Staff Paper

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A BIOECONOMIC MODEL FOR WEED MANAGEMENT IN CORN AND SOYBEAN

Abstract

A bioeconomic model of weed management in corn and soybean called WEEDSIM is introduced. WEEDSIM innovates beyond existing decision support models by incorporating weed population dynamics into the decision rule, while at the same time accommodating multiple weed species and control treatments. The associated WFARM model provides a whole-farm shell, making it possible either to modify WEEDSIM recommendations in a context where field time is limiting, or to evaluate the performance of WEEDSIM recommendations over various states of nature. WEEDSIM and WFARM are modularly programmed and rely on external data files, making them easily modified and expanded.

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Introduction

Weeds cause crop losses to U.S. corn and soybean producers valued annually in the billions of dollars (Chandler et al.). Herbicides are the chief means of weed control for these farmers. The advent of herbicides has permitted U.S. farmers to achieve higher yields with less labor. Herbicides' high efficacy, rapid application, and potential for pre-emergent weed control have also ameliorated the risk of failing to complete field work due to unsuitable weather.

Nonetheless, weed control is expensive. Herbicides accounted for virtually all of the $20.48 per acre spent by the average U.S. soybean grower on agricultural chemicals in 1990. Chemicals constituted the largest single component (29%) of variable operating costs. Herbicides also account for the lion's share of the $22.64 per acre spent by the average U.S. corn grower on chemicals. After fertilizer, chemicals are the second largest component (17%) of variable costs in U.S. corn production (USDA 1991a and 1991b).

The potential health hazard posed by pesticides has raised public concern about their use. Herbicides contribute significantly to groundwater contamination in rural areas. Fully 96% 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) and constituted roughly ten times as much quantity of chemical active ingredient as the total for both insecticides and fungicides on these crops (USDA 1991a). 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). In addition, there is growing evidence that herbicide use may be associated with certain types of cancer (Hoar et al., Wigle et al.).

Cost and health concerns combine to provide farmers with a powerful incentive to manage weed control actions carefully. One means to this end is to base weed management on specific, quantitative information about weed populations. In order to develop suitable models and the agronomic data they require, a regional research project was recently organized.[1] This move toward information-based, integrated weed management represents an important shift from the routine chemical treatment that has become the norm for weed management in U.S. field crops.

Previous Weed Management Models

Integrated management of pests in general--and weeds in particular--identifies pest population thresholds at which control is justified. Existing weed management models can be divided between research models and practical models. The former deepen our understanding of how weed-crop ecology works. However, they tend to be narrowly focused, typically involving a single crop, one or two weed species, and a single control treatment. By contrast, the practical models typically cover a broad range of weed species and controls, but do so in a limited fashion.

Until now, no weed management model has combined dynamic analysis with either multiple individual weed species or 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), Renner and Black (1991), Wilkerson et al. 1991). Pannell (1990a and 1990b) and Deen et al. have modeled static control of a single species in a single crop with variable rates of a single treatment.

Perhaps the most important contribution of the research models has been to demonstrate that the economic threshold for weed control occurs at a lower weed density in a dynamic model (which includes weed population growth parameters) than a static one (which does not) (Auld et al., Cousens et al. 1986, Doyle et al., Murdoch, Pandey 1989). Doyle et al. and Cousens et al. (1986) found that upon reaching a steady state managed weed population, 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. Taylor and Burt used dynamic programming to show that wheat-fallow rotations could provide a nearly optimal control for wild oat in Montana.

The practical models divide into two groups, herbicide efficacy models and bioeconomic models. The efficacy models (e.g., Kells and Black, Kidder et al., Renner and Black (1991)) identify the herbicides that best control a given complex of weed species. They cover a wide range of weed species and herbicides, the latter in both single and tank mix forms. They include soil-applied as well as post-emergent weed control, using herbicide rates from product labels and efficacy ratings from university research. While the efficacy models offer a comprehensive database for identifying the herbicide(s) which will do the best job of killing a given set of weeds, they do not make the connection to yield loss averted.

Basing weed control recommendations upon expected yield loss is the defining characteristic of the bioeconomic weed management models. HERB (Wilkerson et al.) is the first bioeconomic weed management model to be tested over a broad geographic area. Now publicly distributed, HERB makes recommendations on post-emergent weed control in soybeans. It predicts yield loss in response to a competitive index of weed species densities. The index is a linear combination of least squares estimates of relative weed competitiveness (Coble). HERB includes a wide range of post-emergent soybean herbicides.

A bioeconomic model for more comprehensive weed control in continuous corn is being tested at Colorado State University (Lybecker et al. 1991b). The Colorado model offers weed control recommendations for both soil-applied and post-emergent weed control. Recommendations for soil-applied control are based upon weed seed counts. Seed germination is simulated and crop yield loss projected for the resulting weed population. Post-emergent recommendations can be based upon direct observation of field weed density, or on model projections. The Colorado model uses a competitive index developed from weed competitiveness evaluations from a survey of weed scientists.

The existing bioeconomic models for weed management suffer from several drawbacks. First, they do not capture the dynamic effect of weed seed production on the economic threshold for control. Second, they cannot accommodate multiple crops (ergo, crop rotations). Third, the micro, field-level unit of analysis for the existing weed management models ignores time constraints faced by managers who farm many fields. This is especially true of post-emergent weed control, whose efficacy may depend on its timing. Potential yield loss due to untimely planting and weed control in other fields makes optimal field-level decisions depend upon the state of other fields. The only published whole-farm weed management model is Olson and Eidman's MOTAD research study. Designed to analyze response to income risk and public policy, their model makes no attempt to simulate biological systems and includes only two control options: one fully chemical and one fully mechanical strategy.

The rest of this paper introduces WEEDSIM, a bioeconomic model for weed management in corn and soybean. As a dynamic, multiple species, multiple control bioeconomic model, WEEDSIM has the potential to identify weed management strategies that are more profitable than those currently in use. Previous dynamic weed-crop studies suggest that such a model may recommend less herbicide use over the long run than conventional practices which entail regular spraying. 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). An extension of WEEDSIM, WFARM, simulates weed management in a whole-farm setting, allowing re-evaluation of WEEDSIM recommendations in light of field time constraints due to competing tasks and/or inclement weather.

Theoretical framework

The classic static pest management model was set forth by Feder. Consider a slightly modified version of his model with a single weed pest and a single control treatment. Weeds may be controlled by a single mechanical and/or herbicidal treatment applied at the recommended (label) rate. Consequently, the decision to control is a binary one with an implicit pest population threshold at which the net benefits of control become positive (Auld et al.).

Profit maximization leads to the decision rule that weeds should be controlled at any pre-treatment density exceeding the weed population level "at which the cost of control measures equals the increased return on yield which would result" (Cousens 1987, p. 15). Expanding Feder's model to allow for multiple controls with varied efficacy levels, this implies choosing that weed treatment (including no control) which maximizes net revenues at recommended application rates[2].

Omission of weed seeds in the soil (the seed bank) is the major deficiency of this model. As Taylor and Burt observed, the static economic threshold ignores the fundamental recursion relationship inherent in this dynamic problem. The value of the current weed population is a function both of its impact on current season crop yields and of the value of future yields that can be reached from it. Failure to control weeds in the current period not only reduces current crop yields; it also leads to greater weed seed production, which reduces returns in the subsequent periods.

To overcome this omission, recast the Feder model in dynamic form so that the manager's objective is to maximize the present value of cumulative net income over the planning horizon t = 0...T (CNI_T),

$$\max_{h} CNI_T = \sum_{t=0}^{T} \frac{P\{Y_t^0 - D(w_t^h)\} - ch_t - C^0}{(1 + r)^t} \tag{1}$$

subject to the equations of motion,

$$w_t = w(s_{t-1}) \tag{2}$$

$$w_t^h = [1 - k(h)]w_t \tag{3}$$

$$s_t = s(s_{t-1}, w_t, w_t^h) \tag{4}$$

where t is a time subscript, Y^0 is weed-free crop yield, P is product price, $D(\cdot)$ is the yield loss or damage function, w is the weed density, w^h is density of weeds that survive to compete with the crop, and h is a binary weed treatment variable equal to h^r (the recommended treatment rate) or zero. The proportion of weeds killed by treatment h, is denoted $k(h) \in [0,1]$; c is unit cost of weed control, C^0 denotes fixed and variable costs unrelated to pest control, and r denotes the discount rate. It is assumed that damage increases with weed density, so $D'(w^h) > 0$. For simplicity, product and input prices are held constant. The seed bank function in (4), $s(\cdot)$, associates end of season weed seed bank density (s_t) with seed bank density in the previous season, (s_{t-1}), seed loss due to 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 germination function in (2) relates the current weed density to the previous seed bank, with $w'(s_{t-1}) > 0$ assumed.

The presence of the seed bank equation (4) is a distinguishing feature of this contribution to the family of practical models. The seed bank variable links control activities in one period to repercussions in subsequent ones. Under the assumptions stated above, differentiation of equation (1) with respect to the arguments of the seed bank equation (4) reveals that cumulative net income is decreasing with respect to the variables weed seed bank (s_t) and weeds at harvest (w_t^h) 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 cumulative net income 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 (1-4) is considerably more sensitive to control actions than its static analog.[3]

The bioeconomic weed management model

The WEEDSIM bioeconomic weed management decision aid solves the maximization problem in (1-4) for multiple weed species over a two-year time horizon (Swinton). Weeds may be controlled by chemical herbicides before they emerge from the soil as well as by chemical or mechanical means afterwards. The WEEDSIM model recommends an optimal weed control strategy for a two-year time horizon, based on expectations of the estimated weed density, predicted germination (for weed seed density estimates), predicted weed control efficacy, predicted yield loss, and predicted seed production. The model user provides estimates of expected prices, costs, weed-free yield goals, and weed population information. A flow chart of the model appears in Figure 1. In contrast with the simpler dynamic models of Taylor and Burt and King et al., it accommodates multiple weed species and multiple controls, which may include pre-plant incorporated (PPI) or pre-emergence (PRE) treatments as well as post-emergent (POST) ones. Its dynamic decision rule distinguishes it from the multiple species, multiple control models of Lybecker et al. (1991a, 1991b).

The empirical model

The empirical model implements the maximization problem in equations (1-4). It simulates the full range of expected discounted net incomes and associated herbicide loads from every possible pair of soil-applied and post-emergent weed management options in the model database. Management options are recommended based on the ranked distribution of financial outcomes. The model is driven by its component biological equations. These predict yield (the bracketed portion of equation (1)), untreated weed density (2), weeds at harvest (3), and the state of the weed seed pool in the soil (4). The rest of this section describes the form of the empirical equations used to simulate these relationships.

The yield equation is particularly important, since it predicts the relationship between weed pressure and output level for the marketable product. Competing biological theories support sigmoidal (Zimdahl) and hyperbolic (Cousens 1985) yield loss functions. The important economic difference is that sigmoidal functions tend to place the control threshold at a higher weed density than the hyperbolic functions. In an exhaustive comparison of 19 functional forms for the yield-weed density model, Cousens (1985) found the rectangular hyperbola to outperform the others over 22 sets of published field data. While he did not review any sigmoidal forms, Swinton found the Cousens hyperbola to outperform the logarithmic sigmoidal form over several sets of Minnesota and Wisconsin corn and soybean yield-weed density data.

The WEEDSIM model incorporates a multivariate formulation of the Cousens hyperbolic yield equation, which takes the form,

$$Y = Y^0 \left[1 - \frac{\sum I_i w_i}{100 \left(1 + \frac{\sum I_i w_i}{A} \right)} \right] \tag{5}$$

where Y^0, I_i and $A \in [0, +\infty)$ are parameters to be estimated from data. As in equation (1), Y^0 represents weed-free yield, I_i is percentage loss in crop yield per density unit of weed species i as density approaches zero, and A is the maximum percentage crop yield loss asymptote as weed density approaches infinity. The hyperbolic form is approximately linear at low weed densities. At high densities it becomes asymptotic to the minimum yield level

(Y_{min}) given by $Y^0*(1\text{-}A/100)$. The competitive effect of an additional weed of species n is given by the derivative in equation (6).

$$\frac{\partial Y}{\partial w_n} = I_n\left[\frac{-Y^0A^2}{100(A+\sum_i I_iw_i)^2}\right] \tag{6}$$

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. Interspecies weed competition is implicit in (5), since the competitive effect of an additional weed of one species depends in part on the density of the other species. The I_i coefficients differ importantly from the competitive indices developed by Coble and Lybecker et al. (1991b) in that they are estimated from field data including multiple weed species growing together and they do not rely on expert opinion (Swinton).

Weed population dynamics are governed by the germination, survival, and seed production equations (2-4). Experimental evidence suggests that weed seed germination occurs as a proportion of the seeds in the seed bank (Cavers and Benoit, Forcella). For simplicity, this model treats weed seedling germination (equation (2))as a Markovian process, ignoring dormancy. For management purposes, weed seedling germination in row crop fields takes place in three stages (τ = 0,1,2: prior to crop planting, after planting, and after post-emergent weed control). In the absence of weed control, weed seed germination in stage τ of the growing season can be specified as

$$w_{\tau it} = \alpha_{\tau i} s_{it-1} \tag{7}$$

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 fixed coefficient, or treated as a function itself. In the Forcella germination model, cumulative seasonal weed germination is simulated as $\alpha_i = \alpha_i(\text{AGDD})$, where AGDD is cumulative April growing degree days. The proportion of total germination (α_i) occurring at each stage, τ, was estimated from a 1985-86 data set from Morris, MN, reported in Forcella and Lindstrom.

Germination prior to crop planting, w_{0it}, follows equation (7). Only weed species tolerant of cool weather germinate in significant numbers at this stage. These weeds are assumed killed by crop planting in a conventional tillage 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 soil-applied pre-plant incorporated (PPI) and pre-emergent (PRE) herbicides, germination and emergence are not necessarily equivalent. Weeds that emerge can be expressed as those that germinated and survived any control treatment,

$$w_{ijt}^{e} = w_{1it}[1 - k(wsp_i, h1_{jt})] \tag{8}$$

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, but they also reach reproductive maturity and set seed (albeit at a lower rate than larger, early-emerged weeds). Weeds at harvest can be expressed as,

$$w_{ijt}^{h} = w_{ijt}^{e}[1 - k(w_i, h2_{jt})] + w_{2ijt} \tag{9}$$

where $h2_{jt}$ is post-emergence weed control treatment j, and w_{2ijt} is the density of weed species i emerging after POST weed control.

Weed control "efficacy" refers to the lethality of a control treatment to 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 et al.). These are expressed as a set of discrete levels, such as "poor," "fair," "good," or "excellent." 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 PRE herbicides that are sprayed upon the soil before weed seedlings emerge, a necessary condition for the stated effficacy 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 herbicides), required conditions are 1) that no rain wash the chemical from the weed leaves within one to eight hours of spraying, and 2) that weeds be at a susceptible life cycle stage.

The kill function employed here takes the form,

$$k(wsp_i,h_j^r) = \kappa_{ij}w_i,\ \kappa_{ij} = \begin{cases} k_{ij} \text{ if conditions suitable} \\ 0 \text{ otherwise} \end{cases} \tag{10}$$

where h_j^r is treatment j applied at the recommended rate and $k_{ij} \in [0,1]$ is the proportion of weeds of species i killed as a result. The treatment efficacy data set used to run WEEDSIM includes a treatment feasibility dummy variable, as well as efficacy ratings organized by crop, weed species, and timing of weed treatment (ie., PPI, PRE, POST). As will be discussed subsequently, treatment feasibility is partially determined by weed and crop growth stage. These are included in the WFARM model.

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},

$$s_{it} = (1 - \sum_{\tau=0}^{2} \alpha_{\tau i} - \beta_i)s_{it-1} + \sum_{\tau=0}^{2} \gamma_{\tau i}w_{it}^h \tag{11}$$

where $\Sigma\alpha_{\tau i}$ represents the proportion of seeds of species i lost through germination during the three ($\tau = 0,1,2$) stages of period t, β_i represents that of those lost through seed death in the soil. Since late-emerging weeds tend to produce fewer seeds than ones that grow the full season, γ_{ri} distinguishes mean seed production per mature weed according to stage of emergence.

Each of the parameter values appearing in equations (5 and 7-11) is read into WEEDSIM from data files. The model requires separate parameter data files for crop species, weed species, weed-crop competition, weed treatment alternatives, and weed control efficacy ratings.

Other features

An important feature of WEEDSIM is its open programming structure. The model is written in Microsoft QuickBasic 4.5 in highly modular fashion. This allows it to be enhanced by the addition of subprograms to add detail to the functions that drive the program. For example, parameters which are currently read into the model as constants could be calculated internally through new subroutines.

All coefficients used to drive model equations are read in from external files. This facilitates the substitution of existing coefficients with replacements that may be better suited to different geographic conditions. External files also simplify the addition of new crops, weed species, and weed control treatments.

The whole-farm "shell"

WFARM evaluates WEEDSIM recommendations in a whole-farm context where land, labor and machinery resources are limited (Swinton). WFARM is illustrated in Figure 2. The most important whole-farm constraint is the number of days with suitable weather and soil conditions for field work. A function of equipment capacity, labor, and climatic conditions, it can limit gross returns in two ways. First, maximum attainable crop yield is reduced by delayed planting. Second, weed control for some treatments and weed species becomes infeasible when the weeds get too big or the crop reaches a susceptible stage. Since the 3-4 week "window of opportunity" for post-emergent weed control in corn may occur at the same time as the optimal planting stage for soybeans, efficient time utilization is crucial. Although WEEDSIM does not incorporate field time availability into its decision rule, WFARM provides a means to evaluate its recommendations in a context where delays matter.

WFARM provides a whole-farm shell in which WEEDSIM is run to generate recommendations for weed management for each field. In addition to simulating the biological functions in WEEDSIM, WFARM simulates time allocated to field preparation, soil-applied weed control, planting, and post-emergent weed control (Figure 2). It also simulates weed growth during the weeks following planting (a simple quadratic function of days after planting).[4] This allows WFARM to predict the stage at which certain weeds exhibit reduced susceptibility to given herbicides (e.g., green foxtail susceptibility to atrazine declines after the weed height surpasses 1.5 inches).

In addition to the parameter data required by WEEDSIM, WFARM calls for input files containing machinery size, speed and cost parameters, as well as crop and weed quadratic growth rates, and weed and crop size thresholds beyond which specific control treatments become ineffective.

WFARM need not only be run deterministically. It can also be run with stochastic input files for such variables as rainfall, weed-free yield, weed germination rates, days suited for field work, and disturbance terms associated with the coefficients and equations that run the biological equations.

Parameter input data

Prototype input parameters were developed for WEEDSIM for conditions in southwest Minnesota. Data estimation procedures for the yield and seed bank equations (5 and 11) are reported in Swinton. The total weed seedling emergence rates (α_i in (7)) were computed from Forcella's simulation model, with the stagewise emergence proportions (τ in (7)) estimated from data. Efficacy ratings for herbicides were obtained from Durgan et al., while those for mechanical controls (rotary hoe) were obtained from unpublished Minnesota agronomic trial data.

The prototype parameter set allows WEEDSIM to be run for corn and soybean crops, including continuous corn and corn-soybean rotations. The weed species included are those that abound in southwestern Minnesota: green and yellow foxtails (Setaria viridis (L.) Beauv. and S. glauca (L.) Beauv.), redroot pigweed (Amaranthus retroflexus L.), and common lambsquarters (Chenopodium album L.). Key biological parameter values from the prototype data set are reported in Table 1. The main weed control treatment parameters in the prototype data set appear in Table 2.

Model validation

Model verification seeks to answer the question, "Does the model perform as intended?" The focus of verification is on the inner workings of the computer program. As such, it applies to the WEEDSIM and WFARM computer code. Model validation, on the other hand, seeks to answer the question, "Does the model accurately represent the system it purports to simulate?" This is an empirical question, and cannot be answered without comparing model results to those from actual systems.

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 (Swinton). The sequence of program development also reduced the likelihood of programming error: Verification of the model proceeded in tandem with programming individual modules and procedures.

While there remains the possibility of erroneous code in a program of this size, every effort was made to reduce it.

Two general approaches to model validation have been followed. The first is to ascertain whether component equations accurately simulate reality. The second is to determine whether the recommendations of the entire model make sense. Component equations can be validated 1) statistically (against out of sample data) and 2) by expert opinion.

As 1985-86 data from Morris, Minnesota (Forcella and Lindstrom), were used to develop the prototype parameter input data, out-of-sample data from 1990 field trials at Morris were used to validate components of the original version of the WEEDSIM/WFARM model. Since data were available only for the emergence and corn yield functions, statistical validation was not possible for the seed bank, plant growth and soybean yield functions. The 1990 Morris data come from two sites, representing a wide range of weed pressures. The validation tests led to calibration of the germination equations and acceptance of the corn yield equation in its original form.

Discussion of model coefficients with weed scientists at the University of Minnesota and Michigan State University[5] indicated that the seed production values are very low, relative to those in the literature. This is true. The values reported by Forcella and Lindstrom are among the lowest in the weed seed literature, due to their examination of only late-germinating, small weeds. The germination rates reported by Forcella are comparable to those of other scientists using repeated laboratory germination methods, but higher than those of scientists using seed separation methods. The combined effect of low seed production and high germination rates leaves the prototype parameter set internally consistent at generating typical weed populations. The intimate connection between the seed production and emergence equations makes it imperative to estimate both from the same data set in order to insure internal consistency and controllability of the forecasted weed population.

Model recommendations appeared plausible to a committee of weed scientist experts at University of Minnesota. Field experiments to validate the model were begun at Rosemount and Morris, Minnesota, in 1991 (Buhler).

Sample results from the model

Threshold map for weed management

Since WEEDSIM recommendations for weed management are based upon weed density estimates, a convenient way to illustrate what it does is by means of a "threshold map" of management recommendations as a function of weed density. One complication is that maps are two-dimensional, so for more than two weed species they require that something be held constant. The threshold map in Figure 3 illustrates recommendations for weed management in the corn part of a corn-soybean rotation. Grass weed densities are shown on the vertical axis and broadleaf densities on the horizontal axis. The ratio of densities among the broadleaf species is held constant at a level typical of the field observations by Forcella and Lindstrom (2:1 common lambsquarters to redroot pigweed).

At very low densities, the recommended treatment is no control. When moderately low numbers of broadleaf weeds are chiefly present, 2,4-D (POST) is recommended. As these become greater, dicamba (PRE) is also recommended. When grass weeds abound instead of broadleafs, cyanazine is the recommended treatment. At low densities, cyanazine is recommended either PPI or POST. As grass weed numbers get large, it is recommended at both stages. For the broad range of mixed grass and broadleaf weeds, the recommended treatment is cyanazine (PPI) followed by 2,4-D (POST). However, when high levels of grass weeds are in the mix, the recommendation switches to alachlor (PPI) plus cyanazine (POST). This reflects the fact that 2,4-D, while inexpensive and highly effective against most broadleaf weed species, cannot control grasses. Alachlor, on the other hand, is more expensive but highly effective against both foxtails and pigweed, albeit only fair against lambsquarters. The switch from 2,4-D to alachlor substitutes a higher cost, but more efficacious control for the weed mixture at hand.

The threshold map illustrated assumes a corn price of $2.50 per bushel, with soybeans at $6.00 per bushel. At lower crop prices, the map is stretched out. Thresholds appear at higher levels since the value of yield saved is lower. By excluding low-cost, efficacious controls such as atrazine and 2,4-D, the threshold for control is raised at low weed densities, but remains unchanged at higher levels. These controls give the greatest "value for money" in weed control, so they are the first treatments to be recommended over "no control" as weed densities rise.

Effect of the dynamic decision rule

Substituting a myopic, one-year decision rule in place of the two-year time horizon has an similar effect to that of reducing the crop price. Omitting expected yield losses in the second year (due to weed propagation) reduces the expected value of yield saved. As a result, the thresholds for control all become higher. Figure 4 illustrates a myopic threshold map based upon the assumptions underlying Figure 3. Note that while all recommended treatments are the same, the threshold population densities for moving from one to the next are higher in every instance.

A dynamic decision rule has the effect of maintaining the weed population over time at a lower level than a myopic rule. Figure 5 illustrates that under these conditions, the myopic rule would recommend no control in year 2, resulting in a jump to over 600 foxtail seeds per square meter, whereas the two-year rule would wait until year 4 to skip control, resulting in a subsequent seed density half as high.

Effect of farm size on timeliness

The effect of reduced workable field days is illustrated in Table 3, using the WFARM model with historic field day data recorded at the Southwest Experiment Station of the University of Minnesota at Lamberton, Minnesota. Weed management results with the 18 workable field days between April 19 and June 20 in 1982 are contrasted with those for the 55 workable days during the same period in 1987. Results are simulated using the recommendations from Figure 3 for a heavy weed infestation with weed seed densities for mixed green and yellow foxtails, common lambsquarters and redroot pigweed at 1750, 500 and 250 seeds/m^2. Crop prices, weed germination rates and precipitation were held constant at their 1974-90 means for the simulation.

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 other variables are held equal 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 may increase yield loss 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.

Summary and conclusion

Over the past decade, research on integrated weed management has made impressive advances. However, a mismatch has persisted between research discoveries and available decision tools for managers. The WEEDSIM model bridges this gap with a bioeconomic model that incorporates weed population dynamics into the decision rule, while at the same time accommodating multiple weed species and control treatments. The associated WFARM model provides a whole-farm shell, making it possible either to modify WEEDSIM recommendations in a context where field time is limiting, or to evaluate the performance of WEEDSIM recommendations over various states of nature. The modular programming structure of WEEDSIM facilitates the addition of new subroutines to model biological processes more accurately. By accessing external parameter files, the model can easily be extended to include more weed species, control treatments, machinery sets, or states of nature. While field validation of the model is at an early stage, preliminary results are promising.

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Table 1: Key parameter values from the S.W. Minnesota WEEDSIM prototype input data set.

Equation number and variable	Green and Yellow Foxtails	Lambs-quarters	Redroot pigweed
(5) Yield loss (I_i) by first weed			
Corn	0.2	0.8	0.8
Soybean	0.2	1.9	1.9
(7) Seedling emergence proportions			
Total (α_i)	0.269	0.168	0.097
Pre-plant (α_{0i})	0.048	0.067	0
Post crop planting (α_{1i})	0.194	0.091	0.089
After POST treatment (α_{2i})	0.027	0.010	0.008
(11) Seed dynamics			
Seeds produced per plant ($\gamma_{\tau i}$)			
Plants emerged with crop (γ_{1i})	90	120	130
Late-emerged plants (γ_{2i})	9	6	13
Mortality of unemerged seeds in soil (β_i)	0.714	0.818	0.116

Table 2: Efficacy percentage and application time of weed control treatments included in the model, by crop.

		Percentage Killed[1]			Materials cost per acre[2]	
Treatment	Application time[3]	Fox-tail	Lambs-quarter	Pig-weed	PRE	POST
		----- %	-------		-- $ ---	
Corn						
No control	0,1,2	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	5	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	--	--

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
Imazethapyr 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.

Table 3: 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	Number of workable field days (April 19 - June 20) 18 (1982)	55 (1987)
Farm net revenue	dollars	- 6,582	1,675
Herbicide load			
Continuous corn	lbs ai/acre[1]	2.7	4.2
Rotational corn	lbs ai/acre	4.3	4.3
Rotational soybean	lbs ai/acre	0.8	0.8
Percent max. yield			
Continuous corn	percent	71.6	76.6
Rotational corn	percent	70.6	75.9
Rotational 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.

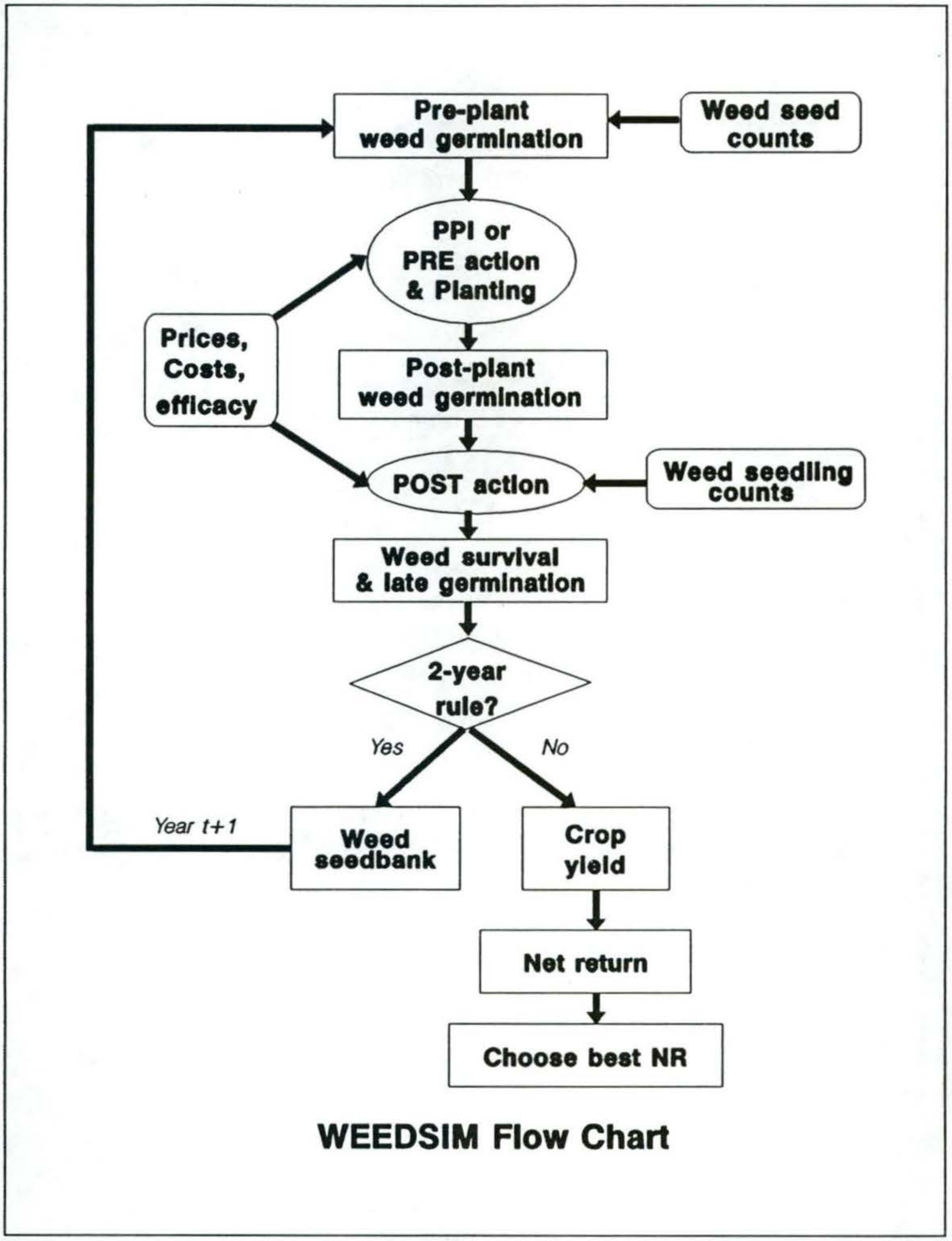

Figure 1: WEEDSIM flow chart.

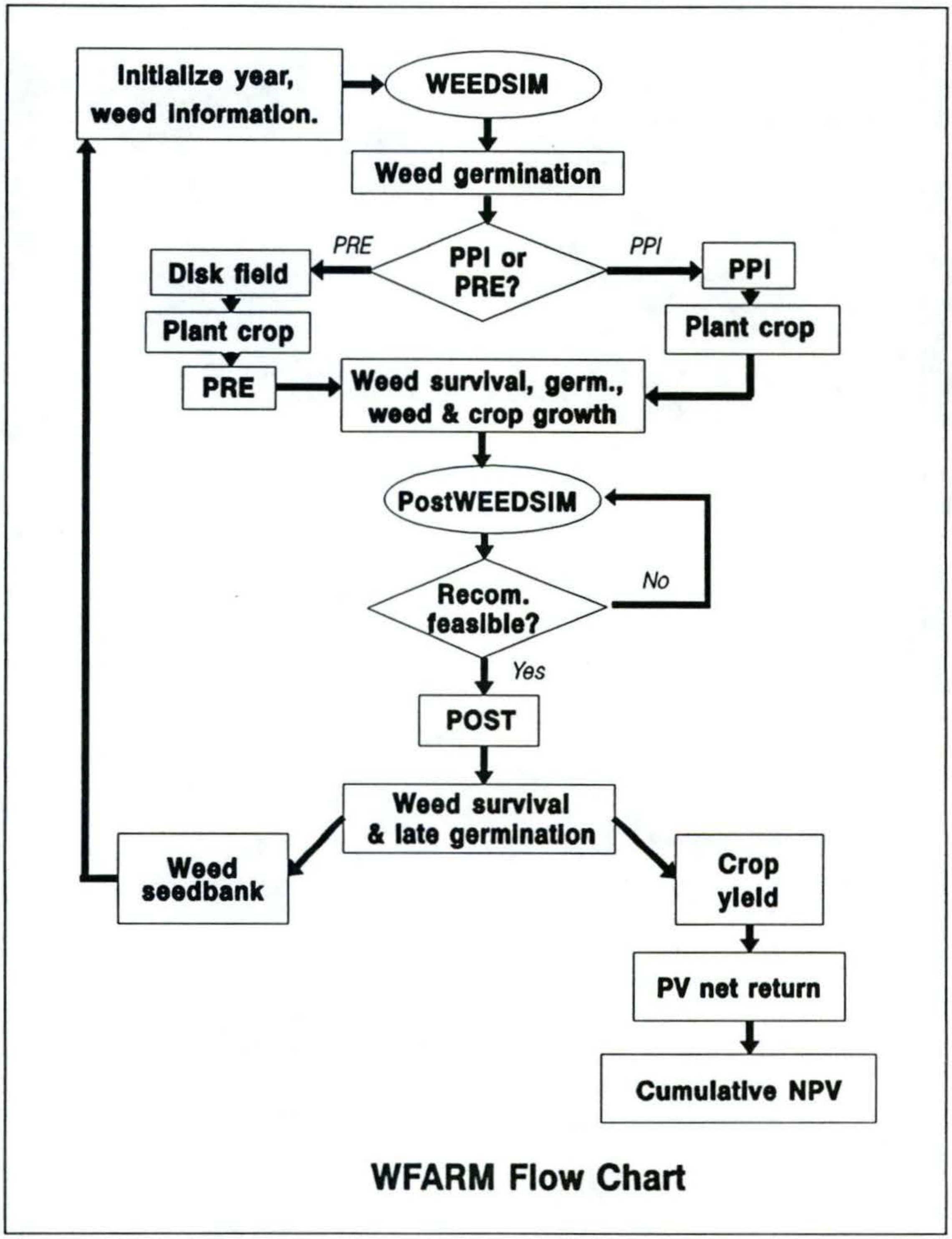

Figure 2: WFARM flow chart.

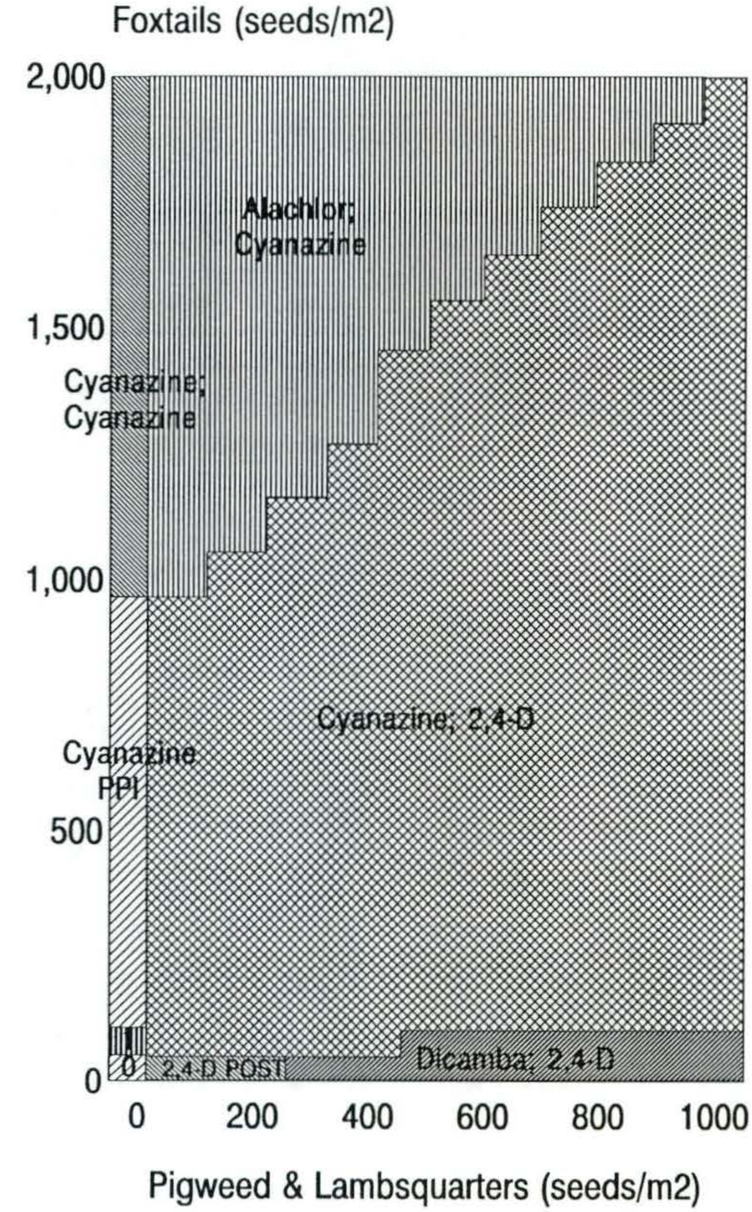

Figure 3: WEEDSIM recommendations map for corn in corn-soybean rotation (two-year decision rule).

[0] No control.

[1] Cyanazine POST.

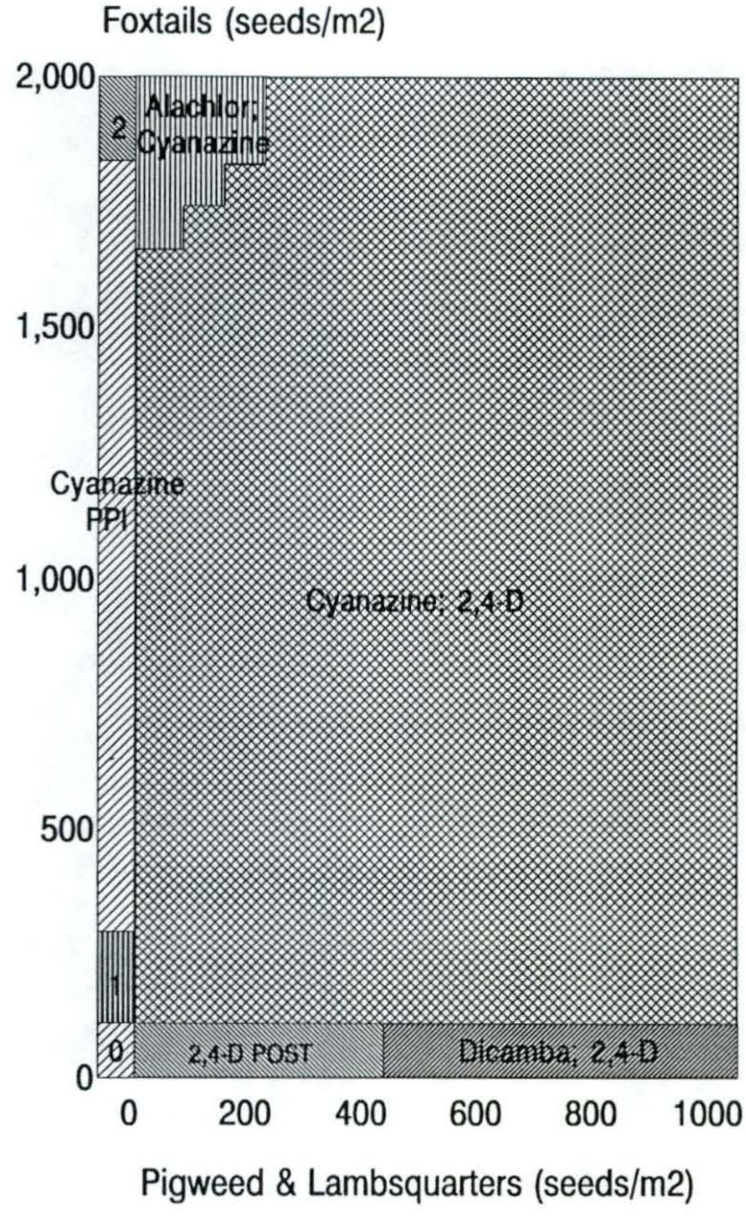

Figure 4: WEEDSIM recommendations map for corn in corn-soybean rotation (one-year decision rule).

[0] No control.

[1] Cyanazine POST.

[2] Cyanazine PPI; cyanazine POST.

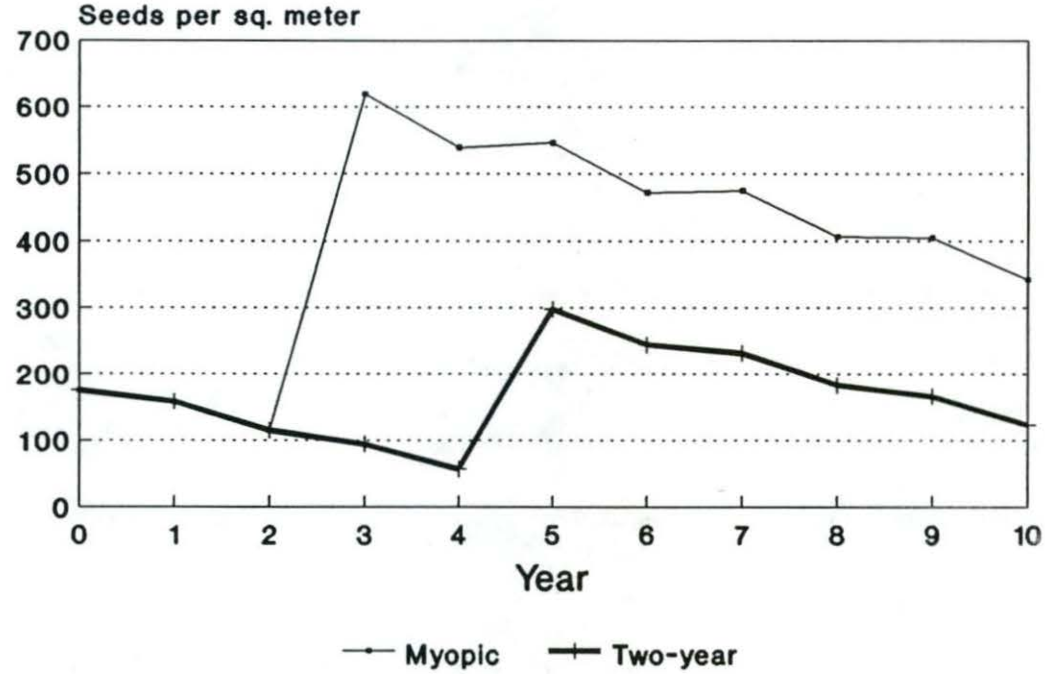

Figure 5: Foxtails seed bank evolution from low initial level in corn-soybean rotation: Myopic and two-year decision rules compared.

ENDNOTES

1. U.S. Department of Agriculture Cooperative State Research Service project NC-202, "Biological and Ecological Basis for a Weed Management Model to Reduce Herbicide Use in Corn," created October 1, 1990.

2. While Pannell (1990a) and Headley have called for a marginal herbicide application rule, Deen et al. have demonstrated that the value of such a rule is small relative to the value of a threshold rule at recommended rates. The higher variance of herbicide efficacy at low rates combined with farmers' loss of legal recourse in the event of failure constitute substantial associated costs.

3. The dynamic optimum weed control path can be expressed using the tools of dynamic programming. To simplify the notation of equations (1-4), 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 stage for the control that maximizes returns for the current stage plus the value of the stage that results from it. For the problem in equations (1-4), the recursive relation can be stated,

$$V_t\{w_t^h\} = \max_{h} \; [\pi_t\{w_t^h, x_t, h_t\} + V_{t+1}\{S\{w_t^h, x_t, h_t\}\}] \qquad \textbf{(A.1)}$$

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, $S\{\cdot\}$ 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.

Now define $DV_{t+1}(w_t^h,x_t,h_t)$ as a value of future yield damage function. The dynamic economic threshold, w_t^{h0*}, is the weed density in period t at which the discounted value of current and future yield damage avoidable by current period control exactly equals the cost of that control. Consequently, weeds should be controlled in period t using the best available control, h^{r*}, if the value of damage function exceeds the cost of control, c^{r*}:

$$h_t^* = \begin{cases} h^{r*} \ \ if \ P\left[D(w_t^{h0}) - D(w_t^{hr*})\right] + DV_{t+1}\{w_t^{h*}, x_t, h_t\} \geq c^{r*} \\ 0 \ \ otherwise \end{cases} \tag{A.2}$$

Because both terms on the lefthand side of (A.2) are non-negative, this rule implies a threshold for current period weed control that is at least as low as that which applies in the static decision rule where the value of future yield damage is omitted. From a practical standpoint, this means that following the dynamic weed control decision rule in (A.2) leads to a control strategy that is more conservative than that of the static decision rule from the Feder and Auld et al. model.

4. 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 (10). The δ_i coefficients estimated for Minnesota are .0048, .0033, and .0038, for mixed green and yellow foxtails, common lambsquarters, and redroot pigweed, respectively.

5. Participants included Douglas D. Buhler Research Agronomist, U.S. Department of Agriculture (USDA), Agricultural Research Service (ARS) and Associate Professor, Department of Agronomy and Plant Genetics, University of Minnesota, St. Paul; Frank Forcella, Research Agronomist, USDA, ARS, North Central Soil Conservation Research Laboratory, Morris, MN; and Jeffrey Gunsolus and Bruce Maxwell, Assistant Professors, Department of Agronomy and Plant Genetics, University of Minnesota; James Kells, Professor, and Karen Renner, Associate Professor, Department of Crop and Soil Sciences, Michigan State University.