + ((machine(ms%).CostAc + fld(f%).precost) *
   fld(f%).fsize)
 newload(f%) = fld(f%).preload
  hrs = hrs + fld(f%).fsize / machine(ms%).AcHr
END IF
preflag% = true%

END SUB
```

```
SUB PrintInitWeedSeeds (nfields%, wnum%, state%, yr%, weedparm() AS
 wfile, s0wf())
'                                    Last update: 04-25-91
'*********************************************************************
'*                           PrintInitWeedSeeds                      *
'*   Subprogram PrintInitWeedSeeds prints weed seed density data     *
'* at the beginning of the current simulation year.                  *
'*                                                                   *
'* Parameters passed to PrintInitWeedSeeds are:                      *
'*      nfields%                Number of fields on farm             *
'*      wnum%                   Number of weed species in model      *
'*      state%                  Current state of nature              *
'*      yr%                     Current year                         *
'*      weedparm()              Record array of weed parameters      *
'*      s0wf()                  Array of initial weed seed densities *
'*********************************************************************
PRINT
PRINT "Initial weed seed counts for State ";
PRINT USING "##"; state%;
PRINT " and Year ";
PRINT USING "#"; yr%
PRINT
"--------------------------------------------------------------------"
PRINT "                  Seedbank (seeds/m2)"
PRINT "Field   ";
FOR w% = 1 TO wnum%
  PRINT weedparm(w%).wname;
  PRINT "  ";
NEXT w%
PRINT
"--------------------------------------------------------------------"
FOR f% = 1 TO nfields%
  PRINT USING "###"; f%;
  PRINT "   ";
  FOR w% = 1 TO wnum%
    PRINT " ";
    PRINT USING "#######"; s0wf(f%, w%);
    PRINT "  ";
  NEXT w%
  PRINT
NEXT f%
PRINT
"--------------------------------------------------------------------"
END SUB
```

```
SUB PrintRecoms (f%, cropname$, fld() AS ftype, topnet)
'                                          Last update: 02-13-91
'**********************************************************************
'*                              PrintRecoms                           *
'*  This subprogram prints weed control recommendations.              *
'* Variables input to the subprogram are:                             *
'*      f%                      Current field                         *
'*      cropname$               Name of current field crop            *
'*      fld()                   Record array of field data            *
'*      topnet                  Expected net revenue by following recoms. *
'**********************************************************************

PRINT USING "###"; f%;
PRINT "    ";
PRINT cropname$;
PRINT "    ";
rot% = fld(f%).rotation
SELECT CASE rot%
  CASE 1
    PRINT "CS   ";
  CASE 2
    PRINT "CC   ";
END SELECT
PRINT "";
PRINT fld(f%).prename;
preApTim% = fld(f%).preApTim
SELECT CASE preApTim%
  CASE 1
    IF fld(f%).precode <> 0 THEN
      PRINT "PPI   ";
    ELSE
      PRINT "       ";
    END IF
  CASE 2
    PRINT "PRE    ";
END SELECT
PRINT fld(f%).postname;
PRINT " ";
PRINT USING "######.##"; topnet

END SUB
```

```
SUB ScreenHeader2
'                                         Last update: 12/29/90
'*********************************************************************
'*                                ScreenHeader2                      *
'* Subprogram ScreenHeader writes introductory remarks to the screen. *
'*********************************************************************
'
PRINT
PRINT
PRINT
PRINT "                             *************                  "
PRINT "                             *  WFARM   *                   "
PRINT "                             *************                  "
PRINT "                                                             "
PRINT "                            by Scott M. Swinton              "
PRINT "              Department of Agricultural and Applied Economics "
PRINT "                University of Minnesota, St. Paul, MN 55108    "
PRINT "                                                             "
PRINT "WFARM generates a weed control strategy for corn and corn-soybean
  rotations "
PRINT "that maximizes the farmer's expected wealth.  Recommendations for
  each  "
PRINT "year are based upon the decision rule elected.  One rule makes
  recommendations"
PRINT "based upon current year information only, the other rule
  incorporates expec-  "
PRINT "tations about next year's likely weed infestation.  Results are
  for the whole "
PRINT "farm, and account for field time limitations.  This version is
  stochastic.    "
PRINT "
          "
PRINT "Press any key to continue."
'resume$ = INPUT$(1)
CLS
END SUB
```

```
SUB SummaryAnnual (wnum%, nfields%, fld() AS ftype, crop() AS cropfile,
 netrev(), load(), yldpct(), d3wf(), s0wf(), csweed(), ccweed(),
 csseed(), ccseed(), farmnr, sum() AS stype)
'                                        Last update: 05-05-91
'*********************************************************************
'*                           SummaryAnnual                           *
'* This subprogram summarizes annual net revenue and herbicide load  *
'* results by crop and rotation, as well as for the whole farm.      *
'*                                                                   *
'*  Parameters passed to SummaryAnnual are:                          *
'*     wnum%               Number of weed species                    *
'*     nfields%            Number of fields                          *
'*     fld()               Record array for field characteristics    *
'*     crop()              Record array of crop characteristics      *
'*     netrev()            Array of net revenue by field             *
'*     load()              Array of chemical loads by field          *
'*     yldpct()            Array of percent max yield realized       *
'*     d3wf()              Array of end-season weed densities        *
'*     s0wf()              Array of end-season weed seed densities   *
'*     farmnet             Farm net income for year                  *
'*     net(1)              Corn net income from CS rotation for year *
'*     net(3)              Corn net income from CC rotation for year *
'*     net(2)              Soybean net income from CS rotation for yr.*
'*     lod(1)              Mean herbicide load on corn in CS rotation *
'*     lod(3)              Mean herbicide load on corn in CC rotation *
'*     lod(2)              Mean herbicide load on soybean in CS rotatn*
'*     net(s)              Cumulative net income from 1. Corn in CS rot
'*                         2. Soy in CS rot., and 3. Corn in CC rot.  *
'*     lod(s)              Cumulative herb. load from 1. Corn in CS rot
'*                         2. Soy in CS rot., and 3. Corn in CC rot.  *
'*     ypct(s)             Cumulative yield pct. from 1. Corn in CS   *
'*                         rot., 2. Soy in CS rot., and 3. Corn in CC *
'*     num%(s)             Cumulative number fields in 1. Corn in CS  *
'*                         2. Soy in CS rot., and 3. Corn in CC rot.  *
'*     farmnr              Cumulative farm net income                 *
'*     cssd(w),ccsd(w)     Final seeds at harvest in CS and CC rotatns*
'*     cswd(w),ccwd(w)     Cum weeds at harvest in CS and CC rotations*
'*     cXseed(w)           Average cumulative ending seed density by  *
'*                         rotation (CS, CC)                          *
'*     cXweed(w)           Average cumulative ending weed density by  *
'*                         rotation (CS, CC)                          *
'*     sum(s).nr           Mean net revenue from 1. Corn in CS rotatn.*
'*                         2. Soy in CS rot., and 3. Corn in CC rot.  *
'*     sum(s).sdnr         St.dev. net rev. from 1. Corn in CS rotatn.*
'*                         2. Soy in CS rot., and 3. Corn in CC rot.  *
'*     sum(s).load         Mean herb. load from 1. Corn in CS rotatn.*
'*                         2. Soy in CS rot., and 3. Corn in CC rot.  *
'*     sum(s).ypct         Mean yield pct.  from 1. Corn in CS rotatn.*
'*                         2. Soy in CS rot., and 3. Corn in CC rot.  *
```

```
'**************************************************************************
REDIM cssd(wnum%), ccsd(wnum%), cswd(wnum%), ccwd(wnum%)
REDIM net(3), lod(3), ypct(3), num%(3)
farmnet = 0
FOR f% = 1 TO nfields%
  cropnum% = fld(f%).cropId
  farmnet = farmnet + netrev(f%)
  IF fld(f%).rotation = 1 THEN
    FOR w% = 1 TO wnum%
      cswd(w%) = cswd(w%) + d3wf(f%, w%)
      cssd(w%) = cssd(w%) + s0wf(f%, w%)
    NEXT w%
    SELECT CASE cropnum%
      CASE 1
        net(1) = net(1) + netrev(f%)
        lod(1) = lod(1) + load(f%)
        ypct(1) = ypct(1) + yldpct(f%)
        num%(1) = num%(1) + 1
      CASE 2
        net(2) = net(2) + netrev(f%)
        lod(2) = lod(2) + load(f%)
        ypct(2) = ypct(2) + yldpct(f%)
        num%(2) = num%(2) + 1
    END SELECT
  ELSE
    FOR w% = 1 TO wnum%
      ccwd(w%) = ccwd(w%) + d3wf(f%, w%)
      ccsd(w%) = ccsd(w%) + s0wf(f%, w%)
    NEXT w%
    net(3) = net(3) + netrev(f%)
    lod(3) = lod(3) + load(f%)
    ypct(3) = ypct(3) + yldpct(f%)
    num%(3) = num%(3) + 1
  END IF
NEXT f%
farmnr = farmnr + farmnet
FOR s% = 1 TO 3
  sum(s%).nr = sum(s%).nr + net(s%)
  sum(s%).sdnr = 0
  sum(s%).load = sum(s%).load + lod(s%) / num%(s%)
  sum(s%).ypct = sum(s%).ypct + ypct(s%) / num%(s%)
NEXT s%
FOR w% = 1 TO wnum%
  csweed(w%) = csweed(w%) + cswd(w%) / (num%(1) + num%(2))
  ccweed(w%) = ccweed(w%) + ccwd(w%) / num%(3)
  csseed(w%) = cssd(w%) / (num%(1) + num%(2))
  ccseed(w%) = ccsd(w%) / num%(3)
NEXT w%
END SUB
```

```
SUB SummaryScenario (scenout$, decrule%, theta, lamseeds%, wnum%,
 nstates%, sumst() AS stype, farmstnr, farmstsd, cswst(), ccwst(),
 cssst(), ccsst(), urp0001#, ura0001#, ura001#)
'                         Last update: 05-20-91
'***********************************************************************
'*                      SummaryScenario                                *
'* This subprogram summarizes end-state revenue, herbicide load, yield*
'* percent, and weed & seed density results by crop and rotation, as  *
'* well as for the whole farm.                                         *
'*                                                                     *
'* Parameters passed to SummaryScenario are:                           *
'*    scenout$           Name of scenario output file                  *
'*    decrule%           Decision rule                                 *
'*    theta              Caution coefficient                           *
'*    lamseeds%          Lambsquarters initial seed density            *
'*    wnum%              Number of weed species                        *
'*    nstates%           Number of states                              *
'*    sumst()            Record array of end-state summary stats.      *
'*    farmstnr           Cumulative end-state mean farm income         *
'*    farmstsd           Cumulative end-state mean income st. dev.     *
'*    urp0001#           Utility of risk preferrer with r(x)=-.0001    *
'*    ura0001#           Utility of risk averter with r(x)=.0001       *
'*    ura001#            Utility of risk averter with r(x)=.001        *
'*    cep0001            Certainty equivalent mean ann NPV for         *
'*                       r(x)=-.0001                                   *
'*    cea0001            Certainty equivalent mean ann NPV for         *
'*                       r(x)=.0001                                    *
'*    cea001             Certainty equivalent mean ann NPV for         *
'*                       r(x)=.001                                     *
'*    cssst(w),ccsst(w)  Cum end-state mean seeds at harvest in CS     *
'*                       and CC rotations                              *
'*    cswst(w),ccwst(w)  Cum end-state mean weeds at harvest in CS     *
'*                       and CC rotations                              *
'***********************************************************************

FOR s% = 1 TO 3
  sumst(s%).nr = sumst(s%).nr / nstates%
  sumst(s%).sdnr = sumst(s%).sdnr / nstates% - sumst(s%).nr ^ 2
  sumst(s%).sdnr = sumst(s%).sdnr ^ .5
  sumst(s%).load = sumst(s%).load / nstates%
  sumst(s%).ypct = sumst(s%).ypct / nstates%
NEXT s%
farmstnr = farmstnr / nstates%
farmstsd = farmstsd / nstates% - farmstnr ^ 2
farmstsd = farmstsd ^ .5
cep0001 = (-LOG(urp0001# / nstates%)) / -.0001
cea0001 = (-LOG(-ura0001# / nstates%)) / .0001
cea001 = (-LOG(-ura001# / nstates%)) / .001
FOR w% = 1 TO wnum%
```

```
  cswst(w%) = cswst(w%) / nstates%
  ccwst(w%) = ccwst(w%) / nstates%
  cssst(w%) = cssst(w%) / nstates%
  ccsst(w%) = ccsst(w%) / nstates%
NEXT w%

Filenum1 = FREEFILE
OPEN scenout$ FOR APPEND AS #Filenum1
WRITE #Filenum1, decrule%, theta, lamseeds%, farmstnr, farmstsd,
  cep0001, cea0001, cea001, sumst(3).nr, sumst(3).sdnr, sumst(3).load,
  sumst(3).ypct, sumst(1).nr, sumst(1).sdnr, sumst(1).load,
  sumst(1).ypct, sumst(2).nr, sumst(2).sdnr, sumst(2).load,
  sumst(2).ypct, cswst(1), ccwst(1), cssst(1), ccsst(1), cswst(2),
  ccwst(2), cssst(2), ccsst(2), cswst(3), ccwst(3), cssst(3), ccsst(3)
CLOSE #Filenum1

END SUB
```

```
SUB SummaryState (wnum%, nyears%, r, sum() AS stype, farmnr, csweed(),
  ccweed(), csseed(), ccseed(), sumst() AS stype, farmstnr, farmstsd,
  cswst(), ccwst(), cssst(), ccsst(), urp0001#, ura0001#, ura001#,
  stateout$)
'                                Last update: 05-20-91
'**********************************************************************
'*                     SummaryState                                   *
'*  This subprogram summarizes annual net revenue and herbicide load  *
'* results by crop and rotation, as well as for the whole farm.       *
'*                                                                    *
'*  Parameters passed to SummaryState are:                            *
'*      wnum%             Number of weed species                      *
'*      nyears%           Number of years                             *
'*      r                 Discount rate                               *
'*      sum()             Record array of annual summary stats.       *
'*      farmnr            Cumulative annual farm net income           *
'*      cXseed(w)         Average cumulative ending seed density by   *
'*                        rotation (CS, CC)                           *
'*      cXweed(w)         Average cumulative ending weed density by   *
'*                        rotation (CS, CC)                           *
'*                                                                    *
'*  Values returned by SummaryState are:                              *
'*      sumst()           Record array of end-state summary stats.    *
'*      farmstnr          Cumulative end-state mean farm income       *
'*      farmstsd          Cumulative end-state mean income st. dev.   *
'*      urp0001#          Utility of risk preferrer with r(x)=-.0001  *
'*      ura0001#          Utility of risk averter with r(x)=.0001     *
'*      ura001#           Utility of risk averter with r(x)=.001      *
'*      cssst(w),ccsst(w) Cum end-state mean seeds at harvest in CS & *
'*                        CC rotations                                *
'*      cswst(w),ccwst(w) Mean end-state weeds at harvest in CS and   *
'*                        CC rotations                                *
'*      stateout$         Name of summary state data output file      *
'**********************************************************************

FOR s% = 1 TO 3
  sum(s%).nr = sum(s%).nr * r / (1 - (1 + r) ^ -nyears%)
  sumst(s%).nr = sumst(s%).nr + sum(s%).nr
  sumst(s%).sdnr = sumst(s%).sdnr + sum(s%).nr ^ 2
  sumst(s%).load = sumst(s%).load + sum(s%).load / nyears%
  sumst(s%).ypct = sumst(s%).ypct + sum(s%).ypct / nyears%
NEXT s%
farmnr = farmnr * r / (1 - (1 + r) ^ -nyears%)
farmstnr = farmstnr + farmnr
farmstsd = farmstsd + farmnr ^ 2
urp0001# = EXP(.0001 * farmnr) + urp0001#
ura0001# = -EXP(-.0001 * farmnr) + ura0001#
ura001# = -EXP(-.001 * farmnr) + ura001#
FOR w% = 1 TO wnum%
```

```
  cswst(w%) = cswst(w%) + csweed(w%) / nyears%
  ccwst(w%) = ccwst(w%) + ccweed(w%) / nyears%
  cssst(w%) = cssst(w%) + csseed(w%)
  ccsst(w%) = ccsst(w%) + ccseed(w%)
NEXT w%
Filenum4 = FREEFILE
OPEN stateout$ FOR APPEND AS #Filenum4
WRITE #Filenum4, sum(1).nr, sum(1).load / nyears%, sum(1).ypct /
  nyears%, sum(2).nr, sum(2).load / nyears%, sum(2).ypct / nyears%,
  sum(3).nr, sum(3).load / nyears%, sum(3).ypct / nyears%, csweed(1) /
  nyears%, ccweed(1) / nyears%, csseed(1), ccseed(1), csweed(2) /
  nyears%, ccweed(2) / nyears%, csseed(2), ccseed(2), csweed(3) /
  nyears%, ccweed(3) / nyears%, csseed(3), ccseed(3)
CLOSE #Filenum4
END SUB

FUNCTION surv (x%)
'                                    Last update: 4/27/91
'**********************************************************************
'*                                surv                                *
'* This function transforms WEEDIR weed control values for corn into *
'* weed survival rates (0,.1,.3,.5,.7,.9) (Kidder et al., Durgan et al)
'*                                                                    *
'* Parameter passed to function surv is:                              *
'*    x%                          WEEDIR efficacy rating (0,1,2,3,4 or 5)
'*                                                                    *
'* Value returned by function surv is:                                *
'*    surv                        Proportion of weeds surviving treatment
'**********************************************************************
'
IF x% <> 0 THEN
  surv = 1 - .2 * x% + .1
ELSE
  surv = 1
END IF
END FUNCTION
```

```
SUB WeedGrowth (f%, wk%, wnum%, weed() AS wfile, fld() AS ftype,
 weedHt(), epswgrow(), betawgro())
'                                        Last update 06-06-91
'*********************************************************************
'*                            WeedGrowth                             *
'*   This subprogram "grows" the weeds in each field as a function of *
'* the number of days since preplant-incorporated (PPI) or pre-emergent*
'* (PRE) weed control.                                               *
'*                                                                   *
'* Parameters passed to WeedGrowth are:                              *
'*     f%                  Current field number                      *
'*     wk%                 Current week number                       *
'*     wnum%               Number of weeds in the model              *
'*     weed()              Record array of weed parameters           *
'*     fld()               Record array of field data                *
'*     epswgrow(w)         Array of additive error terms             *
'*     betawgro(w)         Array of coef. error terms                *
'*                                                                   *
'* Arguments returned by WeedGrowth are:                             *
'*     weedHt(f%,w%)       Array of weed heights (inches) in each    *
'*                         field                                     *
'*********************************************************************

IF fld(f%).precode <> 0 THEN
 IF fld(f%).preApTim = 1 THEN
   dap% = (wk% - fld(f%).plweek) * 7
 ELSEIF fld(f%).preApTim = 2 THEN
   dap% = (wk% - fld(f%).preweek) * 7
 END IF
ELSE
 dap% = (wk% - fld(f%).plweek) * 7
END IF

IF dap% > 0 THEN
 FOR w% = 1 TO wnum%
   IF fld(f%).cropId = 2 THEN
     sigwdgro = weed(w%).sigwint + weed(w%).sigwdap2 * dap% ^ 2
     IF sigwdgro < 0 THEN sigwdgro = 0
     ELSE
     sigwdgro = 1
   END IF
   weedHt(f%, w%) = (weed(w%).growrate + betawgro(w%)) * dap% ^ 2 +
     sigwdgro * epswgrow(w%)
 NEXT w%
END IF

END SUB
```

```
SUB WEEDSIM (f%, wnum%, h1%, h2%, h3%, mf%, ms%, mr%, mp%, t%, r,
 s0wf(), fld() AS ftype, cropnum%, crop() AS cropfile, weed() AS wfile,
 k1%(), k2%(), k3%(), ppiherb() AS hfile, preherb() AS hfile,
 postherb() AS hfile, mach() AS mfile, compmax%, comp() AS cfile,
 theta, nyears%, netpost(), h1n%, h2n%, h3n%, k1n%(), k2n%(), k3n%(),
 ppinext() AS hfile, prenext() AS hfile, postnext() AS hfile, decrule%)
STATIC
'                                              Last update: 05/05/91
'*********************************************************************
'*                              WEEDSIM                               *
'* Subprogram WEEDSIM recommends the net-revenue-maximizing weed      *
'* treatment strategy pair (PRE,POST) for the current year, ignoring  *
'* future ramifications of current action.                            *
'*                                                                    *
'* Parameters passed to WEEDSIM are:                                  *
'*      f%                      Field number                          *
'*      wnum%                   Number of weed species                *
'*      nyears%                 Number of years modeled               *
'*      h1%                     Number of PPI treatments              *
'*      h2%                     Number of PRE treatments              *
'*      h3%                     Number of POST treatments             *
'*      h1n%                    Number of PPI treatments (next year)  *
'*      h2n%                    Number of PRE treatments (next year)  *
'*      h3n%                    Number of POST treatments (next year) *
'*      mf%, ms%, mr%, mp%      Field cultivator, sprayer, rotary hoe, *
'*                              and planter machinery codes           *
'*      decrule%                Decision rule code                    *
'*      ywf                     Weed-free yield                       *
'*      t%                      Year                                  *
'*      r                       Discount rate                         *
'*      s0wf(w%)                Array of initial seedbank densities in *
'*                              this field                            *
'*      fld()                   Record array of field data            *
'*      cropnum%                Crop code for current field           *
'*      crop()                  Record array of crop parameters       *
'*      weed()                  Record array of weed parameters       *
'*      k1%(),k2%(),k3%()       Arrays of efficacy ratings (PPI,PRE,  *
'*                              POST)                                 *
'*      k1n%(),k2n%(),k3n%()    Arrays of efficacy ratings (PPI,PRE,  *
'*                              POST) (for next year)                 *
'*      ppiherb()               Record array of PPI treatment parameters
'*      preherb()               Record array of PRE treatment parameters
'*      postherb()              Record array of POST treatment params. *
'*      ppinext()               Record array of PPI next yr trt params *
'*      prenext()               Record array of PRE next yr trt params *
'*      postnext()              Record array of POST next yr trt params*
'*      mach()                  Record array of machinery parameters  *
'*      compmax%                Number of obs. in competition array   *
'*      comp()                  Record array of weed-crop competition *
```

```
'*                                   data                                    *
'*   theta                           Proportion by which weed treatment      *
'*                                   threshold net revenue to exceed no      *
'*                                   control net revenue level.              *
'*   dlw(),d2w()                     Arrays of emerged weed densities in     *
'*                                   field                                   *
'*   netpost()                       Array of expected net returns           *
'*                                                                           *
'* Arguments returned by WEEDSIM are:                                        *
'*   fld(f%).precode                 Recommended PPI/PRE treatment code      *
'*   fld(f%).preApTim                Recommended PPI or PRE application time*
'*   fld(f%).prename                 Recommended PPI or PRE treatment name   *
'*   fld(f%).precost                 Cost per acre of recommended PPI/PRE trt
'*   fld(f%).preload                 Quantity of active chem. ingredient/ac *
'*   fld(f%).postcode                Recommended POST treatment code         *
'*   fld(f%).postname                Recommended POST treatment name         *
'*   fld(f%).postcost                Cost per acre of recommended POST trt. *
'*   fld(f%).postload                Quantity of active chem. ingredient/ac *
'****************************************************************************
'
SHARED topnet
h12% = h1% + h2% - 1
h12n% = h1n% + h2n% - 1
REDIM precode%(h12%), preAvRat(h12%)
REDIM s0w(wnum%), s1w(wnum%), s2w(wnum%), d1w(wnum%)
REDIM w0(wnum%), w1(wnum%), w2(wnum%)
REDIM d2w(wnum%, h12%), precost(h12%)
REDIM d3w(wnum%, h12%, h3%), d3wij(wnum%), s3w(wnum%), postcost(h12%,
  h3%)
REDIM s0w1(wnum%, h12%, h3%), yldpost(h12%, h3%), netpost(h12%, h3%)
FOR w% = 1 TO wnum%
  s0w(w%) = s0wf(f%, w%)
  w0(w%) = (weed(w%).avgerm * weed(w%).s0propn * s0wf(f%, w%)) +
    (weed(w%).w0int + weed(w%).w0s * s0wf(f%, w%) + weed(w%).w0s2 *
    s0wf(f%, w%) ^ 2)
  w1(w%) = (weed(w%).avgerm * weed(w%).s1propn * s0wf(f%, w%)) +
    (weed(w%).w1int + weed(w%).w1s * s0wf(f%, w%) + weed(w%).w1s2 *
    s0wf(f%, w%) ^ 2)
  w2(w%) = (weed(w%).avgerm * weed(w%).s2propn * s0wf(f%, w%)) +
    (weed(w%).w2int + weed(w%).w2s * s0wf(f%, w%))
NEXT w%
plcost = crop(cropnum%).seedRate * crop(cropnum%).seedPric +
  mach(mp%).CostAc
CALL WSWeedGerm(wnum%, weed(), s0w(), s1w(), s2w(), d1w(), w0(), w1())
CALL WSPreTrt(wnum%, h1%, h2%, mf%, ms%, k1%(), k2%(), d1w(),
  fld(f%).ywf, ppiherb(), preherb(), mach(), fld(f%).fsize, plcost,
  h12%, d2w(), precost(), precode%(), preAvRat())
CALL WSPostTrt(cropnum%, wnum%, h12%, h3%, crop(fld(f%).cropId).expMaxY,
  fld(f%).rotation, k3%(), d2w(), s0w(), s2w(), weed(), crop(),
```

```
  precode%(), preAvRat(), postherb(), compmax%, comp(), mach(), ms%,
  mr%, fld(f%).fsize, d3w(), d3wij(), s3w(), yldpost(), postcost(),
  w2())
CALL WSSeedBank(wnum%, h12%, h3%, d3w(), s3w(), weed(), s0w1(), w2())
CALL WSPostRev(h12%, h3%, crop(cropnum%).price, yldpost(), postcost(),
  precost(), t%, r, fld(f%).fsize, crop(cropnum%).vc, netpost())
IF (t% + 1) < nyears% AND decrule% = 2 THEN
' Foresighted decision rule (2-year horizon)
  REDIM netpost0(h12%, h3%), netpost1(h12%, h3%, h12n%, h3n%)
  FOR i% = 1 TO h12%
    FOR j% = 1 TO h3%
      netpost0(i%, j%) = netpost(i%, j%)
    NEXT j%
  NEXT i%
  REDIM precode%(h12n%), preAvRat(h12n%)
  REDIM d2w(wnum%, h12n%), precost(h12n%)
  REDIM d3w(wnum%, h12n%, h3n%), postcost(h12n%, h3n%)
  REDIM yldpost(h12n%, h3n%), netpost(h12n%, h3n%)
  IF fld(f%).rotation = 1 THEN
    nextcrop% = 1 + cropnum% MOD 2
    plcost = crop(nextcrop%).seedRate * crop(nextcrop%).seedPric +
      mach(mp%).CostAc
    CALL WSNextYear(f%, wnum%, nextcrop%, compmax%, h1n%, h2n%, h12n%,
      h3n%, t%, r, mf%, ms%, mr%, mp%, k1n%(), k2n%(), k3n%(), fld(),
      weed(), mach(), comp(), crop(), ppinext(), prenext(), postnext(),
      s0w(), s0w1(), s1w(), s2w(), s3w(), d1w(), d2w(), d3w(),
      yldpost(), precost(), netpost0(), netpost1(), plcost, theta,
      netpost(), postcost(), precode%(), preAvRat(), h12%, h3%)
    CALL WSTopRev(h12%, h3%, h12n%, h3n%, theta, netpost1(), kimax%,
      kjmax%, topnet)
    ELSE
    nextcrop% = cropnum%
    plcost = crop(nextcrop%).seedRate * crop(nextcrop%).seedPric +
      mach(mp%).CostAc
    CALL WSNextYear(f%, wnum%, nextcrop%, compmax%, h1%, h2%, h12%, h3%,
      t%, r, mf%, ms%, mr%, mp%, k1%(), k2%(), k3%(), fld(), weed(),
      mach(), comp(), crop(), ppiherb(), preherb(), postherb(), s0w(),
      s0w1(), s1w(), s2w(), s3w(), d1w(), d2w(), d3w(), yldpost(),
      precost(), netpost0(), netpost1(), plcost, theta, netpost(),
      postcost(), precode%(), preAvRat(), h12%, h3%)
    CALL WSTopRev(h12%, h3%, h12%, h3%, theta, netpost1(), kimax%,
      kjmax%, topnet)
  END IF
  topnet = topnet / 2
'Myopic decision rule
  ELSE
    CALL WSTopRevMyopic(h12%, h3%, netpost(), theta, kimax%, kjmax%,
      topnet)
END IF
```

```
SELECT CASE kimax%
  CASE IS <= h1%
    fld(f%).preApTim = 1
    fld(f%).prename = ppiherb(kimax%).hname
    fld(f%).precode = ppiherb(kimax%).herbId
    fld(f%).precost = ppiherb(kimax%).unitCost * ppiherb(kimax%).avrate
    fld(f%).preload = ppiherb(kimax%).avrate
  CASE IS > h1%
    fld(f%).preApTim = 2
    fld(f%).prename = preherb(kimax% - h1% + 1).hname
    fld(f%).precode = preherb(kimax% - h1% + 1).herbId
    fld(f%).precost = preherb(kimax% - h1% + 1).unitCost *
      preherb(kimax% - h1% + 1).avrate
    fld(f%).preload = preherb(kimax% - h1% + 1).avrate
END SELECT
fld(f%).postname = postherb(kjmax%).hname
fld(f%).postcode = postherb(kjmax%).herbId
fld(f%).postcost = postherb(kjmax%).unitCost * postherb(kjmax%).avrate
fld(f%).postload = postherb(kjmax%).avrate

END SUB
```

```
SUB WSNextYear (f%, wnum%, cropnum%, compmax%, h1%, h2%, h12%, h3%, t%,
  r, mf%, ms%, mr%, mp%, k1%(), k2%(), k3%(), fld() AS ftype, weed() AS
  wfile, mach() AS mfile, comp() AS cfile, crop() AS cropfile, ppiherb()
  AS hfile, preherb() AS hfile, postherb() AS hfile, s0w(), s0wl(),
  s1w(), s2w(), s3w(), d1w(), d2w(), d3w(), yldpost(), precost(),
  netpost0(), netpost1(), p1cost, theta, netpost(), postcost(),
  precode%(), preAvRat(), h12o%, h3o%) STATIC
'                                                 Last update: 05/01/91
'*********************************************************************
'*                          WSNextYear                               *
'* For each weed treatment strategy pair (PRE,POST) in the current year,
'* subprogram WSNextYear calcuates discounted net returns to each    *
'* possible strategy pair in the next crop season.                   *
'*                                                                   *
'* Parameters passed to WSNextYear are:                              *
'*     f%                      Current field number                  *
'*     cropnum%                Current field crop number             *
'*     wnum%                   Number of weed species                *
'*     compmax%                Maximum number of obs. in weed comp file
'*     h1%                     Number of PPI treatments (next year)  *
'*     h2%                     Number of PRE treatments (next year)  *
'*     h12%                    Number of PPI + PRE trts. (next year) *
'*     h3%                     Number of POST treatments (next year) *
'*     h12o%                   Number of PPI/PRE treatments (this year)
'*     h3o%                    Number of POST treatments (this year) *
'*     s0wl%(w%,i%,j%)         Array of seedbank outcomes from current*
'*                             year by PRE & POST treatment          *
'*     ywf                     Weed-free yield                       *
'*     t%                      Year                                  *
'*     r                       Discount rate                         *
'*     mf%, ms%, mr%, mp%      Field cultivator, sprayer, rotary hoe, *
'*                             and planter machinery codes           *
'*     mach()                  Record array of machinery data        *
'*     crop()                  Record array of crop data             *
'*     comp()                  Record array of weed competition  data *
'*     weed()                  Record array of weed parameters       *
'*     s0w(),s1w(),s2w(),s3w() Arrays of seedbank densities          *
'*     s0germ(w%)              Array of pre-plant germination rates  *
'*     s1germ(w%)              Array of germ. rates before POST trt. *
'*     s2germ(w%)              Array of germ. rates after POST trt.  *
'*     fld()                   Record array of field data            *
'*     cropnum%                Crop code for current field           *
'*     k1%(),k2%(),k3%()       Arrays of effic. ratings (PPI,PRE,POST)*
'*     ppiherb()               Record array of PPI treatment parameters
'*     preherb()               Record array of PRE treatment parameters
'*     postherb()              Record array of POST treatment params. *
'*     compmax%                Number of obs. in competition array   *
'*     theta                   Proportion by which weed treatment    *
'*                             threshold net revenue to exceed no    *
```

```
'*                                  control net revenue level.              *
'*    d1w(),d2w(),d3w()             Arrays of emerged weed densities        *
'*    precost()                     Array of costs before POST trt.         *
'*    precode%()                    Array of PPI/PRE codes                  *
'*    preAvRat()                    Array of average herbicide rates        *
'*    postcost()                    Array of costs from POST trt.           *
'*    plcost                        Cost of planting                        *
'*    yldpost()                     Array of expected yields                *
'*    netpost0()                    Array of expected net returns (cur. yr)*
'*                                                                          *
'* Arguments output by WSNextYear are:                                      *
'*    netpost1(i,j,k,l)             Array of discounted net returns         *
'*                                  resulting from all combinations of      *
'*                                  treatments over two years.              *
'***************************************************************************
REDIM s0wtemp(wnum%), d3wij(wnum%)
REDIM Ew0(wnum%), Ew1(wnum%), Ew2(wnum%)
tt% = t% + 1
FOR i% = 1 TO h12o%
 FOR j% = 1 TO h3o%
   FOR w% = 1 TO wnum%
     s0wtemp(w%) = s0w1(w%, i%, j%)
     Ew0(w%) = (weed(w%).avgerm * weed(w%).s0propn * s0wtemp(w%)) +
       (weed(w%).w0int + weed(w%).w0s * s0wtemp(w%) + weed(w%).w0s2 *
       s0wtemp(w%) ^ 2)
     Ew1(w%) = (weed(w%).avgerm * weed(w%).s1propn * s0wtemp(w%)) +
       (weed(w%).w1int + weed(w%).w1s * s0wtemp(w%) + weed(w%).w1s2 *
       s0wtemp(w%) ^ 2)
     Ew2(w%) = (weed(w%).avgerm * weed(w%).s2propn * s0wtemp(w%)) +
       (weed(w%).w2int + weed(w%).w2s * s0wtemp(w%))
   NEXT w%
   maxyld = crop(cropnum%).expMaxY
   rot% = fld(f%).rotation
   fsize% = fld(f%).fsize
   CALL WSWeedGerm(wnum%, weed(), s0wtemp(), s1w(), s2w(), d1w(),
     Ew0(), Ew1())
   CALL WSPreTrt(wnum%, h1%, h2%, mf%, ms%, k1%(), k2%(), d1w(),
     fld(f%).ywf, ppiherb(), preherb(), mach(), fld(f%).fsize, plcost,
     h12%, d2w(), precost(), precode%(), preAvRat())
   CALL WSPostTrt(cropnum%, wnum%, h12%, h3%, maxyld, rot%, k3%(),
     d2w(), s0w(), s2w(), weed(), crop(), precode%(), preAvRat(),
     postherb(), compmax%, comp(), mach(), ms%, mr%, fsize%, d3w(),
     d3wij(), s3w(), yldpost(), postcost(), Ew2())
   CALL WSPostRev(h12%, h3%, crop(cropnum%).price, yldpost(),
     postcost(), precost(), tt%, r, fld(f%).fsize, crop(cropnum%).vc,
     netpost())
   FOR k% = 1 TO h12%
     FOR l% = 1 TO h3%
       netpost1(i%, j%, k%, l%) = netpost0(i%, j%) + netpost(k%, l%)
```

```
      NEXT l%
    NEXT k%
  NEXT j%
NEXT i%
END SUB


SUB WSPostRev (h12%, h3%, p, yldpost(), postcost(), precost(), t%, r,
  fldSize%, vc, netpost())
  '                                     Last update: 02/05/91
 '***********************************************************************
 '*                              WSPostRev                              *
 '* This subprogram calculates the present value of net revenue by     *
 '* treatment pair after POST treatment.                                *
 '*                                                                     *
 '* Parameters passed to subprogram PostRev are:                       *
 '*      h12%                    Number of PPI/PRE treatments          *
 '*      h3%                     Number of POST treatments             *
 '*      p                       Price of crop                         *
 '*      yldpost(i,j)            Array of expected prdn. after POST trt*
 '*      postcost(i,j)           Array of POST treatment costs         *
 '*      precost(i)              Array of PRE treatment costs          *
 '*      t%                      Year                                  *
 '*      r                       Discount rate                         *
 '*      fldSize%                Field size                            *
 '*      vc                      Variable cost/acre for crop (net of   *
 '*                              weed trt)                             *
 '*                                                                     *
 '* Variables returned by subprogram PostRev are:                      *
 '*      netpost(i,j)            Present value of net revenue by trt pair
 '***********************************************************************
 '
 FOR i% = 1 TO h12%
   FOR j% = 1 TO h3%
     netpost(i%, j%) = ((p * yldpost(i%, j%) - vc) * fldSize% -
       (postcost(i%, j%) + precost(i%))) / (1 + r) ^ t%
     'PRINT i%, j%, netpost(i%, j%)
   NEXT j%
 NEXT i%
 'resume$ = INPUT$(1)
 END SUB
```

```
SUB WSPostReviseTrt (cropnum%, wnum%, h1%, h3%, ywf, rot%, k3%(), d2w(),
  s0w(), s2w(), weedparm() AS wfile, crop() AS cropfile, precode%(),
  preAvRat(), postherb() AS hfile, compmax%, compparm() AS cfile,
  sprayCst, fldSize%, d3w(), d3wij(), s3w(), yldpost(), postcost(),
  w2(), dropcode%, dropost%())
'                                          Last update: 04/29/91
'*********************************************************************
'*      WSPostReviseTrt                                              *
'* This subprogram calculates density of surviving weeds, adds late  *
'* germinating weeds, estimates crop yields, and updates the weed    *
'* seedbank after POST-emergent treatment.  If atrazine (code 103)   *
'* PRE and POST rate will exceed 3 lbs/acre, yield is set at zero (in *
'* order to exclude illegal use of atrazine).                        *
'*                                                                   *
'* Parameters passed to WSPostReviseTrt are:                         *
'*    cropnum%                 Code of current field crop            *
'*    wnum%                    Number of weed species                *
'*    h1%=1                    Number of PPI/PRE treatments          *
'*    h3%                      Number of POST treatments             *
'*    k3%(w%,j%)               Array of POST efficacy ratings by weed *
'*                             species and treatment                 *
'*    w2(w%,i%)                Array of emerged weed seedlings by PRE *
'*                             treatment                             *
'*    s0w(w%)                  Array of initial weed seedbank densitie*
'*    s2w(w%)                  Array of seedbank densities after PRE *
'*    weedparm()               Array of weed germination, death params*
'*    compparm()               Array of competition parameters       *
'*    compmax%                 Number of records in compparm()       *
'*    crop()                   Record array of crop data             *
'*    ywf                      Expected weed-free yield              *
'*    rot%                     Rotation                              *
'*    sprayCst                 Cost of spraying                      *
'*    fldSize%                 Field size                            *
'*    precode%()               PPI/PRE treatment codes array         *
'*    preAvRat()               PPI/PRE treatment avg. rates array    *
'*    postherb()               POST treatment parameter array        *
'*    dropcode%                Code for infeasible recommended POST trt
'*    dropost%(j)              Array of infeasible POST treatments   *
'*                                                                   *
'* Variables returned by WSPostReviseTrt are:                        *
'*    d3w(w%,i%,j%)            Array of weed densities at harvest by *
'*                             PRE and POST treatments.  Assumes cult.*
'*                             kills 80% of d2w().                   *
'*    s3w(w%)                  Array of weed seed densities at harvest*
'*    yldpost(i%,j%)           Array of expected field crop production*
'*                             by PRE & POST treatments              *
'*    postcost(j%)             Array of POST treatment costs         *
'*********************************************************************
'
```

```
FOR i% = 1 TO h1%
  FOR j% = 1 TO h3%
    IF dropcode% = postherb(j%).herbId THEN
      droppost%(j%) = true%
      dropcode% = -1
    END IF
    FOR w1% = 1 TO wnum%
      IF droppost%(j%) = true% THEN
        kill3% = -9
        ELSE
        kill3% = k3%(w1%, j%)
      END IF
'       d3w(w1%, i%, j%) = surv(k3%(w1%, j%)) * d2w(w1%, i%) +
        weedparm(w1%).s2germ * s2w(w1%)
      d3w(w1%, i%, j%) = surv(kill3%) * d2w(w1%, i%) + w2(w1%)
      d3wij(w1%) = d3w(w1%, i%, j%)
    NEXT w1%
    yldpost(i%, j%) = yield2(wnum%, ywf, cropnum%, compmax%, compparm(),
      crop(), d3wij())
    IF (precode%(i%) = 103 AND postherb(j%).herbId = 103 AND
      (preAvRat(i%) + postherb(j%).avrate > 3)) THEN yldpost(i%, j%) = 0
    IF (rot% = 1) AND (precode%(i%) = 103 OR postherb(j%).herbId = 103)
      THEN yldpost(i%, j%) = 0
    IF postherb(j%).herbId = 0 THEN
      appcost = 0
      ELSE
      appcost = sprayCst
    END IF
    postcost(i%, j%) = (postherb(j%).unitCost * postherb(j%).avrate +
      appcost) * fldSize%
  NEXT j%
NEXT i%
'
FOR w% = 1 TO wnum%
' s3w(w%) = (1 - weedparm(w%).s2germ) * s2w(w%) - weedparm(w%).s3death
* s0w(w%)
  s3w(w%) = s2w(w%) - w2(w%) - weedparm(w%).s3mortpn * (1 -
    weedparm(w%).avgerm) * s0w(w%)
NEXT w%
END SUB
```

```
SUB WSPostTrt (cropnum%, wnum%, h12%, h3%, ywf, rot%, k3%(), d2w(),
  s0w(), s2w(), weedparm() AS wfile, crop() AS cropfile, precode%(),
  preAvRat(), postherb() AS hfile, compmax%, compparm() AS cfile, mach()
  AS mfile, ms%, mr%, fldSize%, d3w(), d3wij(), s3w(), yldpost(),
  postcost(), w2()) STATIC
'                                               Last update 04/22/91
'***********************************************************************
'*                                       WSPostTrt                     *
'* This subprogram calculates density of surviving weeds, adds late    *
'* germinating weeds, estimates crop yields, and updates the weed      *
'* seedbank after POST-emergent treatment. If atrazine (code 103)      *
'* PRE and POST rate will exceed 3 lbs/acre, yield is set at zero (in  *
'* order to exclude illegal use of atrazine).                          *
'*                                                                     *
'* Parameters passed to WSPostTrt are:                                 *
'*      cropnum%               Code for current field crop             *
'*      wnum%                  Number of weed species                  *
'*      h12%                   Number of PPI/PRE treatments            *
'*      h3%                    Number of POST treatments               *
'*      compmax%               Number of records in compparm()         *
'*      ms%,mr%                Sprayer and rotary hoe machine codes    *
'*      fldSize%               Field size                              *
'*      k3%(w%,j%)             Array of POST efficacy ratings by weed  *
'*                             species and treatment                   *
'*      d2w(w%,i%)             Array of emerged weed seedlings by PRE  *
'*                             treatment                               *
'*      w2(w)                  Expected post-cult weed emergence       *
'*      s0w(w%)                Array of initial weed seedbank densitie*
'*      s2w(w%)                Array of seedbank densities after PRE   *
'*      weedparm()             Array of weed germination, death params*
'*      compparm()             Array of competition parameters         *
'*      crop()                 Record array of crop data               *
'*      mach()                 Record array of machinery data          *
'*      ywf                    Expected weed-free yield                *
'*      rot%                   Rotation                                *
'*      precode%()             PPI/PRE treatment codes array           *
'*      preAvRat()             PPI/PRE treatment avg. rates array      *
'*      postherb()             POST treatment parameter array          *
'*                                                                     *
'* Variables returned by WSPostTrt are:                                *
'*      d3w(w%,i%,j%)          Array of weed densities at harvest by   *
'*                             PRE and POST treatments.  Assumes cult.*
'*                             kills 80% of d2w().                     *
'*      s3w(w%)                Array of weed seed densities at harvest*
'*      yldpost(i%,j%)         Array of expected field crop production*
'*                             by PRE & POST treatments                *
'*      postcost(j%)           Array of POST treatment costs           *
'***********************************************************************
'
```

```
REDIM seedmort(wnum%)

FOR i% = 1 TO h12%
  FOR j% = 1 TO h3%
    FOR wl% = 1 TO wnum%
'       d3w(wl%, i%, j%) = surv(k3%(wl%, j%)) * d2w(wl%, i%) +
      weedparm(wl%).s2germ * s2w(wl%)
      d3w(wl%, i%, j%) = surv(k3%(wl%, j%)) * d2w(wl%, i%) + w2(wl%)
      d3wij(wl%) = d3w(wl%, i%, j%)
    NEXT wl%
    yldpost(i%, j%) = yield2(wnum%, ywf, cropnum%, compmax%, compparm(),
      crop(), d3wij())
    IF (precode%(i%) = 103 AND postherb(j%).herbId = 103 AND
      (preAvRat(i%) + postherb(j%).avrate > 3)) THEN yldpost(i%, j%) = 0
    IF (rot% = 1) AND (precode%(i%) = 103 OR postherb(j%).herbId = 103)
      THEN yldpost(i%, j%) = 0
    IF postherb(j%).herbId = 0 THEN
      appcost = 0
      ELSEIF postherb(j%).herbId = 10 THEN
        appcost = mach(mr%).CostAc
        IF cropnum% = 1 THEN yldpost(i%, j%) = .985 * yldpost(i%, j%)
        'NB: This 1.5% yield loss corresponds to stand loss of 2-5%
          (Gunsolus)
      ELSE
      appcost = mach(ms%).CostAc
    END IF
    postcost(i%, j%) = (postherb(j%).unitCost * postherb(j%).avrate +
      appcost) * fldSize%
    'PRINT USING "######"; i%; j%; d3w(1, i%, j%); yldpost(i%, j%);
      postcost(i%, j%)
  NEXT j%
NEXT i%
'resume$ = INPUT$(1)
'
FOR w% = 1 TO wnum%
'  s3w(w%) = (1 - weedparm(w%).s2germ) * s2w(w%) - weedparm(w%).s3death
* s0w(w%)
  s3w(w%) = s2w(w%) - w2(w%) - weedparm(w%).s3mortpn * (1 -
    weedparm(w%).avgerm) * s0w(w%)
NEXT w%
END SUB
```

```
SUB WSPreTrt (wnum%, h1%, h2%, mf%, ms%, k1%(), k2%(), d1w(), ywf,
  ppiherb() AS hfile, preherb() AS hfile, mach() AS mfile, fldSize%,
  plcost, h12%, d2w(), precost(), precode%(), preAvRat())
'                                            Last update: 02/05/91
'*************************************************************************
'*                                  WSPreTrt                             *
'* This subprogram calculates density of surviving weeds and corres-     *
'* ponding yields after PRE-emergent treatment.                          *
'*                                                                       *
'* Parameters passed to subprogram WSPreTrt are:                         *
'*      wnum%                   Number of weed species in model          *
'*      h1%                     Number of PPI treatments                 *
'*      h2%                     Number of PRE treatments                 *
'*      h12%                    Number of PPI + PRE treatments (-1)      *
'*      mf%                     User-designated field cultivator code    *
'*      ms%                     User-designated spray rig machinery code
'*      k1%(w%,g%)              Array of PPI efficacy ratings            *
'*      k2%(w%,i%)              Array of PRE efficacy ratings for contrl
'*                              i% on weed species w%                    *
'*      d1w(w%)                 Array of weed densities prior to PRE trt
'*      ywf                     Weed-free yield for this field           *
'*      ppiherb()               Record array of PPI trt. costs, rates    *
'*      preherb()               Record array of PRE trt. costs, rates    *
'*      fldSize%                Field size (acres)                       *
'*      mach()                  Array of machinery names, costs, rates   *
'*      plcost                  Cost of planting crop                    *
'*      fldSize%                Field size                               *
'*                                                                       *
'* Variables returned by subprogram WSPreTrt are:                        *
'*      d2w(w%,i%)              Array of emerged weed densities          *
'*      precost(i%)             Array of total PRE treatment costs       *
'*      preAvRat(i%)            Array of PRE/PPI average rates           *
'*      precode%(i)             Array of PRE/PPI treatment codes         *
'*************************************************************************
FOR g% = 1 TO h1%
  FOR w% = 1 TO wnum%
    d2w(w%, g%) = surv(k1%(w%, g%)) * d1w(w%)
  NEXT w%
  IF ppiherb(g%).herbId = 0 THEN
    appcost = mach(mf%).CostAc
    ELSE
    appcost = (mach(mf%).CostAc + mach(ms%).CostAc)
  END IF
  precost(g%) = (ppiherb(g%).unitCost * ppiherb(g%).avrate + appcost +
    plcost) * fldSize%
  precode%(g%) = ppiherb(g%).herbId
  preAvRat(g%) = ppiherb(g%).avrate
NEXT g%
j% = h1%
```

```
FOR i% = 1 TO h2%
  IF preherb(i%).herbId = 0 THEN GOTO DropNoControl:
  j% = j% + 1
  FOR w% = 1 TO wnum%
    d2w(w%, j%) = surv(k2%(w%, i%)) * d1w(w%)
  NEXT w%
  appcost = (mach(mf%).CostAc + mach(ms%).CostAc)
  precost(j%) = (preherb(i%).unitCost * preherb(i%).avrate + appcost +
    plcost) * fldSize%
  precode%(j%) = preherb(i%).herbId
  preAvRat(j%) = preherb(i%).avrate
DropNoControl:
NEXT i%
END SUB
```

```
SUB WSSeedBank (wnum%, h12%, h3%, d3w(), s3w(), weed() AS wfile, sOwl(),
  w2())
'                                      Last update: 05-02-91
'***********************************************************************
'*                                 WSSeedBank                          *
'* This subprogram calculates the post-harvest weed seed bank for each*
'* species.                                                            *
'*                                                                     *
'* Parameters passed to subprogram WSSeedBank are:                     *
'*      wnum%                Number of weed species                    *
'*      h12%                 Number of PPI/PRE treatments              *
'*      h3%                  Number of POST treatments                 *
'*      d3w(w%,i%,j%)        Array of weed densities at harvest for each *
'*                           PRE/PPI and POST treatment.               *
'*      s3w(w)               Post-cult weed seed density               *
'*      w2(w)                Post-cult weed germination                *
'*      weed(w%).w1propag Mean seeds per mature post-plant weed        *
'*                           NB: 80% post-plant weeds assumed killed by *
'*                           cultivation                               *
'*      weed(w%).w2propag Mean seeds per mature post-cult. weed        *
'*      experr(w)            Array of expected values for error term   *
'*                                                                     *
'* Variables returned by subprogram WSSeedBank are:                    *
'*      sOwl(w%,i%,j%)       Array of expected seed bank densities post- *
'*                           harvest, by weed species and PPI/PRE and POST*
'***********************************************************************
REDIM experr(wnum%)
experr(1) = 407
experr(2) = 95
experr(3) = 198
FOR i% = 1 TO h12%
  FOR j%= 1 TO h3%
    FOR w% = 1 TO wnum%
      sOwl(w%, i%, j%) = s3w(w%) + weed(w%).w1propag * .2 * (d3w(w%, i%,
        j%) - w2(w%)) + weed(w%).w2propag * w2(w%) + experr(w%)
      IF sOwl(w%, i%, j%) < 0 THEN sOwl(w%, i%, j%) = 0
    NEXT w%
  NEXT j%
NEXT i%
END SUB
```

```
SUB WSTopRev (h12o%, h3o%, h12%, h3%, theta, netpostl(), kimax%, kjmax%,
 topnet)
'                                        Last update: 02/12/91
'**********************************************************************
'*                                  WSTopRev                          *
'* This subprogram identifies the strategy with the highest net revenue*
'* exceeding the B/C threshold.                                       *
'*                                                                    *
'* Parameters passed to subprogram WSTopRev are:                      *
'*       h12%                       Number of PPI/PRE treatments (year 0)  *
'*       h3%                        Number of POST treatments (year 0)  *
'*       h12o%                      Number of PPI/PRE treatments (year 1)  *
'*       h3o%                       Number of POST treatments (year 1)  *
'*       netpostl(i,j,m,n)          Array of net revenues from 2-yrs strats*
'*       theta                      Proportion by which weed treatment  *
'*                                  threshold net revenue to exceed no  *
'*                                  control net revenue level.        *
'*                                                                    *
'* Variables returned by subprogram WSTopRev are:                     *
'*       topnet                     Highest net revenue of 2-yrs strategies*
'*       kimax%                     PRE trt. no. earning highest net revenue
'*       kjmax%                     POST trt. no. earning highest net rev. *
'**********************************************************************
'
topnet = (1 + theta) * netpostl(1, 1, 1, 1)
kimax% = 1
kjmax% = 1
FOR i% = 1 TO h12o%
  FOR j% = 1 TO h3o%
    FOR m% = 1 TO h12%
      FOR n% = 1 TO h3%
        IF netpostl(i%, j%, m%, n%) > topnet THEN
          topnet = netpostl(i%, j%, m%, n%)
          kimax% = i%
          kjmax% = j%
        END IF
      NEXT n%
    NEXT m%
  NEXT j%
NEXT i%
ERASE netpostl
END SUB
```

```
SUB WSTopRevMyopic (h12%, h3%, netpost(), theta, kimax%, kjmax%, topnet)
'                                              Last update: 04/21/91
'***********************************************************************
'*                                  WSTopRevMyopic                     *
'* This subprogram identifies the strategy with the highest net revenue*
'* exceeding the B/C threshold among myopic 1-year strategies.         *
'*                                                                     *
'* Parameters passed to subprogram WSTopRevMyopic are:                 *
'*     h12%                        Number of PPI/PRE treatments        *
'*     h3%                         Number of POST treatments           *
'*     netpost(i,j)                Array of net revenues from 1-yr strats.*
'*     theta                       Proportion by which weed treatment  *
'*                                 threshold net revenue to exceed no  *
'*                                 control net revenue level.          *
'*                                                                     *
'* Variables returned by subprogram WSTopRevMyopic are:                *
'*     topnet                      Highest net revenue of 2-yrs strategies*
'*     kimax%                      PRE trt. no. earning highest net revenue
'*     kjmax%                      POST trt. no. earning highest net rev. *
'***********************************************************************
'

topnet = (1 + theta) * netpost(1, 1)
kimax% = 1
kjmax% = 1
FOR i% = 1 TO h12%
  FOR j% = 1 TO h3%
    IF (netpost(i%, j%) > topnet) THEN
      topnet = netpost(i%, j%)
      kimax% = i%
      kjmax% = j%
    END IF
  NEXT j%
NEXT i%
END SUB
```

```
SUB WSWeedGerm (wnum%, weed() AS wfile, s0w(), s1w(), s2w(), d1w(),
  w0(), w1())
'                                          Last update: 04/19/91
'***********************************************************************
'*                              WSWeedGerm                             *
'* This subprogram calculates weed seedling germination as a function *
'* of seeds from previous season.                                      *
'*                                                                     *
'* Parameters passed to subprogram WeedGerm are:                       *
'*    wnum%                     Number of weed species                 *
'*    s0w(w%)                   Array of initial seedbank densities for*
'*                              species w% (seeds/m2)                  *
'*    weed(w%).s0germ           Array of pre-plant germination props.  *
'*    weed(w%).s1germ           Array of germination proportions at PRE*
'*                              treatment                              *
'*    w0(w%)                    Array of pre-plant germ. densities     *
'*    w1(w%)                    Array of post-plant germ. densities    *
'*                                                                     *
'* Variables returned by subprogram WeedGerm are:                      *
'*    s1w(w%)                   Array of seedbank densities for species*
'*                              w% at planting                         *
'*    d1w(w%)                   Array of emerged weed densities prior to
'*                              PRE treatment                          *
'*    s2w(w%)                   Array of seedbank densities prior to PRE
'*                              treatment                              *
'***********************************************************************
'
FOR w% = 1 TO wnum%
'  s1w(w%) = (1 - weed(w%).s0germ) * s0w(w%)
' d1w(w%) = weed(w%).s1germ * s1w(w%)
 s1w(w%) = s0w(w%) - w0(w%)
 d1w(w%) = w1(w%)
  s2w(w%) = (s1w(w%) - d1w(w%))
NEXT w%
'  swlost(f%, w%) = w0germ(f%, w%) + w1germ(f%, w%)
END SUB
```

```
FUNCTION yield2 (wnum%, ywf, cropnum%, compmax%, comp() AS cfile, crop()
 AS cropfile, d())
'                                        Last update: 12/16/90
'*************************************************************************
'*                           yield2                                      *
'* This function calculates expected yield based upon weed density.      *
'*                                                                       *
'* The yield equation is from Cousens' hyperbolic model with individual*
'* weed species.  At weed densities approaching zero, percent yield loss
'* is given by comp().i for species w% in crop c%.  Maximum percent yld*
'* loss density of all weeds approaches infinity is crop().a.            *
'*                                                                       *
'* Parameters passed to function yield are:                              *
'*    wnum%                  Number of weed species                      *
'*    ywf                    Expected weed-free yield                    *
'*    cropnum%               Crop code                                   *
'*    compmax%               Number of observations in competition       *
'*                           array                                       *
'*    comp()                 Record array of weed-crop competition       *
'*                           parameters, including comp().i              *
'*    crop()                 Record array of crop parameters, incl.      *
'*                           crop().a, maximum percent yield loss        *
'*                           from weed competition                       *
'*      d(w%)                Array of weed densities/m2                  *
'*                                                                       *
'* The value returned by function yield is:                              *
'*    yield2                 Expected crop yield                         *
'*************************************************************************
'
a% = crop(cropnum%).a
idsum = 0
FOR c% = 1 TO compmax%
  cropId% = comp(c%).cropId
  IF cropId% = cropnum% THEN
    w% = comp(c%).weedId
    id = comp(c%).i * d(w%)
    idsum = idsum + id
  END IF
NEXT c%
yield2 = ywf * (1 - idsum / (100 * (1 + idsum / a%)))
END FUNCTION
```

```
FUNCTION ypen (cropId%, ywf, plwk%)
'                                                    Last update: 05-02-91
'**********************************************************************
'*                              ycpen                                  *
'*    Function ypen() calculates a crop yield penalty due to late      *
'* planting.  Value returned by ycpen is the proportion of potential   *
'* yield lost.                                                         *
'*                                                                     *
'* Parameters passed to ypen are:                                      *
'*          cropId%              Crop identification code              *
'*          ywf                  Maximum weed-free yield               *
'*          plwk%                Planting week                         *
'*                                                                     *
'* Data for yield penalty functions from: J.L. Gunsolus, "Mechanical and
'* Cultural Weed Control in Corn and Soybeans," Am. J. Alt. Ag.        *
'* 5(1990): 114-119.                                                   *
'**********************************************************************
'
plday% = 112 + plwk% * 7
SELECT CASE cropId%
CASE 1
  SELECT CASE plday%
    CASE IS <= 120
      ypen = 0
    CASE 121 TO 130
      ypen = .07
    CASE 131 TO 145
      ypen = .13
    CASE IS >= 146
      ypen = .24
  END SELECT
CASE 2
  SELECT CASE plday%
    CASE IS <= 135
      ypen = 0
    CASE 136 TO 145
      ypen = .03
    CASE 145 TO 156
      ypen = .09
    CASE 157 TO 166
      ypen = .18
    CASE 167 TO 176
      ypen = .3
    CASE IS >= 176
      ypen = .43
  END SELECT
END SELECT
END FUNCTION
```

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