Staff Paper

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December 1992

No. 92-80

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East Lansing, Michigan

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by

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The authors thank Roy Black, Derek Byerlee, and Jack Meyer for helpful comments. This research received support from the Michigan Agricultural Experiment Station, a University of Minnesota Doctoral Dissertation Fellowship, and a grant from the Agricultural Research Service of the U.S. Department of Agriculture.

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Introduction

Managing weeds poses an important challenge to U.S. crop farmers. Weeds cause annual crop losses to U.S. corn and soybean producers valued in the billions of dollars (Chandler et al.). In response, farmers invest large sums to control weeds. Agricultural chemicals were the largest component of mean variable operating costs for U.S. soybean growers in 1990 ($20.48 per acre) and the second largest component for corn growers that year ($22.64 per acre) (USDA 1991a and 1991b). Most of these expenses covered herbicides. Additional costs were incurred for mechanical operations, including herbicide application and cultivation.

The challenge of weed management reaches beyond financial costs to environmental ones. 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). Growing evidence points to a link between herbicide use and certain types of cancer among farm workers (Hoar et al., Wigle et al.). Yet herbicide use is pervasive. On the U.S. corn and soybean crops, herbicides accounted for roughly ten times as much active chemical ingredient as did insecticides and fungicides combined in 1990 (USDA 1991a). 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).

The high cost and potential health hazards of weed control give farmers ample reason to manage their control actions with care. One approach is to apply integrated pest management principles, scouting weed populations in order to base the control strategy on a prediction of likely value of yield loss. Bioeconomic models that support this approach are proliferating (Lybecker et al. 1991b; Mortensen and Coble; Swinton and King; Wilkerson et al.), and have become the subject of a U.S. Department of Agriculture regional research project (NC-202). These decision support models all require more information than current management approaches. Yet with the exception of Gillmeister et al., no formal attempt has been made to estimate the value of that information.

Results reported by King et al., Gillmeister et al., and Lybecker et al. (1991a) suggest that recommendations based on weed population information help farmers reduce herbicide use while increasing net returns. However, these studies suffer from several weaknesses. First, all three ignore the timeliness of weed control. Second, the King et al. and Gillmeister et al. studies are confined to a narrow range of weeds and control methods. Third, risk enters only into the Gillmeister et al. article, and there it is restricted to uncertainty about the initial weed density. Finally, the Gillmeister et al. and Lybecker et al. studies ignore weed population dynamics across seasons.

Timeliness, in particular, is critical to weed management. Weeds that emerge within the first four weeks after corn or soybean planting have the potential to compete strongly for light, water and nutrients with the juvenile crop plants. Unless controlled early, before resources become limiting, the crop will suffer yield losses. But delayed planting, too, reduces potential yields, and early post-emergence weed control competes for field time with planting tasks. One way to mitigate the conflict is to kill weeds before they emerge. This limits control alternatives to herbicides, which may be incorporated into the soil before planting (pre-plant incorporated, or PPI) or else sprayed onto the surface of the soil at some point before the weeds emerge, possibly after planting (pre-emergent, or PRE). Since weeds are not visible when either of these actions is taken, the population can only be predicted from sampling the weed seed population in the soil or extrapolating from the previous year's observations. Once weeds emerge, post-emergent (POST) weed management options include both herbicidal and mechanical controls. Since weeds are visible, information is available on the size and composition of the actual pest population to guide decision making. By this time, however, planting tasks compete for the farmer's attention during a critical period when available work time is limited by the risk of unsuitable weather.

Pest management decisions are made in the presence of many sources of risk (Pannell 1990). In addition to the uncertainties noted above regarding initial pest population (Gillmeister et al.) and the number of workable field days, these include pest-free yield, crop price, pest control efficacy, pesticide damage to the crop, and a variety of factors influencing the rate of pest population growth. Only by taking these risky variables into account can the value of pest population information be properly evaluated.

The value of information, such as information on pest populations, depends on its potential to induce a better management decision than that which would have been taken in its absence. Chavas and Pope have demonstrated that (accurate) costless information cannot reduce net income. Information value may be calculated for a particular prediction or for the predictor itself, across a range of states of nature (Byerlee and Anderson). Note that for certain states of nature, a given predictor (such as a decision support model using appropriate information) may lead to sub-optimal outcomes in spite of the fact that on average outcomes are superior to those obtained without the predictor. The value of the predictor depends upon its performance over a range of states of nature. Of interest here is the predictor embodied in a bioeconomic management model that makes weed control recommendations.

Previous studies of information value in agriculture have focused upon one or two stochastic variables with relatively few management options (Bosch and Eidman; Byerlee and Anderson; Chiao and Gillingham; Mjelde et al.). With the important exception of Mjelde et al., they have ignored the timeliness of information. In order to estimate information value in a realistic stochastic setting, this study incorporates numerous biological and climatic random variables. Weed control strategies are developed from partially overlapping sets of individual control alternatives available at the PPI/PRE and POST decision nodes. In order to incorporate information value from the decisions on both **whether** to control and **how** to control, this study includes 5 - 8 control alternatives for corn and 3 - 6 for soybean at each of the two weed control decision nodes.

Information value can be measured against either a no-information scenario or a perfect-information scenario. The former is of practical usefulness to managers, but is subjective in that what an actor chooses to do in the absence of the predictor may vary considerably from one agent to another. The latter provides an unchanging standard against which information value can be judged; unfortunately, it does not measure the value that a decision-maker could expect to obtain by switching from his or her current strategy to one that uses the predictor. Most previous studies have estimated the value of information in agricultural production against a "perfect information" benchmark (Bosch and Eidman; Byerlee and Anderson; Chiao and Gillingham; Mjelde et al.). In order to provide a measure of potential gain over current practice, this study opts for a "no information" benchmark based on repeated use of the strategy which maximizes expected returns for a heavy initial weed infestation (assuming that weeds do not develop herbicide resistance). This represents a consistent strategy to insure adequate weed control in the absence of weed population information. Relying on a static profit-maximizing strategy represents a more internally consistent approach than relying on extension recommendations.

The value of a predictor also depends on the decision-maker's attitude toward risk. The most broadly applicable results come from studies which use stochastic dominance to identify strategies that would be preferred by a general class of decision makers. Bid prices for stochastically dominant distributions have been used to calculate value of information (Schoney and McGuckin). While this approach covers a broad range of decision makers, the range of technologies that exhibit any form of stochastic dominance is often narrow. Sacrificing generalizability for discriminatory power, Bosch and Eidman estimated a money metric value of information using generalized stochastic dominance over a range of absolute risk aversion intervals. Others have obtained more narrowly applicable results by varying the degree of risk aversion for a single, specific utility function (Byerlee and Anderson, Mjelde et al.). This study takes the latter approach, calculating certainty equivalents of expected utility for a set of utility functions with constant absolute risk attitudes (CARA).

In the paper, we develop a framework for measuring the value of information on weed populations. We use it to measure the value of differing levels of scouting information for a typical corn-soybean farm in southwest Minnesota. In the sections that follow, we first present a simplified, dynamic representation of the weed management problem facing a farmer and show how the value of weed information can be measured in that context. We then describe a set of stochastic simulation experiments that measure the value of weed population information used in a bioeconomic weed management model. The value of weed information is examined under two scenarios for herbicide restrictions, as well as the status quo. In the concluding sections, we briefly discuss the cost of providing weed population information and the implications of these findings for future research.

Theoretical framework

Feder's model of pest management under uncertainty provides the basis for the approach taken here. The problem is to choose the pest control input that will maximize expected utility when the input acts only indirectly on crop yields, via a kill function which reduces the population of a yield-reducing pest. Departing from Feder for reasons of product liability and the availability of response information, it is assumed that feasible levels of the weed control input are not variable; rather, managers must apply a chemical treatment at the recommended rate. For both chemical and mechanical weed control, the decision is thus a binary one: to control or not to control at the recommended rate.[1]

The Feder model is extended in three ways. First, multiple (weed) pests are introduced having differing susceptibilities to the available controls. Second, multiple control measures enrich the decision from one of *whether* to control, to one of *how* to control. Finally, this model follows Taylor and Burt in explicitly recognizing the dynamic nature of the weed control problem by incuding seed bank equations for each weed species.

This analysis defines expected utility over the present value of cumulative end-period net income (CNI_T). For the risk-neutral case, the model can be stated,

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

subject to the equations of motion,

$$w_t^h = [1 - k(h)]w_t \tag{2}$$

$$w_t = w(s_{t-1}) \tag{3}$$

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

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, h is a binary weed treatment variable equal to h^r (the recommended treatment rate) or zero, c is unit cost of weed control, C^0 is fixed and variable costs unrelated to weed control, and r is the discount rate. The density of weeds at harvest that survive to compete with the crop, w^h, in equation (2) is the product of w is the density of weeds that emerge, and one minus k(h) $\in$ [0,1], the proportion of weeds killed by treatment h. It is assumed that damage increases with weed density, so $D'(w^h) > 0$. The germination function in (3) relates the current weed density to the previous seed bank, with $w'(s_{t-1}) > 0$ assumed. 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 $s'(w_t^h) > 0$.

In the static, risk-neutral model with a single pest, the derived decision rule is to control weeds if the expected value of yield saved exceeds the cost of control (Auld et al.; Cousens 1987). Since yield is a function of damage induced by pest density, there is implicitly a threshold density on which this decision hinges. The seed bank element makes the threshold a dynamic one. By differenting equation (1) with respect to the arguments of the seed bank equation, it can be seen that the dynamic threshold occurs at a lower weed density than the static one, since CNI_T is decreasing in the weed seed bank (s_t) and weeds at harvest (w_t^h) in any time period. The effect is greatest in early periods because increases in the weed seed bank cause increased weed populations and yield losses of longer duration.

Under the assumption that intertemporal risk preference is entirely captured by the discount rate, the expected utility of a given distribution of expected CNI's can be calculated for hypothetical CARA decision makers (Pratt; Arrow). Denoting these utility functions over cumulative net income as u(CNI), the certainty equivalent of outcomes on CNI, CNI_{ce}, is

$$CNI_{ce} = \begin{cases} -\dfrac{\ln E[-u(CNI)]}{\lambda} & for\ \lambda > 0 \\ E[CNI] & for\ \lambda = 0 \\ -\dfrac{\ln E[u(CNI)]}{\lambda} & for\ \lambda < 0 \end{cases} \tag{5}$$

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

The bioeconomic weed management model

The theoretical model in equations (1-4) was implemented using the WEEDSIM bioeconomic model. Described more thoroughly in Swinton and King, WEEDSIM evaluates all combinations of PPI/PRE and POST weed control treatments in its database to recommend the initial treatment of the sequence which maximizes expected cumulative net income over a two-year planning horizon. The model is driven by weed population information in the form of 1) weed seed density estimates (s_{t-1}), for PPI and PRE weed control treatments, or 2) emerged weed density (w_t) for POST weed control.

The two-year time horizon provides a first approximation to the less tractable problem of identifying an infinite horizon optimal control. A dynamic programming model to do the latter would have to limit the permissable number of weed species and would require a highly simplified discrete rendering of the seed bank state variable for each species. As discussed above, differentiation of the seed bank variable suggests that an infinite time horizon would be characterized by a lower weed density control threshold and higher estimates of weed information value, compared with the two-year time horizon.

The value of weed population information is estimated using a whole-farm simulation model called WFARM (Swinton and King), illustrated in Figure 1. WFARM models implementation of the WEEDSIM recommendations in a context of limited land, machinery, and labor resources. Workable field days depend upon weather, soil type, and machinery specifications. Limits on their availability can reduce crop yields in two ways. Failure to complete planting in a timely fashion leads to decreases in potential yield. Failure to control weeds on time can allow some weeds to grow beyond the stage at which they can be controlled by the recommended treatment, requiring a revised (and ex ante suboptimal) POST treatment. The overlap between the optimal periods for soybean planting and post-emergent weed control in corn tends to result in yield loss due to one or the other of these processes.

WFARM simulates stochastic biological and climatic processes (Figure 1), leading to random net returns to any given management strategy. In addition to the yield function in brackets in (1) and equations (2-4) for each weed species, it includes equations for weed growth during the weeks following planting (a simple quadratic function of days after planting). This allows WFARM to capture the reduced susceptibility of some weeds to certain herbicides once past the seedling stage.

Three methods are employed to incorporate stochasticity into the WFARM model. First, additive pseudo-random disturbance terms are simulated from the empirical distributions used to estimate the WEEDSIM and WFARM equations. For example, the crop yield and weed seed production equations use deterministic coefficients with empirically distributed additive errors. Second, pseudo-random multivariate normal disturbances are added to parameters. The weed growth equations take the form $Y = (\beta + \epsilon) X + u$, where ϵ is distributed multivariate normal $(0, \sum)$ and u is an empirically distributed, heteroscedastic additive disturbance term. Third, historical data are incorporated into suitable equations. Historical field time, weather, and weed-free yield data from southwestern Minnesota in 1974-90 are used to capture year-to-year variation. The stochastic weed emergence equations are a hybrid, composed of Forcella's annual temperature-dependent predicted emergence plus a heteroscedastic disturbance term. Some herbicides are not effective after weed seedlings exceed several inches in height. When tardy timing makes a recommended treatment infeasible, the WEEDSIM module re-evaluates the feasible treatments to identify a revised best alternative. Rainfall makes the efficacy of unincorporated PRE herbicide treatment stochastic, since it is effective only if a minimum of one-half inch of rain falls in the following week.

Scouting of weed seed and seedling density is assumed to yield perfect knowledge of the underlying populations. While on the surface this seems an unrealistic assumption, it is 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 already implicitly reflect the sampling error associated with weed seed and seedling density data from Forcella and Lindstrom that were used to estimate model parameters.

The stochastic, whole-farm model allows evaluation of weed management strategies based on three levels of weed population information. The "high information" case includes scouting 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" relies on the best fixed soil-applied weed control for heavy weed pressure, using scouting information on post-emergence weed seedling density for POST weed control. Finally, the "no information" case follows the best fixed strategy for weed control assuming high initial weed pressure. 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).

Under these three weed information scenarios, the certainty equivalent of expected utility, CNI_{ce}, is calculated for four hypothetical CARA decision makers having risk aversion coefficients of -.0001, 0, .0001 and .001. These correspond to the range CARA coefficients on annual farm income reported in Raskin and Cochran's review of studies of elicited risk aversion.

Simulation Experiment Design

The specific objectives of the stochastic simulation experiments conducted with WFARM were to test the null hypotheses:

H1: EU(CNI) with weed information = EU(CNI) without weed information, and

H2: Amount of chemical use (pounds of active ingredient per acre, lb ai/ac) with weed information = amount of chemical use without weed information.

These were to be evaluated for the three levels of information, HIGH, POST and NONE. In the event that H1 was rejected, a secondary objective was to estimate the differences in certainty equivalents of CNI between information levels as a rough measure of potential willingness to pay for weed population information.

The resource endowment of the base case farm used in simulations is presented in Table 1. It is a 480-acre cash grain farm located in southwestern Minnesota, divided into six 80-acre fields. Two fields each are devoted to continuous corn, rotational corn and rotational soybean, all farmed using conventional tillage. 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. 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.

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 are shown in Table 2. They represent approximate bottom and top quartiles of a 1985-86 data set from Morris, Minnesota reported in Forcella and Lindstrom. 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.

For the simulations where no weed population information was used, recommendations were those which optimized a deterministic model with "high" initial weed density. Those recommendations were (1) for continuous corn, cyanazine pre-plant incorporated (PPI) followed by atrazine and oil post-emergence, 2) for corn in rotation with soybean, alachlor PPI followed by cyanazine post-emergence, and 3) for soybean, trifluralin PPI followed by rotary hoe. For simulations where POST information was used, the "no information" PPI recommendations were implemented for pre-emergence weed control.

Stochastic Simulation Results

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 (Table 3). Moreover, the distributions of annualized net income under the high and intermediate information strategies dominate the no information distribution by first degree stochastic dominance under high initial weed pressure and second-degree stochastic dominance under low initial weed pressure.

The hypothesis that strategies using and ignoring weed population information yield equal annualized net income (Hypothesis H1), is evaluated against the alternative hypothesis that using weed information gives higher net income. Two sets of one-tailed, paired difference t-tests are presented in Table 4. In one set of tests, POST-only seedling count information is compared with no information. Under both initial weed pressures, the hypothesis can be rejected in a three-way comparison with 99% confidence (the one-tailed

$t(19;.01/3) \approx t(19;.002)$ critical value is 3.88).[2] In the other set of tests, the annualized net income with high information is compared to that with POST-only information. The hypothesis of equal returns can be rejected with 95% confidence for low initial weed pressure, but only with 80% confidence with high initial weed pressure. The total value of information is highest 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, Gillmeister et al. and King et al.

The mean herbicide loads in Table 5 do not offer the same consistent ranking. Hypothesis H2, that the same level of herbicide is applied regardless of information level, is evaluated against the alternative hypothesis that the level of herbicide applied is not the same. The null hypothesis is soundly rejected in the two-tailed, paired difference t-tests presented in Table 6. Only for rotational soybean were chemical loads unchanged between high and POST information levels. While chemical load differs across information levels in all the corn cases, *more information does not necessarily lead to lower chemical use*, contrary to the findings of King et al. and Lybecker et al. (1991a). Weed population information often leads to the selection of different weed control treatments, but these may either exceed or fall below the quantity of chemical in the no information case. Compared to no information, high information leads to significantly lower herbicide load for both corn rotations, but not for soybean. Compared to POST information, high information leads to significantly lower herbicide loads on continuous corn and rotational corn with low initial weed pressure, but not on rotational corn with high initial weed pressure. Compared with no information, POST weed seedling counts lead to herbicide loads that are lower in corn (both rotations) and higher in soybean. In general, herbicide load increases are smaller in magnitude than herbicide load decreases.

The value of information is linked to the decision maker's attitude toward risk (Byerlee and Anderson). The value of weed population information is highest when weed pressure is high, as shown in Table 7. 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 no control is needed. 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. Similar results have been obtained by Wiles et al.

The value of weed population information increases with risk aversion when initial weed pressure is high and decreases with risk aversion when it is low. This result comes from the fact that weed population information increases net return variance (risk) when weed pressure is low, but decreases it when weed pressure is high (Table 3). When weed pressure is low, an information-based flexible strategy occasionally calls for no control, which causes a sharp drop in net returns and boosts variance. When weed pressure is high, an information-based strategy is prone to tailor the control more precisely to the nature of the weed problem than a fixed strategy, thereby reducing net return variance.

In a recent literature review, Pannell (1991) observes that increased pest control does not necessarily reduce net return risk, since the effect of pest control on risk depends upon the source of risk. He finds that for convex yield functions, such as the hyperbolic one used here, uncertainty about weed density, yield loss per weed, and weed control efficacy may be expected to reduce income risk. By contrast, uncertainty about weed-free crop yield or product price may be expected to increase it. This is partly confirmed in a recent empirical study by Deen et al. Risk in the present study comes from various sources having conflicting effects. Previous pest management research has not addressed uncertainty about field time or pest reproduction. The results presented here highlight the fact that with mixed sources of risk, the value of information need not vary systematically with the level of information.

The estimated value of weed population information ranges from \$2.87 per acre for the strong risk averter facing low initial weed pressure to \$25.94 per acre for the strong risk averter confronting high initial weed pressure (Table 7). These values are for post-emergence weed seedling counts ("low" information). This range includes the \$25/acre estimated value of information for post-emergent cocklebur control in soybeans at low weed densities found by Deen et al. The supplementary value of seed counts can be estimated as the difference between the value of "high" information and that of the "low" (POST) information alone. To decision makers with the four specified utility functions, it would be worth up to \$2.07 per acre more to obtain seed bank estimates. For the most risk-averse decision maker, however, the low information case was actually preferable to the high one, as it provides prophylactic pre-emergent weed control that is not subject to the uncertainty of soil seed sampling. The commercial viability of seed counts from soil sample is marginal from these results.

Effect of Herbicide Bans

Rising public concern about the presence of atrazine in groundwater has led the U.S. Environmental Protection Agency to examine closely whether or not to reregister it for use on corn. A broader issue is whether to ban the entire family of triazine herbicides, of which atrazine is a member. Given that atrazine offers the least expensive broad-spectrum weed control, the WEEDSIM model recommends its use under a wide range of weed infestations in continuous corn. Consequently, a ban on its use could be expected to affect the value of weed population information utilized in a bioeconomic weed management model. In the atrazine ban scenario, the "no information" recommendation for all corn called for cyanazine PPI and 2,4-D POST. In the triazine ban scenario, the "no information" recommendation for all corn called for alachlor PPI followed by 2,4-D POST. The bans did not change the base recommendation for soybean of trifluralin PPI followed by rotary hoe.

The effect on value of weed population information resulting from bans on atrazine or the triazine family (including atrazine) is presented in Table 8. A ban on atrazine sharply reduces the value of weed information at all levels of risk aversion except the highest. The reduced value of information for the moderate to neutral risk attitudes come about because mean annualized net farm income for the "no information" case rises while it changes little for the POST and high information scenarios. This incongruous outcome results from two factors. First, stochastic field time tends to make the atrazine and oil POST treatment infeasible on at least one field, requiring a revised POST control decision. Since the PPI/PRE control was chosen conditional upon atrazine POST, the PPI/PRE choice is not necessarily the best one for the revised POST treatment. Second, over the six year simulation, repeated use of the "no information" cyanazine - 2,4-D treatment reduces lambsquarters and pigweed populations below the levels achieved by cyanazine - atrazine in the base scenario without herbicide restrictions. This suggests that cyanazine and 2,4-D might have been a preferred treatment pair given a longer planning horizon than two years. The increased information value for the highly risk averse case results from the sharp increase in the variance of annualized net farm income in the "no information" case compared with slight reductions in the corresponding variances of the POST and high information cases.

A ban on all the three triazines in the model (atrazine, cyanazine, and metribuzin) results in a decrease in value of weed information across the board, relative to the atrazine case. Again, the mean and standard deviation of annualized net farm income in the "no information" case increase slightly (due to better pigweed control), while the means for the information-using strategies decrease. The decreased value of weed information is directly attributable to the reduction in control alternatives, reducing the number of instances in which information will lead to a different decision than that which would have been taken otherwise.

Cost of Weed Population Information

The evidence that weed population information may have significant value invites examination of the likely costs of obtaining the information required for a model such as WEEDSIM. The costs of information are divided between those involved in obtaining weed population estimates and those of using the predictor embodied in the recommendations 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.

A thorough cost analysis would be a valuable extension of this research. One approach would be to calculate the cost of obtaining weed population information based upon statistical sampling theory (see, e.g., Wilson et al.). For a normal probability distribution, the statistical formula for minimum 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. 58-59). If 1) and 2) are held constant across weed species, multiple species sampling intensity is determined by the species with the largest $\tilde{\sigma}$. Assuming that weed scouting exhibits constant costs, the cost of attaining a desired sampling intensity can be calculated by multiplying the required number of samples by the expected cost per sample. A more empirically based approach would be to survey the fee structures of crop consultants who offer scouting services for emerged weeds and for soil samples (since weed seed scouting services are not commercialized at present).

A rough estimate of weed seed sampling cost to obtain results within 50% of the mean 80% of the time comes to \$ 0.30 to \$ 1.00 per acre for pooled estimates of 80-acre fields. For weed seedling counts, the estimated cost is approximately half of this (Swinton). Informal conversation with a crop consultant places a considerably higher cost on weed seedling counts, on the order of $ 1.15 per acre. This suggests that in practice, higher confidence estimates than those hypothesized may be required.

At these costs, sampling weed seedlings appears highly feasible, while sampling weed seeds does not. By extension, the ex ante value of the model as a decision aid -- net of private information acquisition costs -- is significantly positive for post-emergence weed management. The growing popularity of HERB (Wilkerson et al.), a static bioeconomic model for POST weed management, bears this out. Improvements in predictive models and sampling methods could conceivably reduce uncertainty surrounding weed population forecasts to the level where expected net benefits from weed seed information also become positive.

Conclusion

The experimental framework based on stochastic simulation that is used to undertake this inquiry can be adapted to measure the value of other kinds of biological scouting information. The whole-farm nature of the model captures interactions among risk-inducing management factors more effectively than do models which examine one source of random variability at a time (e.g., Pannell 1990). This model also permits evaluation of weed management recommendations in a dynamic setting. As such, this simulation approach is suited to measuring returns to information on other types of pest populations.

The key finding of this study is that information-based weed management can significantly improve expected earnings over those from following a fixed decision rule. While a careful cost analysis is needed, indicative figures suggest that information-based post-emergent weed control in corn and soybean is quite remunerative. However, analysis of potential herbicide bans indicates that the value of weed information declines with the number of cost-effective control alternatives. In many--but not all--cases, information-based weed management also reduces herbicide load in the environment. However, this result is an artifact of the benchmark weed control practice rather than an implication of information-based management.

For farm managers, the significant value of pest population information is important for two reasons. First, it offers an opportunity to improve net returns by using more information as an input. Second, it illustrates how imperfect management information may lead to privately suboptimal decisions. Since increased information may reduce the use of agricultural chemicals by the private utility-maximizing manager, information deficiency constitutes an alternative to the economic externality explanation of environmental contamination. The imperfect information diagnosis suggests untested policy alternatives such as pest information subsidies as a means to achieve the twin social objectives of reduced chemical use and increased producer income.

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Table 1. Characteristics of the base case farm used in simulation.

Characteristic	Unit	Amount
Labor		
Workers	number	2
Max. days per week	number	7
Max. hours/day	number	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 2: Levels of experimental factors employed in stochastic simulation.

Experimental factor	Unit	Low	Medium	High
Initial weed seeds				
Foxtails	seeds/m^2	175		1750
Lambsquarters	seeds/m^2	25		250
Pigweed	seeds/m^2	50		500
Information on weed population	sample counts	none[1]	seedlings[2]	seeds & seedlings

[1] Strategies are, for continuous corn, cyanazine PPI and atrazine and oil POST; for rotation corn, alachlor PPI and cyanazine POST; for soybean, trifluralin PPI and rotary hoe POST.

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

Table 3.: Mean annualized net farm income by information level for a 480-acre farm: stochastic simulation of 6-year periods under 20 states of nature.

Initial weed seed density and cropping unit	Information Level		
	No information	Seedling counts	Seed and seedling counts
Low Initial Weeds			
Farm	5,809 (7,034)[1]	9,766 (8,896)	10,014 (8,827)
Continuous Corn	-2,112 (4,002)	-464 (4,426)	-325 (4,492)
Rotational Corn	-1,517 (3,253)	-272 (3,662)	-28 (3,693)
Rotational Soy	9,438 (3,331)	10,501 (3,098)	10,458 (3,060)
High Initial Weeds			
Farm	-14,549 (8,066)	-4,021 (7,437)	-3,751 (7,587)
Continuous Corn	-7,041 (4,542)	-4,284 (3,728)	-4,251 (3,771)
Rotational Corn	-9,369 (3,855)	-4,888 (2,812)	-4,626 (2,928)
Rotational Soy	1,862 (3,937)	5,150 (3,093)	5,127 (3,125)

[1] Standard deviations in parentheses

Table 4.: Paired difference t-tests of annualized income over 20 states of nature: Gains in annualized net farm income due to high and POST information.

	HIGH over POST			POST over NO		
Initial Weed Density	Mean Difference	Standard Deviation	t Statistic	Mean Difference	Standard Deviation	t Statistic[1]
Low	339	474	3.19	3,957	4,141	4.27
High	271	586	2.06	10,527	6,669	7.06

[1] One-tailed critical values with 19 degrees of freedom for joint, three-way comparisons are as follows: t(.20) = 1.73, t(.05) = 3.17, t(.01) = 3.88.

Table 5.: Mean annual herbicide load (pounds of active ingredient per acre) by information level for a 480-acre farm: Stochastic simulation of 6-year periods under 20 states of nature.

	Information Level		
Initial weed seed density and cropping unit	No information	Seedling counts	Seed and seedling counts
Low Initial Weeds			
Continous Corn	4.35	3.68	2.94
Rotational Corn	4.18	3.17	3.05
Rotational Soy	0.75	0.79	0.79
High Initial Weeds			
Continuous Corn	4.35	3.85	3.58
Rotational Corn	4.18	3.12	3.50
Rotational Soy	0.75	0.78	0.78

Table 6.: 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						Change from POST info.		
	Over POST Information			Over NO information			Over NO information		
Initial Weed Density	Mean Difference	Standard Deviation	t Statistic [1]	Mean Difference	Standard Deviation	t Statistic [1]	Mean Difference	Standard Deviation	t Statistic
Low initial weeds		- lb ai/acre -			- lb ai/acre -			- lb ai/acre -	
Cont. Corn	-0.74	0.26	-12.55	-1.41	0.37	-16.83	-0.67	0.21	-14.01
Rotn. Corn	-0.12	0.25	-2.13	-1.12	0.22	-22.56	-1.00	0.09	-48.68
Rotn. soybean	-0.01	0.02	-1.46	0.26	0.36	3.22	0.04	0.04	4.41
High initial weeds									
Cont. Corn	-0.27	0.19	-6.14	-0.77	0.27	-12.57	-0.50	0.19	-12.05
Rotn. Corn	0.38	0.28	6.01	-0.67	-0.22	-13.77	-1.05	0.09	-53.89
Rotn. soybean	-0.00	0.01	-1.26	0.03	0.02	6.41	0.03	0.02	6.51

[1]Two-tailed critical values with 19 degrees of freedom for joint, three-way comparisons are as follows: $t(.10) = 1.73$, $t(.05) = 2.86$, $t(.01) = 3.88$.

Table 7.: Calculated value of weed population information per acre for a 480-acre corn-soybean farm under four expected utility functions.

	Coefficient of absolute risk aversion			
Experimental Factor	-.0001	0	.0001	.001
	-------- $ equivalent --------			
Low initial weeds				
High information	11.42	8.95	6.22	4.94
Low information	10.80	8.24	5.34	2.87
High initial weeds				
High information	19.37	22.50	21.86	25.89
Low information	18.69	21.93	21.57	25.94
Difference between high and low information				
Low initial weeds	0.62	0.71	0.88	2.07
High initial weeds	0.68	0.56	0.29	-0.05

Table 8.: Effect of bans on atrazine and all triazines on the calculated value of weed population information per acre for a 480-acre corn-soybean farm, by level of risk aversion.

	Coefficient of absolute risk aversion			
Experimental Factor	-.0001	0	.0001	.001
	- - - - - - - - $ equivalent - - - - - - - -			
ATRAZINE BAN				
Low initial weeds				
High information	5.46	5.21	5.63	15.10
Low information	3.24	3.68	3.38	3.64
High initial weeds				
High information	8.32	10.17	14.34	33.44
Low information	7.88	10.98	16.26	31.31
TRIAZINES BAN				
Low initial weeds				
High information	3.11	2.31	2.28	10.96
Low information	1.77	1.80	0.65	-1.98
High initial weeds				
High information	2.25	3.99	9.70	31.39
Low information	3.12	6.25	13.04	30.24

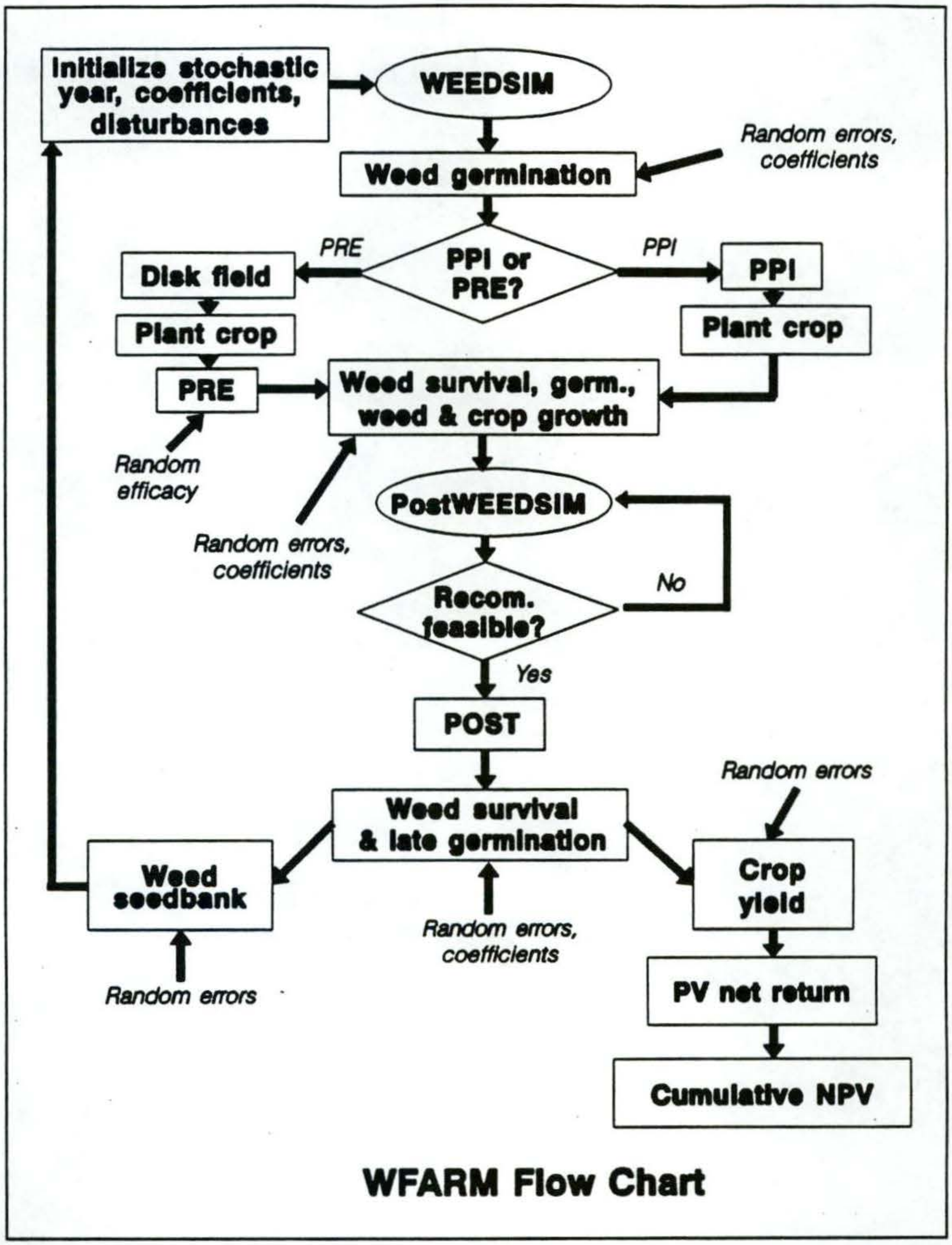

Figure 1: Stochastic WFARM flow chart.

ENDNOTES

1. This approach runs counter to the marginalist recommendations of Pannell (1990) and Headley. However, Deen et al. have demonstrated empirically that a marginal herbicide application rule may have little value compared to a threshold rule at recommended rates. The reduced reliability of herbicide efficacy at sub-label rates combined with farmers' loss of manufacturers' guarantees constitute substantial associated costs.

2. By the Bonferroni inequality, a simultaneous three-way confidence interval of 95% can be constructed by insuring that the individual component intervals have confidence coefficients (1 - .05/3) = 98.3% (Mendenhall et al.). Hence individual 99% confidence intervals insure a joint 95% interval. Similarly, individual 99.8% intervals insure a joint 99% interval.