A BIOECONOMIC ANALYSIS OF SITE-SPECIFIC MANAGEMENT AND DELAYED PLANTING STRATEGIES FOR WEED CONTROL

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This is to certify that I have examined this bound copy of a doctoral thesis by

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Dedicated to the memory

of my father

Mr. Joel Oriade

and my brother

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ABSTRACT

The potential economic and environmental benefits of two emerging tools for low input weed management are examined in this research. Site-specific weed management (SSM) prescribes herbicide treatment for only the portion of a field exposed to weed infestations, rather than the entire field. Delayed planting allows weeds to emerge prior to planting. Since these weeds are eliminated during pre-plant tillage operations, the potential for subsequent weed problems is greatly reduced.

The potential benefits of these instruments are simulated using a variant of WEEDSIM, a dynamic bioeconomic weed management model. Differences in model performance under SSM and delayed planting strategies as compared to performance under standard practices impute value to these weed control tools. Simulations with the model were conducted within a deterministic framework.

Simulated results suggest that patchiness in weed distributions is the most crucial factor justifying the use of SSM. Other factors such as weed populations and weed species mixes only play secondary roles. There is a substantial environmental gain from SSM practices under a considerably high degree of weed pressure and aggregation. However, the impact of such practices on profit is generally modest. For this reason, it is doubtful if farmers will be willing to adopt this strategy without some public support, particularly when cost and risk considerations are factored in.

Outcomes from static simulation experiments for delayed planting strategy suggest that the practice can be a valuable instrument for optimizing net income and

herbicide use, especially at high weed populations. The practice may lead to an effective control of pre-plant weeds through mechanical means to the extent that the use of pre-emergence herbicides is not required. Furthermore, the economic benefits of delayed planting strategies are not sensitive to hybrid varieties and rotational practices in the short run.

In view of the desirable environmental attributes of these two strategies, their use deserves support. Cheap and affordable technology, cheap and easy access to information on weed population dynamics and crop yield-planting date relationships are means of enhancing the adoption of these environmentally-friendly practices.

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LIST OF ABBREVIATIONS

SSM	Site-specific management
NBD	Negative binomial distribution
NCSCRL	USDA-ARS North Central Soil Conservation Res. Lab., Morris, MN
EIQ	Environmental impact quotient
PIE	Pesticide Index Equation
TPI	Total Pesticide Index
PPWC	Pre-Plant Weed Control
WSSA	Weed Science Society of America
PPI	Pre-plant Incorporated
VRT	Variable rate technology
USDA	United States Department of Agriculture
GDD	Growing degree day
CGDD	Cumulative growing degree day
WTA	Willingness-to-accept
WTP	Willingness-to-pay
MN	Minnesota
bu	Bushel
Pers. comm.	Personal Communication

I. INTRODUCTION

I.1 Weeds, Herbicide Use and the Environment

The deleterious effects of weeds in agricultural production are well known. By competing with crops for soil nutrients and moisture, weeds reduce crop yields. In a study commissioned by Weed Science Society of America, Chandler et al. (p.2) estimate the value of average annual yield loss caused by weeds in sixty-four crops at about US$7.5 billion in the United States during the period 1975-1979. In Canada, they estimate an annual loss of about US$ 909 million in thirty-six crops considered during the period.

Before the development of herbicides, cultivation was the standard post-emergence weed control practice worldwide. However, interest in improving the effectiveness of mechanical weeding began to wane as herbicides became the principal method of managing weeds in developed countries (Mulder and Doll). Herbicides account for over 60% of total pesticides used annually on U.S. crops. This translates to approximately 460 million pounds of active ingredient per year (Giannessi and Puffer, p. 1) and expenditure of close to $3 billion at 1994 herbicide prices.

Cost considerations and growing environmental concerns are rousing interest in lowering pesticide usage and implementing other forms of reduced chemical weed control. Since misapplication of herbicides can be counterproductive in terms of both yield loss and high control costs, information that leads to optimal herbicide use should be of interest to farmers.

Recently, renewed efforts to prevent indiscriminate use of pesticides stem from concerns about their environmental effects. Herbicides are increasingly being implicated as a potential source of ground and surface water pollution and the attendant health hazards. Nielsen and Lee (p.vi) estimate that over 50 million Americans rely on potentially contaminated groundwater for their drinking needs. Furthermore, a connection is now being established between direct exposure to herbicide application and some types of cancer (Hoar et. al).

These adverse effects have led to imposition of regulatory actions which range from herbicide restrictions to severe measures such as quotas. In the United States, atrazine, the most commonly detected herbicide in groundwater, is currently a restricted use product. In the Netherlands and Denmark, quotas have been imposed to regulate the amount of pesticides that can be used for crop production. The Netherlands aims for 30% reduction in herbicides (active ingredient) by 1995 when compared to 1984-1988 use levels. The target reduction by year 2000 is 45% (Wossink and Renkema, p.3). Denmark's goal is to reduce current herbicide use levels by 50% in 1997 relative to 1987 use levels (Thompson et al. p. 254).

The above evidence suggests that as people become more sensitive to pesticide hazards, the current use levels cannot be sustained globally without attracting further imposition of stricter regulatory measures. Consequently, the questions of identifying low input control strategies that do not have severe adverse effects on crop yields and profits are becoming increasingly relevant in Integrated Pest Management (IPM) research.

I.2 Directions in Economic Modeling for Weed Management

Bioeconomic models for weed management aim at identifying control strategies that are consistent with the objective of maximizing either expected utility or net returns. The models by Moffitt et al.; Taylor and Burt ; King et al, (1986); and Olson and Eidman all fall within this category. These models employ economic threshold concepts to prescribe weed control strategies that are responsive to field conditions. In contrast, farmers' standard practices often treat weeds prophylactically. As a result, bioeconomic models have proved quite useful in optimizing weed control and in causing significant reduction in the use of both pre- and post-emergence herbicides (Thornton et al.).

Representations of the biological relationships between weed populations and crop yields are a key component of these models. In representing these relationships, the average density of quadrat samples of weeds is used as an index of weed population. This approach implicitly assumes that weeds are uniformly distributed throughout the fields or that they are characterized by a Poisson distribution. If this assumption is not valid, the consequence is that yield estimates may be distorted and recommended strategies may not be truly optimal particularly if weeds occur in patches.

However, it is becoming evident that biological data rarely follow a Poisson process in nature (Bliss and Fisher). Most studies that have investigated the nature of weed distributions in fields have indicated that a patchy, rather than a Poisson random distribution, is a better characterization (Marshall; Wiles et al.(1992a)). Furthermore, Auld and Tisdell have shown that patchiness in weed distributions causes significant errors in estimated yield losses. Based on the strict convexity of the crop yield-weed density functions, they prove that models of uniform weed distributions overestimate yield losses for clumped weeds. This implies that there is probably a value to weed management information that helps farmers account for the pattern of weed distribution.

Site-specific management (SSM) for weed control prescribes herbicide treatment only for the portions of a field infested by weeds, rather than the entire field. SSM, otherwise known as variable rate technology (VRT) or precision farming, is already a well-established practice for managing soil fertility. For weed control, the practice can become a part of preferred management strategies in fields that display considerable spatial variability in weed populations. The likelihood of developing increasingly affordable geographic positioning systems and spray applicators that permit automated selective spraying is now making SSM more attractive. This weed control strategy may provide the means for balancing the profit motive of weed control with environmental needs. The prospects of reducing herbicide loads, controlling costs and reducing attendant health hazards by implementing SSM account for the growing interest in this area of research (Hughes; Thompson et al.; Wiles; Brain and Cousens).

Thornton et al. show the effects of spatial distribution of weeds on economic thresholds. Using simulation techniques to account for spatial weed distribution, they conclude that as weeds get more clumped, the threshold level increases and chemical application becomes less likely to be the dominant economic strategy. However, their simulation experiments were conducted for the static control of a single weed species (wild oats) in a single crop (winter wheat).

Wiles et al. (1992a) conducted simulation experiments to investigate the value of information about weed patchiness for improving the recommendations of a microcomputer weed management model for soybean, HERB. By fitting theoretical distributions to the quadrat counts of broadleaf weeds, they identified a negative binomial as the appropriate distributional form. They contend that no significant error in decision making will be made by assuming a Poisson or uniform distribution, although a modest improvement in the value of information is obtained when the model accounts for weed spatial patterns. Their simulation experiments were limited to only broadleaf weeds in soybeans. Also, the economic potential of SSM was examined for post-emergence weed control decisions only.

Cognizant of the fact that Cousens's rectangular hyperbola - which is widely used to describe weed/crop competition - implicitly assumes uniform distribution of weeds, Brain and Cousens have reformulated the model to incorporate weed distribution effects. Under the assumptions that:(i) a negative binomial distribution characterizes weeds in the field; (ii) the field can be sub-divided to a number of sub-plots; and (iii) weeds are uniformly distributed within each sub-plot so that hyperbolic function relates yield to weed density in each sub-plot, they have developed a statistical model which can be evaluated using numerical integration.

These attempts at incorporating weed distribution into bioeconomic models have been very limited in scope. The models have been developed for a single weed species and a single control within a static framework (Thornton et al.; Brain and Cousens) or for multiple broadleaf weeds and a single control within a static framework (Wiles). None of the studies has examined the influence of weed distribution within a dynamic, multiple species, multiple control setting, which truly reflects farmers' decision environment. Also, the interest in SSM as a weed control tool has been mainly economical; its environmental attributes have received little attention.

A second potential tool for reducing pesticide use and cost is delayed planting coupled with mechanical weeding. Some farmers now wholly depend on pre-plant tillage supplemented with only inter-row cultivation to control weeds rather than herbicides (Fernholz). Delayed planting allows weeds to emerge prior to planting. Since all these emerging weeds are destroyed by field operations required for final seed-bed preparation, the potential for subsequent weed problems is greatly reduced.

A number of studies have been undertaken to determine the optimum planting date and the effect of delayed planting on crop yields (Rocheford et al.; Wolf and Edmisten; Seymour et al.). Seymour et al. conclude that a piecewise linear relationship generally describes the data obtained from various locations in the United States and United Kingdom, although the threshold date after which yields are reduced by planting varies considerably with locations and varieties.

The effects of delayed planting on economic returns are rather mixed in the literature. Further studies are required for conclusive evidence about its influence. For instance, Gunsolus contends that producers who delay planting and adopt mechanical weed control may be balancing the yield loss due to late planting with the potential yield gains from improved weed control without herbicides. Mulder and Doll observe that while delayed planting lowers herbicide use, higher economic returns are obtained from early plantings with herbicide use. Forcella et al. (1993) demonstrate how the knowledge of seed-bank ecology of annual weeds is an essential prerequisite for optimizing delayed planting and mechanical control of weeds. This can be accomplished through proper modeling of weed seedling emergence, weed seed production, weed density/crop relations, yield penalty and seed-bed preparation functions.

It is clearly evident from all these studies that delayed planting is a low input strategy. The strategy might become more attractive as incentives are put in place to induce the adoption of low input strategies or make herbicide users bear responsibility for social costs of chemical usage. Further research to address other pertinent issues is required. An example is that of establishing the threshold time periods within which farmers could achieve effective mechanical control of weeds by delaying planting while optimizing yields and net returns under a wide range of environmental and resource conditions.

These two approaches to weed control have costs as well as benefits. SSM may require additional cost for acquiring information on the spatial distribution of current and potential weeds and equipment for selective spraying. On its part, delayed planting can result in yield losses. The time-lag in carrying out fieldwork and harvest operations may also have costly implications. Therefore, weed management models need to balance the private benefits of lower herbicide costs and the social benefits of reduced herbicide usage with the costs of implementing SSM and delayed planting before these tools can become a part of preferred weed management strategies.

1.3 Objectives

This study will examine how fuller pest management information obtained by accommodating intra-field weed management and delayed planting strategies in bioeconomic pest management models improve farmers' weed management decisions. Consequently, the broad objective of this study is to explore the benefits and costs of SSM and delayed planting strategies as low input weed control instruments. Since over 60% of herbicides used on U.S. crops are applied to corn and soybean (Giannessi and Puffer, p.3), the analysis will focus on these two crops.

The specific objectives of the research are as follows:

(i) To modify WEEDSIM, the dynamic bioeconomic model for the control of multiple weed species (Swinton; Swinton and King) such that its decision rules accommodate site-specific weed management and delayed planting strategies;

(ii) to use simulation experiments to assess the potential economic and environmental benefits of managing for intra-field weed variability under varying weed populations, weed species mixes and dispersion;

(iii) to determine planting thresholds that balance the benefits of delayed planting strategy against its costs and describe the set of environmental and resource conditions under which delayed planting and mechanical weed control can become a part of preferred weed management strategies.

1.4 Organization of the Thesis

Chapter two examines the conceptual issues involved in modeling for optimal weed management strategies. It discusses the methodology used in assessing the potential economic and environmental benefits of SSM and delayed planting as low input weed control instruments. Simulation and geostatistical routines that permit implementation of these strategies are discussed. Chapter three highlights the salient features of WEEDSIM - the kernel bioeconomic weed management model - and discusses its variant, MODWSIM, which incorporates SSM and delayed planting effects as weed control instruments. It presents the nature and sources of data, and also discusses the techniques employed in generating parameter estimates for model simulation. Chapter 4 presents the assumptions underlying simulation experiments of SSM. It discusses the outcomes of the deterministic, dynamic model runs for measuring the potential economic and environmental benefits of SSM under varying degrees of weed populations and aggregation. Chapter 5 shows the results of static simulation experiments for evaluating the potential benefits of delayed planting strategies under: (i) varying degrees of weed population and weed species mixes; (ii) varying degrees of weed aggregation; (iii) different corn hybrids; and (iv) different rotational practices. The final chapter presents the summary of major findings and suggests directions for future research.

II. CONCEPTUAL ISSUES IN WEED MANAGEMENT MODELING

This chapter sets out the conceptual issues involved in modeling for optimal weed control. It discusses the relevance of SSM and delayed planting strategies in such models. Finally, it presents the methodology used in assessing the potential economic and environmental benefits of these tools as weed control instruments in subsequent chapters of the thesis.

2.1 General Pest Management Model

Pest control inputs, such as herbicides, are damage control agents whose distinctive features rest in their ability to increase the share of potential outputs that producers realize by reducing damage caused by weeds. The literature is fairly rich with suitable models of pest management under both the assumptions of risk neutrality and aversion (Feder; Lichtenberg and Zilberman; Olson and Eidman; Swinton and King).

The typical risk neutral, static single weed management model takes the form:

$$\max_{(H)} \Pi = PY - RZ - SH \tag{2.1}$$

subject to:

$$\begin{aligned} Y &= Y^{\circ}(1 - D(W)) \\ W &= W^{\circ}(1 - K(H)) \\ Y^{\circ} &= f(Z) \end{aligned}$$

where Π is the profit, P is the crop price, Y is the yield, R is the unit price of other variable inputs (Z) that are not connected with weed control and S is the unit price of weed control strategy H. Y^o is the weed-free yield and D(W) is a damage function which establishes the extent of yield loss attributable to weeds. W is the average weed density (usually per square meter or foot) and W^o is the initial weed population prior to any weed control measure. $K(H) \in [0, 1]$ is the"kill" function or a measure of herbicide effectiveness. By assuming that the profit function in the above model is strictly concave and twice differentiable, one can solve for the unique herbicide level that maximizes profit (e.g., Pannell). Alternatively, the model is sometimes treated as a discrete decision problem whereby the set of actions that maximizes profit is identified by evaluating profit for all feasible sets of weed control actions (Swinton and King, 1994).

Static single weed models such as (2.1) abstract considerably from reality. They fail to capture the dynamic effects of weed seedbank on control strategies. To overcome this drawback, Swinton and King (1994) have recast the model into its dynamic form which also allows for the control of multiple weed species as shown in (2.2):

$$\underset{h_t}{Max}\ \pi_t = \sum_{t=0}^{T} \rho_t \left(P(Y_t^o \iota_j - D(W_t^h)) - RZ^o - (S_t' I_j)h_t\right) \tag{2.2}$$

subject to the following state equations :

$W_t = W(S_{t-1})$

$S_t = S(S_{t-1}, W_t, W_t^h)$

$W_t^h = [I - k(h)]W_t$

where π_t is a vector of net profit at t that follow t-path of j control treatments. S_t is a vector function of ending weed-seed bank densities and S_{t-1} refers to the corresponding vector of seedbank densities in the previous season. W_t is a vector of cumulative weed seedling emergence during the season, W_t^h is the vector of weed populations surviving to reproduce after the control h, has been applied. ρ is equal to 1/1+r where r is the discount rate.

2.2 Weed Spatial Distribution and Yield Loss

The implicit assumption underlying most weed management models is that of either uniform or Poisson weed distribution. The damage function, D(.), that is used to estimate the quantity of yield loss assumes that weed density, W, is homogeneous. However, the estimated yield may be biased if the weed distribution is not uniform.

There is a controversy about which functional form best describes the nature of the relationship between weeds and crop yields. However, the hyperbolic function, which specifies a strictly convex relationship between crop yield and weeds, enjoys wide support (Cousens; Pannell; Swinton and King.). For single weed species, Y in equation (2.1), under the assumption of hyperbolic relationship, takes the form:

$$Y = Y_o \left[1 - \frac{iw}{\left(1 + \frac{iw}{a} \right)} \right] \tag{2.3}$$

where Y_o is the weed free yield, a is the yield loss as weed density (w) tends to infinity, and i is the yield loss as weed density tends to zero. Following Brain and Cousens, if one denotes i/a by c, then the percentage yield loss in (2.3) is:

$$\%Y_L = 100 \frac{acw}{(1 + cw)} \tag{2.4}$$

Modeling for multiple weed species requires a slight modification of single weed models. Swinton and King develop the following variant of equation (2.3) for multiple weeds:

$$Y = Y_o \left[1 - \frac{\sum_{i=1}^{n} I_i \; w_i}{1 + \frac{\sum_{i=1}^{n} I_i \; w_i}{a}} \right] \tag{2.5}$$

where the subscript i denotes the weed species. The percent yield loss due to multiple weeds in (2.5) is:

$$\%Y_L = \frac{100 \sum_{i=1}^{n} I_i \; w_i}{1 + \frac{\sum_{i=1}^{n} I_i \; w_i}{a}} \tag{2.6}$$

Following similar notation as in (2.4), the yield loss in (2.6) can be rewritten as:

$$\%Y_L = \frac{100 \; a \sum_{i=1}^{n} c_i w_i}{1 + c_i w_i} \tag{2.7}$$

The above yield loss models are appropriate if the assumption of random Poisson weed distribution holds. This can be checked by testing whether the hypothesis of a Poisson distribution holds when fitted to quadrat counts of weed seeds or seedlings. If this assumption fails, there is a need to determine the appropriate distributional form. A negative binomial distribution (NBD) has been found to be appropriate in most cases (Marshall; Wiles; Brain and Cousens).

A NBD is described by two parameters, m, the mean, and K, which is the index of aggregation or patchiness. Both parameters are positive but need not be integers. For NBD, if the proportion of quadrats with r weeds is denoted by P_r, then the probability that the quadrats will contain r = 0, 1,2...... weeds is given by (Brain and Cousens; Ross and Preece):

$$P_r = \binom{r+K-1}{K-1} \left(\frac{m}{m+K}\right)^r \left(\frac{K}{m+K}\right)^K \tag{2.8}$$

where m is the mean weed density over the entire field. The variance (σ^2) of the distribution is given by (Ross and Preece):

$$\sigma^2 = m + \frac{m^2}{K} \tag{2.9}$$

from (2.9), one can see that the variance will approach the mean as K tends to infinity, or the distribution approaches random or Poisson process as K increases. On the other hand, the lower the value of K, the more clumped the weeds appear in natural populations. Therefore, low K values are consistent with a NBD. Although approximate values of K can be obtained from (2.9), its precise estimates can be generated by using either the maximum likelihood iterative method proposed by Bliss and Fisher or the appropriate computer software, e.g. MLP (Ross and Preece).

Under certain assumptions, single weed models can be easily modified to account for weed distribution effects. If it is assumed that: (i) the field can be subdivided into a number of sub-plots; (ii) weeds are uniformly distributed in each sub-plot; and (iii) each sub-plot contains x weeds, then for the entire field, the equivalent percentage yield loss in (2.4) is:

$$\%Y_L = 100\ a \sum_{x=0}^{\infty} \left(\frac{cx}{1 + cx} \right) P_x \qquad (2.10)$$

where P_x is the probability density function of the observed counts of x weeds in each sub-plot. Brain and Cousens prove that the average yield loss function in (2.10) reduces to:

$$Y_L = 100\ a \int_0^1 z^{1/c}\ G'\ (z)\ dz \qquad (2.11)$$

where $G'(z)$ is the first derivative with respect to z of the probability generating function (PGF) of the underlying distribution and z is a variable usually lying between 0 and 1. Probability generating functions are known for many discrete distributions. For a negative binomial distribution, the PGF is (Ross and Preece; Brain and Cousens):

$$G(z) = \left(\frac{K}{K + w(1-z)} \right)^K \qquad (2.12)$$

where w is the weed density and K the index of aggregation. By substituting the derivative of the PGF in (2.12) for $G'(z)$ in (2.11), Brain and Cousens estimate the average yield loss in (2.11) using a numerical integration procedure.

For multiple weeds, the joint density function of all weed species present in the field is required to predict expected yield loss. If it is assumed that weed species are statistically independent, then the joint density will be the product of marginal densities of individual weed species. If significant correlations between weed species are indicated, then the joint density will also need to account for the nature of interdependency among weeds.

There are a number of alternative approaches that simplify the problem of defining joint density function required for extending Brain and Cousens's method to multiple weeds. Wiles et al. (1992a) estimate yield loss due to weeds from the frequency distribution for quadrat counts of weeds and the functional relationship existing between yield and weed densities. A similar approach used in this study is to discretize the field into a finite number of subfields or management units. Under the assumption of uniform weed distribution within each subfield, percent yield loss can be estimated for each subfield. In essence, SSM has shifted the decision-making unit from the whole field to subfields, and the concept of defining a threshold level for the whole field is no longer appropriate. Rather, SSM implies a strategy whereby appropriate weed control actions are established for each management unit or subfield. Based on conditions in each subfield, a decision will be made regarding whether and how to control weeds in that portion of the field. Control decisions will usually vary from one segment of the field to another, depending on the pattern of weed distribution. Therefore, rather than the entire field, equation (2.1) will be estimated and recommendations will be made for each subfield. Then SSM becomes the preferred management strategy if :

$$\sum_{i=1}^{s} \pi_t^s \geq \Pi_t \tag{2.13}$$

where i is an index of s number of subfields, π_t is the profit at t in each subfield and Π_t is as defined in (2.1).

The main challenge of this alternative approach is how to partition the field into a suitable number of subfields and distribute the field weed population across all subfields. There are a number of ways to approach the problem. The first technique is to use weed population maps produced via geostatistical analyses such as Kriging. This method provides a commercial approach to implementing SSM in practice. Another approach is to simulate weed population of the subfields from the parameters of the parent field weed population. The next two sub-sections further discuss the conceptual issues involved in both approaches and the extent to which they are employed. In this study, estimation of the potential economic and environmental benefits of SSM is undertaken from subfields whose weed populations are obtained through simulation.

2.2.1 Geostatistical Analysis and Field Partitioning

Patchiness in weed distributions suggests that weeds are spatially dependent. For this type of data, a geostatistical interpolation technique known as Kriging is a suitable approach for establishing how the weeds are distributed in space. Mortensen et al. define Kriging as a process based on spatial autocorrelation that permits precise estimation of variables between sampling points for use in mapping a population.

The first step in Kriging is to quantitatively assess the spatial dependency of the process by defining the functional relationship between the spatial pattern of sampled points and their observed values. If D is a fixed subset of R^{d++}, and $\{Z(S) : s \in D\}$ is a realization of a random or stochastic process, then a variogram function is defined as:

$$2\gamma(S_1 - S_2) = Var(Z(S_1) - Z(S_2)) \tag{2.14}$$

for all S_1, $S_2 \in D$. If the assumption of second-order stationarity property is imposed, then the above equation reduces to:

$$2\gamma(h) = Var\ (Z\ (S + h) - Z(S)) \tag{2.15}$$

where h is the distance between two points. For Kriging purposes, half of the variogram, γ(h), otherwise called a semivariogram, suffices. Following Marx and Thompson, a semivariogram can be defined as:

$$\gamma(h) = \frac{1}{2} \sum_{i=1}^{m} (Z(S_i+h) - Z(S_i))^2 \tag{2.16}$$

where m is the number of couples or pairs included in the summation.

Semivariograms must be positive definite to ensure that estimated variances are non-negative. Therefore, only a limited number of functions that are positive definite in more than one dimension are suitable for constructing semivariograms. The most commonly used functions are the spherical, exponential, Gaussian, linear and logarithmic.

In practice, a scatter diagram of fitted semivariogram values against various distances (h's) will suggest the appropriate functional form. Parameters of the fitted functions are used to construct Kriged values. These Kriged values are in turn used to produce graphic maps which provide the basis for partitioning fields into subfields or management units (MU) in practice.

Computer programs are now available for producing these maps. One of such programs, a geostatistical software for environmental sciences, otherwise known as GS+2, was used to generate graphic maps of weed seed and seedling distribution of a typical field in the study area. Kriged maps for the field used in this study are shown in Appendix 4.

The need to produce Kriged maps for implementing SSM of post-emergence weed control may disappear with time. For example, technological advances which lead to development of information-based technologies such as sensor sprayers may eliminate the need for prior weed mapping. For post applications, such sensor technologies can let control decisions be made automatically based on the foliar characteristics of weeds. This has the tendency to reduce costs and enhance the feasibility of implementing SSM in the long run.

2.2.2 Simulation Method for Partitioning Fields

As mentioned earlier, the use of geostatistical techniques offers a practical way of adopting SSM. However, for evaluating the potential economic and environmental benefits of SSM prior to implementation, the simulation approach suffices. Since simulated variates are not exact representations of weed distribution in the fields, this method abstracts from reality. However, the strength of the approach lies in its considerable flexibility. By continuously reparameterizing the mean, the index of patchiness and the correlation matrices, simulation permits the evaluation of potential net benefits of SSM under a wide range of weed populations, mixes and dispersion. On the other hand, while graphic maps produced by Kriging may be a better depiction of weed patterns in the field, the irregular structure of weed distributions in the maps does not facilitate easy estimation of SSM gains.

Under the simulation approach, parameters of the discrete distribution characterizing the weeds can be employed to generate variates of the distribution. In this study, parameters of the negative binomial distribution - the mean and an index of patchiness(k) - were employed in generating random variables of the distribution. There are a number of computer algorithms for simulating such variates (See Ahrens and Dieter, p.244). In this study, the relationship between the negative binomial, gamma and Poisson distributions was employed in simulating the variables. Following the approach suggested by Rubinstein (p.106), random variables of gamma distribution were first generated. These variables were then fitted to a Poisson algorithm using the acceptance-rejection algorithm described by Kelton and Law (p.256). The resultant simulated random variables are from a negative binomial distribution. In cases when the algorithms are sensitive to small values of K or large mean values or both, rescaling these parameters such that the transformed variables are invariant to the scale of transformations, often proves useful. The program code for the negative binomial simulation model, NEGBIN, which is written in QuickBasic language, can be found in Appendix 2.

Since the above procedure is suitable for generating single random variables from univariate distributions, and such variates do not reflect the nature of interdependency occurring among weeds, the multivariate process generator developed by King (pp. 226-239) was used in transforming these marginal distributions to their multivariate forms. The procedure employs the correlated disturbance error terms of empirical equations in generating the interdependent variables. Fackler points out the only drawback of this method which has to do with the input product moment correlation coefficients that are not invariant to transformations of the underlying marginal distributions. To sidestep this probable problem, non-parametric rank correlation matrices were used in place of product moment correlation. Each sample vector drawn from the joint distribution of weeds constitutes the weed population information for a subfield. The difference in model performance for the aggregate of all subfields when compared to uniform management of these subfields imputes value to SSM.

2.3 Late Planting, Yield Loss and Weed Control

Yield declines if planting is carried out after some optimal planting period. Therefore, if planting date becomes an argument in the yield function, then the weed-free yield, Y_o, becomes:

$$Y_o = Y^*_o[1 - D(P_d)] \tag{2.17}$$

where Y^*_o is the weed-free yield obtained when timely planting is carried out. $D(P_d)$ is the yield loss function relating crop yield to planting date.

Late planting, on its plus side, holds a potential for effective mechanical weed control of emerging weeds. As noted earlier, delaying planting allows weeds to emerge prior to planting since both crops and weeds require similar conditions for germination. The emerging weeds can be controlled by pre-plant tillage. Therefore, if weed-seed emergence and seed-bed preparation dates are properly modeled, the cost of achieving a comparable effective level of weed control may be less for mechanical control than for its chemical counterpart (Forcella; Mulder and Doll). If S represents the cost of weed control, then:

$$SY^{*o}[1-D(P_d)] \leq SY_o^* \tag{2.18}$$

The objective of optimizing delayed planting is met if one can identify the planting date regions (P_ds) such that:

$$\Big((P_y - S)(Y_o^*[\ 1 - D(P_d)\ ]) \Big) \geq P_y\ Y_o^* - S(Y_o^*) \tag{2.19}$$

The planting date (P^{**}_d) for which (2.19) holds with equality defines the planting date threshold.

2.4 Economic Thresholds and Spatial Weed Distribution

The Economic threshold (ET) concept hinges on the notion that as weed density increases per unit area, the benefit from improved yields exceeds the cost of controlling weeds. The threshold weed density (number of plants per acre) is the level of weed density at which cost equals the benefit of control. Therefore, for static single weed models , control strategy, h, should be chosen at any weed density levels exceeding or equal to the threshold density w^{hx} i.e.:

$$h = \begin{cases} h^{x} \text{ if } P[D(w^{ho}) - D(w^{hx})] \geq C^{hx} \\ 0 \quad \text{otherwise} \end{cases} \tag{2.20}$$

where h^x represents the control strategy that maximizes net revenue at the recommended rate, $D(w^{ho})$ is the damage function if weeds are not controlled and $D(w^{hx})$ is the corresponding damage function of the surviving weeds after control strategy h, has been applied. C^{hx} is the cost of control. For multiple weeds, h in (2.20) is a vector of control strategies.

Static threshold models fail to account for carryover effects of weeds. Consequently, the dynamic threshold levels normally occur at lower weed densities than the static models. The dynamic version of (2.20) can be written as (following Swinton, p.18) :

$$h_t = \begin{cases} h_t^{x} \text{ if } P[D(w_t^{ho}) - D(w_t^{hx})] - DV_{t+1}(w_t^{hx}, s_t, h_t^{x}) \geq C_t^{hx} \\ 0 \quad \text{otherwise} \end{cases} \tag{2.21}$$

where s_t represents other variables and $DV_{t+1}(.)$ is the value of future yield damage function.

Since SSM has shifted the decision-making unit from the whole field to subfields, the concept of defining a weed density threshold level for the whole field is no longer appropriate. Rather, SSM implies multiple density threshold levels whereby threshold level is established for each management unit or subfield. Actually, the variation that exists among the threshold levels of all subfields of a field is the conceptual basis for SSM.

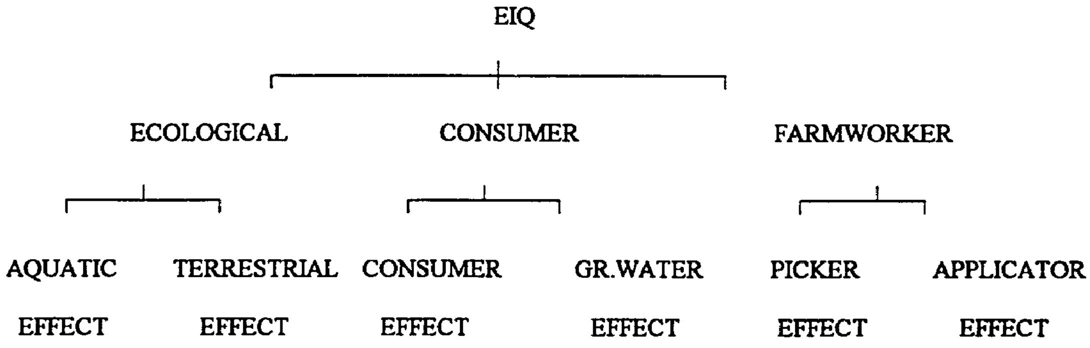
2.5 Environmental Impact of Weed Control Strategies

The potential environmental benefit of SSM and delayed planting strategies is a major factor that makes these weed control instruments intuitively appealing. By promoting the use of nonchemical weed control strategies, delayed planting has a tendency to reduce herbicide use. However, the effects of SSM on the environment are not so clear-cut. For optimal weed control under SSM, herbicide use may be required for some or all portions of the field. Its intra-field management capability based on multiple threshold concepts may necessitate the use of more than one herbicide product in a field. Since various herbicide products are different in terms of their toxicological impact on the environment, numerical herbicide loads may be inappropriate for comparing environmental effects of control strategies under SSM with standard practices. For instance, while numerical loads of herbicide usage may be less under SSM, environmental effects can be more severe if control strategies that use more toxic herbicide products are selected.

Kovach et. al propose a method used for computing environmental impact quotients (EIQs) for different herbicide products. The EIQ field rating is suitable for comparing different pesticide and pesticide control programs to ultimately determine their environmental effects. EIQs are computed from diverse sources of information regarding the health and environmental effects of various pesticide products. Based on the ranking of available toxicological information on the impact of pesticide products on every segment of the ecosystems, EIQs assign penalty weights on various pesticide products. Thus, the resultant EIQs are a synthesis of environmental concerns of farm workers, consumers and ecological considerations as shown in Figure 2.1.

EIQs for common pesticide products can be found in Kovach et al. However, these values do not consider the frequency and rates of pesticide applications. Therefore, they are not suitable for comparing alternative pest management strategies. The variant of EIQs which facilitates such comparison is EIQ field use rating. The EIQ field use rating is obtained by multiplying EIQ by the percentage active ingredient in the formulation and the label rate of the pesticide. Forcella and Wyse have reformulated this EIQ field use rating to produce a Pesticide Index Equation (PIE) suitable for assessing the environmental impact of pest control strategies in North Central Region of United States. The PIE is given by:

Figure 2.1: Components of Environmental Impact Quotients



(Source: Kovach et. al, p.2)

$$PIE_i = 1 - \left(\frac{EIQ}{100} \left(Dose_i \quad X \quad \frac{NAppl_i}{Label_i} \right) \right) \qquad (2.22)$$

where PIE_i is the Pesticide i Index Equation, $Dose_i$ is the amount of active ingredient per application in the formulation for pesticide i, $Nappl_i$ is number of applications and Label i is the legal labeled rate for pesticide i. $PIE_i \in [0, 1]$. The closer the value is to unity, the better the strategy is in terms of its desirable environmental attributes. If more than one pesticide is applied to a crop during a growing season, then the above PIE_i needs to be modified. Simple summation of PIE values for all applications may yield values that exceed one, which is not appropriate. Also, averaging PIE values over all herbicide applications may not reveal the potential environmental hazards of using more than one herbicide product on a field. One possible solution to the problem is the use of Total Pesticide Index (TPI) which is the product of the individual indexes of pesticide applied to the crop, i.e.:

$$TPI = \prod_{i=1}^{n} PIE_i \qquad (2.23)$$

Like PIE_i, TPI values are $\in [0, 1]$ and the closer the values are to one, the more desirable the control strategies are.

Although the primary decision criterion is the selection of a control strategy that yields highest expected net return, TPIs can serve a number of purposes. They facilitate comparisons of environmental impacts associated with site-specific and delayed planting strategies to those for standard practices for weed control. Furthermore, the difference between net returns of the profit maximizing strategy and one with more environmentally-desirable attributes is an indication of tax premiums or willingness-to-accept (WTA) that can induce the use of preferred strategies by farmers.

111. MODEL DEVELOPMENT AND INPUT PARAMETERIZATION

WEEDSIM (Swinton p.28; Swinton and King) is the foundation for efforts to incorporate SSM and delayed planting strategies into decision support models. WEEDSIM is a computer-based weed management model for corn and soybeans. The program, which is written in Microsoft QuickBasic, is an innovative bioeconomic weed management model which incorporates weed population dynamics into decision framework while accommodating multiple weeds and control treatments.

WEEDSIM identifies the path of weed control treatments that maximizes net returns over a two-year time horizon. Weed control treatments in the model include herbicides and mechanical control, as well as a no control option for instances when weed densities are below economic threshold levels. In recommending strategies ranked on the basis of their net returns, WEEDSIM employs information on crop prices, input costs, weed-free yield and weed population provided by the user. This two-year time horizon captures the dynamic impact of weed control decisions. It enables the model to track the carryover effects of current weeds and weed control measures on the levels of weed pressures, weed control strategies and profit in the succeeding year. Further information regarding the program and its flow chart can be found in Swinton and Swinton and King.

In this study, the basic WEEDSIM model is extended in two main dimensions, by adding a weed emergence model and by expanding the decision modules to incorporate SSM and delayed planting strategies. In the next section, specific modifications made to WEEDSIM will be discussed.

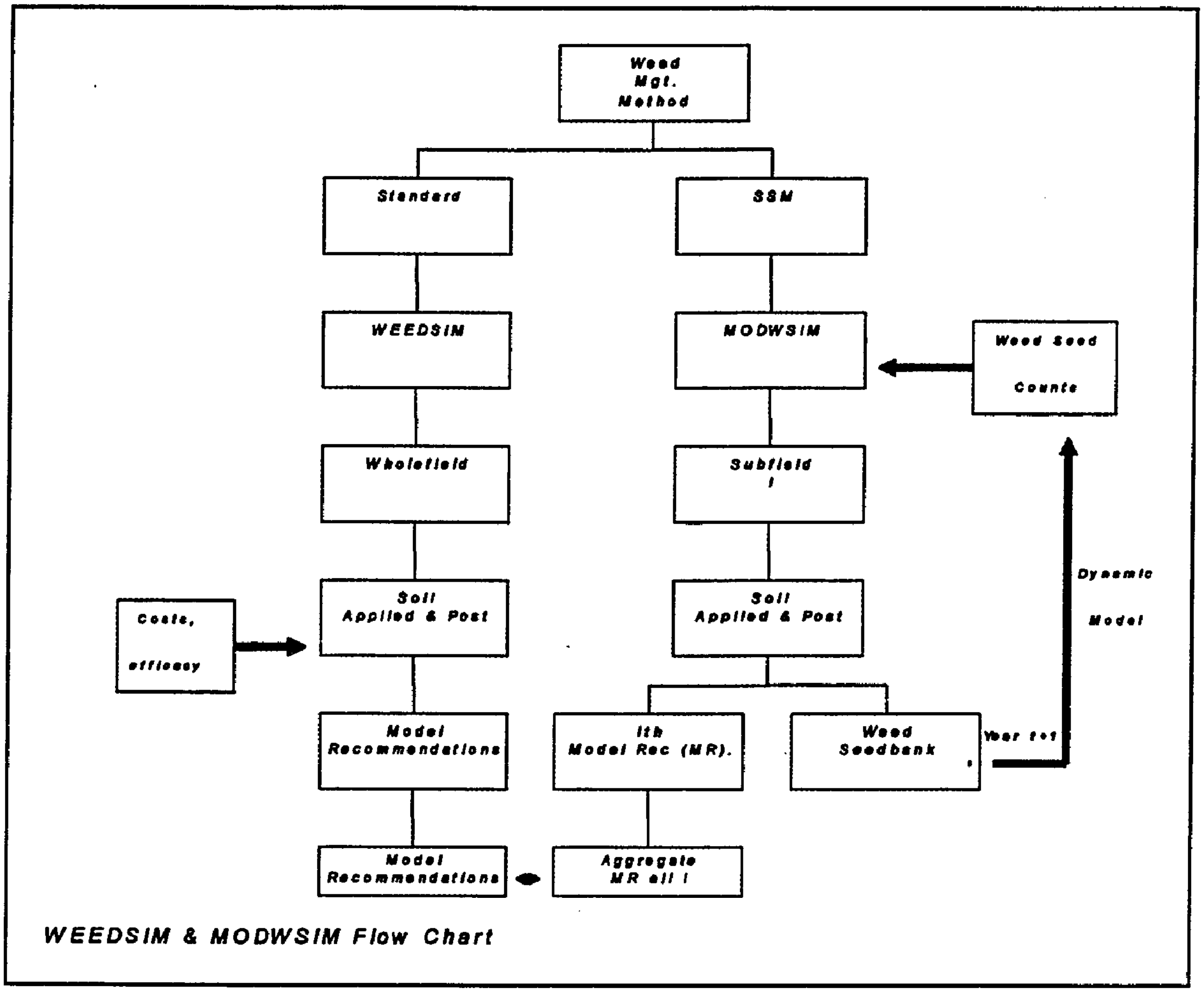
3.1 Model Development

MODWSIM is an extension of WEEDSIM which is specifically developed to improve upon existing models by incorporating two new types of weed control strategies into its decision rules. MODWSIM retains most of the essential features of WEEDSIM. It computes expected pre- and post-planting weed germination based on the initial weed seed counts supplied by the user. Thereafter, it employs specified levels of weed population, crop yields, output prices and input costs to evaluate the expected net returns and yields of all feasible combinations of pre- and post-emergence weed control treatments. Optimal strategies are ranked on the basis of net returns.

MODWSIM has some unique attributes. As shown in its program flow in Fig. 3.1, the decision-making unit in MODWSIM is the subfield, rather than the entire field as in WEEDSIM. Its main routine prompts the user for the type of weed control recommendations, i.e., whether recommendations should be based on standard practices of uniform weed distribution or SSM. A choice of the second option directs MODWSIM to use routines designed for evaluating SSM. Model recommendations over all subfields are eventually aggregated to indicate overall performance for the field. The composite model recommendations can be compared to WEEDSIM recommendations to determine if SSM improves upon standard practices.

MODWSIM includes a weed seedling emergence routine which associates time with proportional extent of weed emergence. This is an essential feature of delayed planting strategies. Also, the subroutine for penalizing crop yield in MODWSIM has been expanded in view of its importance in establishing delayed planting thresholds.

Figure 3.1: Program Flow of MODWSIM & WEEDSIM



Cognizance of the fact that implementing SSM may involve substantial startup costs, and that such costs may be spread over a considerable length of time, MODWSIM is capable of implementing dynamic maximization problems for any finite number of years. This is accomplished through seasonal revision of weed seedbank which serves as a link between current and future potential weed problems. However, its recommendation module still prescribes strategies for any year based on a two-year planning horizon.

Finally, MODWSIM also calculates herbicide indexes which may be a better measure of environmental impact of herbicide usage than numerical loads that WEEDSIM provides. Full program code of MODWSIM is shown in Appendix 1.

3.2 Input Parameterization

Simulation with MODWSIM requires extensive data on a wide range of activities connected with corn and soybean production. In this study, input data will focus on weeds that are economically relevant to the production of these crops in Minnesota. These are mainly annual weeds. The major ones are: Green and yellow foxtails (Setaria spp L.) (SET sp) , common lambsquarters (Chenopodium album L.), (CHEAL), redroot pigweed, (Amaranthus retroflexus L.), (AMARE), Pennsylvania smartweed, (Polygonum pensylvanicum L.), (POLPY) and wild mustard (Brassica kaber (DC.) L.C.Wheeler), (SINAR). Their Weed Science Society of America (WSSA) approved computer codes are shown in parentheses. Though some perennial weeds - e.g. Canada thistle, (Cirsium arvense L.) - are also pertinent, biological information about their weed population dynamics is too limited to permit their inclusion in dynamic bioeconomic models at the moment.

Swinton (p.58) presents some input parameters for running WEEDSIM. Some of these parameters were estimated from a limited data set obtained from 1985-1986 experiments conducted in Morris, MN. This has important ramifications for generalizing the parameters. For this reason, the input parameters that MODWSIM share in common with WEEDSIM have been re-estimated to take advantage of the availability of additional data. Also, new input parameters for additional features of MODWSIM have been developed. The remaining sections of this chapter discuss the techniques used in producing input parameters of both the biological and economic components of the model.

3.2.1 Characterizing Weed Spatial Distribution

A number of probability distributions have been employed to describe biological data. These include Poisson with zeros, Neymann Type A, logarithmic with zeros and negative binomial. These distributions have been chosen because they cover the extremes with respect to kurtosis and skewness (Mortensen et al.). For weeds, the relevant distribution has either been Poisson or a negative binomial. For Poisson distribution, the expected variance is equal to the mean, hence a simple test of the distribution is to compare the value of its sample variance to sample mean. Fit can be determined by using the Chi-squared (χ^2) test.

The negative binomial distribution indicates weed aggregation. It is characterized by two parameters, mean and K. The latter is the index of aggregation. A small value of K suggests there is a considerable patchiness in weed distribution. This value increases as the distribution tends toward Poisson.

The data for testing consistency with a negative binomial distribution were obtained from actual farmers' fields in west central Minnesota. These farmers are collaborating with the USDA North Central Soil Conservation Research Laboratory (NCSCRL), Morris, MN in the execution of its research agenda. The frequency distribution of weed seed extraction estimates per core was tested for conformity with Poisson and negative binomial distributions. While the assumption of Poisson weed distribution was rejected in all cases, the hypothesis of a negative binomial distribution could not be rejected at the 5% level in about eight out of ten sets of weed distribution data examined. Using the approach suggested by Bliss and Fisher, fitted K values range from 0.08 to 0.4 for all weed species in the models. These values fall within the 0.01 and 2.79 range of K values estimated for broadleaf weed populations in fourteen double-cropped soybean fields in North Carolina by Wiles et al. (1992a). The values suggest that weed distributions are indeed patchy, and that there is variation in the degree of weed patchiness across weed species and from one field to another.

3.2.2 Weed Population Dynamics

Weed population dynamics is the kernel of dynamic bioeconomic weed management models. The seedbank and seed production set a limit to potential weed problems in the current and succeeding seasons. The patterns of seed emergence, germination and mortality all play a vital role in deciding the choice of control strategies and annualized values of net returns over the entire planning horizon.

Parameters of weed emergence models and other components of weed population dynamics that were not developed for WEEDSIM have been estimated. As noted earlier, other input parameters that MODWSIM shares with WEEDSIM have been re-estimated.

New data are now available from experiments conducted in various parts of Minnesota between 1985 and 1993. Employing this richer data set than 1985-86 experimental data used for previous estimation improves the quality of parameter estimates.

3.2.2.1 Soil Seedbank

Soil seedbank is the source of future weed infestations. It is the reasonable starting point for deciding whether and what form of pre- and post-emergence control decisions will be necessary. However, estimates of weed seed production are rather varied in literature, and these estimates are contingent upon a host of conditions. Production estimates per plant for foxtails have ranged from 600 to 3200 and between 12,000 and 42,000 for pigweed and lambsquarters, respectively (Crook and Renner; Harris). Cultivation and tillage practices, soil depth, pattern of competition among weeds and between crops, crop rotation and prior weed control strategies are among the factors affecting soil seedbank and production.

Tillage and cultivation practices have a mixed impact on weed seed production. Tillage may increase seed production by stimulating increased germination of otherwise dormant seeds in the seedbank (Mulder and Doll). It can also reduce seedbank population by exposing buried weed seeds to predation. Herbicides are known to reduce seed production by increasing plant mortality and seed production per surviving plant (Yenish et al.; Schreiber). Yenish et al. also observe that weeds surviving herbicide treatments produce far fewer seeds than survivors of exclusive mechanical treatments.

For the above reasons, the literature does not provide satisfactory estimates of seed viability and mortality rates for seeds of certain weed species as these values tend to be specific to cropping patterns under consideration. Following a similar approach used by Swinton and King, total seedbank in a particular season is defined as a function of seedbank, seed emergence and mortality rates and the control practices in the preceding season as follows:

$$S_{t+1} = (1 - \alpha_t - \beta_t) S_t + \gamma_t (W_t [1 - \theta]) \tag{3.1}$$

where S_{t+1} is the total seedbank in year t+1, $\alpha_t \in [0, 1]$ is the proportion of seeds that geminate in year t, $\beta_t \in [0, 1]$ is the seed mortality rate, $\gamma t \in [0, \infty)$ is the number of seeds produced by weeds that survive control strategy that eliminates θ proportion of weeds in year t .

One way of obtaining the parameters of the equation (3.1) is through statistical estimation. However, there are only few instances when such parameters have been estimated statistically (e.g. King et al., 1986) as a suitable pooled data set that permits such estimation is often lacking. The alternative approach is to employ a simulation routine to search for the range of values that are consistent with the observed patterns of seed populations over time.

Seedbank and seedling emergence data were obtained from weed seedling emergence experiments conducted by NCSCRL in Rosemount between 1990 and 1993. These on-going experiments were designed to gather information on the seedbank, timing and proportional emergence of weed seedlings on designated plots for a consecutive number of years. At present, the data are too meager to permit statistical estimation of the parameters. Therefore, parameters of equation (3.1) were simulated.

For the simulation, some of these parameters were determined exogenously. θ is the efficacy rating of a typical control treatment in the model. The efficacy ratings of these herbicides were obtained from Durgan et al. The proportion of seedling counts in relation to seedbank population averaged over a number of years was used to approximate the proportion of seeds that germinates in a year (α). Estimates of seed mortality rates (β) were inferred from literature (Egley and William; Yenish et al.; Crook and Renner; Swinton and King). Using these parameters, specification searches were conducted to figure out seed production numbers (γ) that are consistent with observed weed and seed populations over time. The resultant parameter estimates are shown in Table 3.1.

Apart from seed production levels, the parameters fall within ranges reported in other studies (Egley and William; Yenish et al. ; Crook and Renner). Moreover, all the parameter values compare favorably with the estimates by Swinton and King. The two sets of parameter estimates have one feature in common; the seed production estimates (γt) are considerably lower than some estimates in the literature (Schreiber et al.; Harris; Crook and Renner). However, under the specified conditions of seed mortality, seed emergence and herbicide efficacy ratings, the modest seed production figures in Table 3.1 are those that support observed seed and weed populations in cultivated fields of west central Minnesota. Perhaps the rivalry among weeds and

Table 3.1: Simulated Weed Population Parameters

Weed (WSSA Code)	γt Seed prod. per plant	β_t Seed mortality	α_t Seedling emergence
Foxtails (SET)	150 (90*)	0.83 (0.71)	0.27
Lambsq. (CHEAL)	200 (120)	0.84 (0.82)	0.15
Pigweed (AMARE)	200 (130)	0.89 (0.17)	0.10
Mustard (SINAR)	100	0.88	0.33
Smartwd. (POLPY)	100	0.91	0.31

*Values in parentheses are corresponding estimates by Swinton and King (1994, p. 323)

competition between weeds and crops do not permit such high production of weed seeds per plant under cultivation conditions.

These parameter estimates have important consequences regarding the optimality of choice strategies. Model recommendations are very sensitive to the parameter values.

Therefore, dynamic weed management models will undoubtedly benefit from agronomic research that provides more precise information on the ranges of these parameter estimates.

3.2.2.2: Seedling Emergence Models

The effectiveness of weed control from pre-plant tillage operations is a key factor in opting for delayed planting. Therefore, proper modeling of weed seedling emergence patterns is an important step in simulating potential benefits of this strategy as a weed control tool. Seedling emergence models forecast the timing and magnitude of weed seedling emergence based on seedbank and other factors.

The literature is fairly rich in models for predicting seedling emergence of annual weeds (Forcella; Forcella et al.(1993); Harvey and Forcella). These models generally fall into two categories, the seedling emergence models based on soil temperature and rainfall and models based on growing degree day concept. For the first category of emergence models (based on soil temperature and rainfall), data for model estimation were obtained from observed patterns of seedling emergence in the growth chambers under controlled experimentation. Based on the observed timing and extent of seedling emergence as a function of daily soil temperature within the seed zone (5cm. soil depth) and daily rainfall in these experiments, Forcella and Harvey and Forcella have come up with the following emergence models for some weed species that are important in corn/soybean fields:

$$EMERG_{(i+1)} = EMERG_{(i)} + \frac{GR_{(i)}(1-EMERG_i)}{100} \qquad (3.2)$$

where $EMERG_{(i+1)}$ is the predicted cumulative daily emergence percentage at day i +1 of the weed species, $EMERG_{(i)}$ is the predicted cumulative daily emergence percentage at day i , $GR_{(i)}$ is the germination rate of the weed species at day i. The germination rates for some of the weed species considered in this study are:

For Lambsquarters:

$$GR_{(i)} = \begin{cases} 5.89\exp^{-35.22/TEMP_i} & IF\ TEMP_i \le 22^o\ C \\ -9.05 + \frac{526.08}{TEMP_i} - \frac{6818.31}{TEMP_i} & IF\ TEMP_i \ge 22^o\ C \end{cases} \qquad (3.3)$$

Giant foxtails: $GR_{(i)} = 466 - 0.082TEMP_i - 36.938/TEMP_i$

Yellow foxtails: $GR_{(i)} = 3.643 - 0.71TEMP_i - 23.32/TEMP_i$

Green foxtails: $GR_{(i)} = -0.375 + 0.145 - 0.036TEMP_i$

Redroot Pigweed: $GR_{(i)} = 1.39TEMP_i - 12$

where $TEMP_i$ is the soil temperature, preferably within the seed zone (5cm. depth), at day i measured in degrees centigrade.

The high predictive capabilities of these models have been demonstrated and they are regarded as a better predictor of seedling emergence than models based on growing degree day concept (Forcella; Harvey and Forcella). The major weakness of these models is that they are specific to individual weed species. They may be difficult to incorporate into bioeconomic models for multiple weeds particularly when the GR models have not been established for all weed species of interest. Also, data for soil temperature may not be readily available. For these reasons, an alternative statistical model based on the concept of growing degree day has been developed. This has a wider appeal since the model can be fitted to any weed species. The statistical model specifies seed emergence as a finite distributed lag model of growing degree days weighted by cumulative growing degree days and the seedbank:

$$X_{interv} = \sum_{i=1}^{interv.} \beta_{i-1} \frac{GDD_{i-1}}{CGDD_{i-1}} S_{i-1} D_{i-1} \qquad (3.4)$$

where X_{interv} is the cumulative total of emerged weed seedlings that are counted on the scouting day, GDD_i is the April growing degree days on day i, $CGDD_i$ is the cumulative April growing degree days on day i, i=1 to interv. are daily lagged values of the variables within the scouting intervals, β_{i-1} is the estimated coefficient and D_i is a dummy variable which takes the value of zero if $CGDD_i$ is below the threshold CGDD level for which seedling emergence is possible. Full discussion of the estimable model and estimation technique of (3.4) can be found in Appendix 5.

There is a dearth of information about the threshold CGDD below which no emergence takes place for weeds. Consequently, specification searches were conducted to determine the threshold CGDDs of weed species by successively increasing the CGDDs and choosing threshold CGDDs on the basis of statistical properties. For most weeds, these CGDDs fall between 50 and 75.

The estimable form of equation (3.4) was fitted to experimental weed emergence data from Rosemount, Minnesota between 1990 and 1993. For the average scouting interval of seven days, a specification search was conducted to determine the appropriate lag length. Criteria used for choosing lag length include sequential F-tests and Akaike Information Criterion (Green, p.515). Using both criteria, a maximum lag length of between 2 and 3 days suffices for most weed species. The advantage of the short lag length is that the problem of multicollinearity is not severe. When multicollinearity is present, eliminating one of the lagged variables usually resolves the problem.

Models of finite distributed lagged variables often suffer from severe problems of serial correlation of error terms. Ordinary least squares estimation of such models may yield biased and inconsistent estimates. For this reason, generalized least squares (GLS) method which yields unbiased and consistent estimates was employed.

Table 3.2 presents the parameter estimates for all the weed species in the model. From the Table, the t-tests suggest that the estimated coefficients are significant at the 5% level. In most cases, one lagged regressor is sufficient for predicting the seedling emergence. Often, the coefficients of other lagged variables are not significantly different from zero at any level and omitting them does not affect the power of the models.

Table 3.2: Parameters of the Statistical Model for Weed Seedling Emergence

Weed (WSSA Code)	Threshold $CGDD_{t-1}$	β_{I-1}	β_{I-2}	R^2
Foxtails (SET)	50		0.1305 (9.42)	0.53
Lambsquarters (CHEAL)	50	0.0594 (6.55)		0.18
Pigweed (AMARE)	75	0.0455 (4.05)		0.28
Wild Mustard (SINAR)	50	0.0983 (3.00)		0.06
Smartweed (POLPY)	50		0.1736 (4.65)	0.26

n=54. t-statistics are in parentheses. Missing values are not significant at any level.

3.2.2.3 Validation of Seedling Emergence Models

The objective of model validation is to examine how accurately the model estimates mirror the real systems under investigation. Results of validation exercises are useful in evaluating goodness of fit and in deciding whether further calibration is required before the models are considered fair representation of actual processes. Kelton and Law (p.338) outline three main steps in validation exercises which are:

(i) testing the validity of a model;

(ii) testing underlying theoretical assumptions;

and (iii) testing how closely a given model resembles the actual systems.

The seedling emergence models were developed jointly with experts in weed management, and the underlying assumptions are logically appealing. Therefore, the models satisfy the first two conditions. The third criterion can be accomplished through statistical validation. Statistical tests used to validate the models are the t-tests and correlation coefficients. Testing how closely a given model resembles the real system is similar to testing how model forecasts diverge from real observations. By estimating the differences between both sets of values, one can test the hypothesis that the true mean of these differences is zero. Non-rejection of the hypothesis indicates that the model is unbiased and fairly approximates the real process. Pindyck and Rubinfeld (p.38) indicate that the appropriate paired-t difference test is given by:

$$t = \frac{\bar{X}}{S_x/N} \tag{3.5}$$

where $\bar{x}$ is the mean, S_x is the standard deviation of the differences and N the number of observations.

Correlation coefficients are scale-free, normalized measures of association between model forecasts and actual observations. Correlation coefficient which is another measure of the goodness of fit lies between -1 and 1. The closer the absolute value is to one, the higher the degree of linear dependency between predicted and actual values.

The two sets of emergence models were validated to evaluate their predictive abilities using data from seedling emergence experiments conducted in Morris and Rosemount, Minnesota between 1990 and 1993 by NCSCRL. For forecasting the emergence level for any given year, the averages of long run weather variables were used to run the models based on daily soil temperature and rainfall. The timing and proportional extent of weed seedling emergence were predicted from the long run averages (from 1983 to 1993) of these weather variables for Morris and Rosemount obtained from Seeley et al.

For the seed emergence models based on the growing degree day concept, the pooled weed seedling data between 1990 and 1993 constitute the observed data. Statistical models were fitted to a subset of the data and the fitted equations were used to predict seedling emergence for periods excluded from the regression models. For instance, parameters obtained from fitting the model to 1990 -1992 data were used to obtain 1993 seedling forecasts. Thus, validation of statistical models was undertaken with out-of-sample data. Table 3.3 presents the results.

Table 3.3 shows how the weed seedling forecasts of the models compare with actual observations. The first set of results in the second column compares actual observations with forecasts of models based on soil temperature and rainfall. The next

Table 3.3: t-statistics and Correlation Coefficients of Actual against Predicted Weed Seedling Emergence Levels

Weeds	Actual Vs Forecasts by Models of Soil Temp. & Rainfall (MSTR)		Actual Vs Forecasts by Models of Growing Degree Day (MGDD)		MSTR Forecasts Vs. MGDD Forecasts	
	R^2	t-stat.	R^2	t-stat.	R^2	t-stat.
Foxtails*	0.87	0.78	0.81	2.04[a]	0.91	1.36
Lambsq.	0.93	0.36	0.95	1.31	0.97	0.58
Pigweed	0.92	1.17	0.88	1.22	0.96	2.70[a]
Mustard	n.a	n.a	0.95	0.58	n.a	n.a
Smartw.	n.a	n.a	0.92	2.36[a]	n.a	n.a

For Foxtails*: the model for yellow foxtails was used. n.a implies not available as their Germination Rate models have not been developed. [a]Significant at the 5% level column shows how actual observations compare with forecasts obtained from emergence model based on growing degree day concept. The last column in the Table compares the forecasts of both models. In general, the results of the validation exercises show that both models predict observed emergence levels fairly accurately. In some cases, the correlation coefficients approach unity and the paired-t difference test is statistically different from zero at the 5% level in only two instances. These results are similar to those reported by Harvey and Forcella.

The t-tests that compare forecasts of both models show that the differences in the forecasts are only significant at the 5% level in one instance. Their correlation coefficients are also high and close to unity. It is therefore safe to conclude that the predicted weed seedling emergence levels of both models compare favorably well. Thus, the validation exercise finds some merit in using emergence models of growing degree day concept once the functional relationship is properly specified.

While the validation tests suggest that either of the emergence models will suffice, the models of soil temperature and rainfall are preferred because they involve some elements of process simulation. Consequently, these models were used for relevant weed species in the model. The alternative model of growing degree day concept was used to simulate seedling emergence levels for weed species whose process models are not readily available.

3.2.3 Crop Yield-Weed Relations

Swinton (p.94) suggests a linear way of fitting hyperbolic function to crop yield-weed density data which tends to overcome some of the problems associated with non-linear estimation of yield loss from experimental data. By setting the asymptotic maximum percentage yield loss (A) to 100, and the weed-free yield (Y_{wf}) to the experiment's maximum yield, the model can be expressed as a linear function of weed densities which is given by:

$$\frac{QA}{A-Q} = \sum_{i} I_i \, w_i \tag{3.6}$$

where:

$$Q = 100\left(1 - \frac{Y}{Y_{wf}}\right) \tag{3.7}$$

Y is the yield and w the weed density. A and Y_{wf} are as previously defined.

Experimental data from Morris and other sites in Minnesota between 1985 and 1992 were used to estimate the competitive indices of weeds in corn and soybeans. Although the experiments were designed for a number of different objectives, the data set includes information on crop yields and weed populations at harvest. These variables are all that are required to fit Cousens's hyperbolic function for estimating yield loss due to weed infestations. However, data of such diverse backgrounds need be examined for the presence of influential observations. For this reason, regression diagnostic procedures were undertaken to detect the presence of such variables.

Belsey et al. (p.6+) provide a number of diagnostic tests for checking the presence of influential variables. The hat matrix, 'H, measures the leverage of the observation. Its value is high for an observation that is quite different from the majority of other observations. The rule of thumb is to suspect 'H whose absolute value exceeds 2K/N where K and N are the number of variables and observations in the model, respectively. Studentized residuals are measures designed to detect large errors. These residual values are approximated by t-distribution, hence, absolute values that are less than 2 are generally acceptable. The final diagnostic test employed is DFFITS. This examines the influence of the i_{th} observation on the model prediction. Also, the higher its value, the greater is its influence. The rule of thumb for DFFITS is to regard absolute values in excess of 2(√K/N) as being influential. The diagnostic results of these tests are shown in Table 3.4. The results suggest that a significant number of observations are influential. For the data, one method of ensuring that classical regression assumptions will not be violated for OLS estimation is to omit the influential observations. However, Belsey et al. (p.6-28) and Judge et al. (p.887-897) have shown that omitting such observations from the regression can impair efficiency. On the other hand, if the observations are included, least square estimators will no longer produce efficient and asymptotic efficient estimates of coefficients and variance of β. For this reason, an alternative estimation procedure which overcomes this problem was used.

Robust estimation techniques (e.g. least absolute error (LAE), Trimmed least squares) yield reasonably efficient estimates irrespective of the underlying distributions.

Table 3.4: Diagnostic Tests to Detect Influential Observations in Corn/Soybean Data

tests/ parameters	Number of observations	
	Corn	Soybeans
N	298	96
K	11	11
$\lvert \mathcal{H} \rvert > 2K/N$	109	10
$\lvert \text{Residuals} \rvert > 2$	8	7
$\lvert \text{DFFITS} \rvert > 2(\sqrt{K/N})$	12	9

Judge et al. (p.903) show that LAE estimation will be more efficient than least squares particularly in distributions where outliers are prevalent. Most econometric programs, e.g. SHAZAM, now incorporate routines that detect the presence of influential variables and perform robust estimation.

Table 3.5 presents the estimated coefficients of the model obtained with the LAE and Tukey Trimmed Mean procedures. Although asymptotic t-tests show that these coefficients are, in general, statistically significant at the 5% level, except for smartweed, Judge et al. indicate that Likelihood Ratio (LR) or Langrange Multiplier (LM) tests with χ^2-distributions are more appropriate for testing the significance of the β coefficients. However, coefficients that are significant under LM tests are consistent with t-distribution in Table 3.5.

Table 3.5: Competitive Indices of Common Weeds in Corn/Soybean Fields

Weeds (WSSA Code)	Corn (n=296)	Soybeans (n=98)
Foxtails	0.00178	0.00121
(SET)	(2.589)	(4.023)
Lambsquarters	0.01756	0.01113
(CHEAL)	(5.91)	(2.58)
Pigweed	0.01350	0.00602
(AMARE)	(9.469)	(4.42)
Mustard	0.00186	0.00342
(SINAR)	(3.14)	(3.18)
Smartweed	-0.0337	0.00629
(POLPY)	(-2.17)	(O.21*)
Other broadleafs	0.0115	0.00131
	(6.74)	(7.42)

Asymptotic t-statistics are in parentheses. * not significant at any level

From the results, one can see that lambsquarters and pigweed are the most competitive of all weeds in both crops. Foxtail grasses are not as competitive as broadleaf weeds. For smartweed, which is not significant in soybeans and whose value for corn is suspect, the coefficients for other broadleafs are used instead. In general, the parameter estimates are satisfactory and the ranking of these weeds is consistent with ranking of major weeds in United States based on survey results (Burnside (Pers. Comm.)). Nonetheless, the estimated competitive indices are rather low. This may be attributed to the inherent bias in the use of experimental data. Due to superior management practices, crops under controlled experimentation compete more vigorously with weeds than crops in farmers' fields. For this reason, estimates of the potential yield loss due to weed infestations may be lower when they are based on experimental data.

3.2.4 Planting Date, Varietal Selection and Yield Penalty Functions

A number of factors influence the choice of planting dates for crops. These include potential crop yield, varietal selection, planting depth, planting rate, planting location, frost, weed control, fertilizer and harvest considerations. Hicks and Peterson explain how these factors influence the choice of planting dates. Early planting produces the maximum yield, usually from full-season varieties. Yield declines as planting is delayed, which for corn and soybeans, beyond the early weeks in May.

Varietal selection plays a role in the choice of planting dates. Corn, for instance, is usually classified into three categories namely; full-season, mid-season and short-season varieties. Full season corn requires 110-115 days to mature. Full season varieties have the highest yield potential but they are also very sensitive to late planting. Mid-season and short-season hybrids have fewer days to mature. They have less yield potential but are not as sensitive to delayed planting as full season corn.

Early planted crops may be susceptible to frost damage from late spring frost. Shallow planting and lower percent seed germination due to low soil temperatures are also common. Harvest considerations, however, support the choice of early planting. The effects of weed control and fertilizer applications are rather mixed.

It is clear from the above that an ideal model of crop yield- planting date relationships should also account for the influence of all factors. However, due to the stochastic nature of some of these variables, existing models have simply expressed yield as a stepwise linear function of planting dates, while assuming that the influence of all other factors is constant.

Based on the results of delayed planting experiments conducted in various parts of Minnesota over several years, Hicks and Hicks and Peterson have developed estimates of yield loss for soybeans and three corn hybrids as a function of planting dates as reported in Table 3.6. These yield loss estimates were incorporated into MODWSIM so as to penalize crop yields as planting is delayed. A simple interpolation routine was included to estimate yield for planting at any day within the range in Table 3.6. Due to institutional constraints, e.g. crop insurance programs, delaying planting beyond June 14 is prohibited by setting the potential yield loss at 100 percent.

At the moment, work is in progress towards developing more rigorous models of crop yield as a function of planting date and other variables[1]. However, tentative results

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[1] G. Toichoa Buaha and Jeff Apland of the department of Applied Economics, University of Minnesota are presently developing models of crop yield as a function of planting dates, varietal selection and planting locations using experimental time-series data from several locations in Minnesota.

Table 3.6: Crop Yield Potential as a Function of Planting Dates

	% Crop Yield Potential			
	Corn			Soybean
	Full	Mid	Short-season	Full
Potential Yield(bu/acre)	110	96	84	40
Planting Date				
May 1	100	100	100	100
May 10	94	96	98	97
May 20	88	92	96	92
May 30	83	88	94	85
June 9	77	83	91	75
June 14	75	81	90	69

Compiled from Hicks and Hicks and Peterson.

from this modeling endeavor do not suggest a significant departure from results shown in Table 3.6. In general, soybeans tend to be more sensitive to late planting than corn. Inclusion of yield potentials for various corn hybrids facilitates evaluation of varietal selection on the choice of delayed planting strategies. For instance, when there is a preponderance of high populations of late-emerging weeds, delayed planting and short season corn may provide a superior weed control strategy.

3.2.5 Herbicide Costs, Efficacy Ratings and Environmental Indexes

Information on herbicide efficacy ratings and application rates was obtained from extension literature (Durgan et. al, p.16, 54). The effectiveness of herbicides on major weeds of corn and soybeans is assigned qualitative ratings of good, fair, poor or none. These ratings are believed to vary depending on soil characteristics, management factors, environmental variables and rates applied. These ratings are the qualitative counterparts of the "Kill function" concept that was discussed in section 2.1 of Chapter 2.

The assumption governing this analysis is that herbicide treatment, if required, will be applied at recommended rates under suitable conditions such that the ratings of herbicide effectiveness conform to those given by Durgan et. al and reproduced in Table 3.7. These qualitative ratings of herbicide effectiveness were transformed to percentage efficiency ratings based on subjective but informed expert opinion (Gunsolus; Forcella, (Pers. Comm.)). Herbicide treatments that are included in the model are not exhaustive of all effective herbicide products for major weeds in corn and soybeans in

Table 3.7: Herbicide Costs, Efficacy Ratings and Environmental Indexes

Control Treatment	Dose (a.i lb/A)	Applic. Type	Cost ($/acre)	Herbicide Effectiveness Rating					
				FOXT	LAMB	PIG	MUSTA	SMART	EIQ
Corn:									
Cyanazine	4.750	PPI	31.89	G	G	F	G	G	0.80
Eradicane	6.000	PPI	26.60	G	F/G	F	P	P	0.87
Alachlor	3.000	PPI	23.85	G	F/P	G	P	P	0.79
Cyanazine	4.750	Pre	28.47	G	G	F	G	G	0.80
Dicamba	0.500	Pre	10.08	P	G	G	G	G	0.83
Alachlor	3.000	Pre	20.43	G	F/P	G	P	P	0.79
Rotary Hoe	n.a	Pre	3.00	F	P	P	P	P	1.00
No Control	n.a	Pre/Post	0.00	N	N	N	N	N	1.00
Cyanazine	2.000	Post	12.80	G	G	F	G	G	0.80
Dicamba	0.500	Post	10.08	N	G	G	F	G	0.83
Bromoxynil	0.380	Post	10.36	N	G	F/G	G	G	0.75
Nicosulfuron	0.031	Post	19.21	G	P/F	G	G	G	0.70
2-4-D	1.000	Post	3.88	N	G	G	G	P	0.44
Bentazon	0.750	Post	13.26	N	F	P	G	G	0.61
Soybeans									
Alachlor	3.000	PPI	23.85	G	F/P	G	P	P	0.79
Imazethapyr	0.063	PPI	22.69	F/G	F/G	G	G	G	0.81
Metribuzin	0.500	PPI	17.74	F	G	G	G	G	0.65
Trifluralin	1.000	PPI	11.89	G	F/G	G	N	P	0.73
Alachlor	3.000	Pre	20.43	G	F/P	G	P	P	0.79
Rotary Hoe	n.a	Pre	3.00	F	P	P	P	P	1.00
Metribuzin	0.500	Pre	17.74	F	G	G	G	G	0.65
No Control	n.a	Pre/Post	0.00	N	N	N	N	N	1.00
Bentazon	0.750	Post	13.26	N	F	P	G	G	0.61
Imazethapyr	0.063	Post	19.27	G	P	G	G	G	0.81
Acifluorfen	0.380	Post	12.37	P	P	G	G	G	0.48
Sethoxydim	0.190	Post	15.27	G	N	N	N	N	0.73
Thifensulfuron	0.004	Post	8.27	N	G	G	G	G	0.78

PPI= Pre-plant incorporated; Pre= Post-emergence control; Post=Post-emergence control;

a.i=active ingredient;lb/A=pound/acre; Applic. Type= Application Type.

G=Good;F=fair; P=Poor;N=No control which may imply insufficient information. The quantitative equivalents of these ratings are G=92%;F/G=80%; F=70%;F/P=50%; P=30%; and N=0%.

Herbicide efficacy ratings are culled from Durgan et al. (p.16, 54), Most of the EIQs are from Kovach et al.

Costs which include both material and application costs are obtained from Fuller et al.

Minnesota. Rather, they were chosen on the basis of a number of factors, which include cost considerations, spectrum of effectiveness and farmers' preferences.

Periodic crop budgets and custom rate bulletins for various parts of Minnesota by Fuller et al. served as a source of information on crop prices as well as herbicide and other input costs. This was supplemented by data collected during the 1994 retail herbicide price surveys conducted by Gunsolus (Pers. Comm.). Costs shown are material and application costs of the corresponding control strategies at the recommended rates. The environmental impact quotients (EIQs) and pesticide indexes of all possible control strategies included in the model are also shown in Table 3.7. EIQ values were extracted from Kovach et al (p.6). The indexes were estimated using the formula in equation (2.22). Based on the composite recommendations for both soil-applied and post-emergence control strategies, MODWSIM uses pesticide indexes of individual herbicide products to compute Total Pesticide Index (equation 2.23) which is furnished as part of model recommendations' package.

As noted earlier, the closer the pesticide index is to one, the more desirable the strategy is in terms of its favorable environmental attributes. Consequently, no control and mechanical weed control exert the least adverse effects on the environment. On the other hand, 2-4-D and Blazer for corn and soybeans respectively are the most toxic in terms of their adverse environmental effects among the treatments included in the model. While the simulation model prescribes weed control options on the basis of an optimal path that yields the highest net returns, TPI information can aid decision-maker in switching to more environmentally-friendly strategies.

IV. POTENTIAL BENEFITS OF SITE-SPECIFIC WEED MANAGEMENT

This chapter reports the results of simulation experiments conducted to assess the potential environmental and economic benefits of site-specific management practices. The first section describes the structure and the assumptions governing the experiments. The remaining sections evaluate SSM under varying degrees of weed pressure and dispersion.

4.1 Assumptions Underlying the Simulation Experiments

All simulations were conducted for corn-soybean rotations within a deterministic framework. A corn selling price of $2.15 per bushel and a maximum yield of 110 bushels per acre were assumed for all simulation experiments. For soybeans, a selling price of $5.65 per bushel was used, and the maximum yield was set at 40 bushels per acre. Except when indicated, it is assumed that the full-season hybrids of these crops are grown. Variable costs, other than weed control costs, of $126.15 and $62.70 per acre were employed for corn and soybeans, respectively. These cost estimates obtained from Fuller et al. are close to Minnesota averages for these crops that are grown on owned lands.

One set of herbicide material and application costs was assumed under standard practices and SSM. Although this is rather simplistic, the technology for carrying out SSM for weed control is not yet in place. Therefore, its market price is not known. However, the economic benefits of SSM can be regarded as the willingness-to-pay (WTP) for the technology under the specified conditions of weed population and dispersion. The higher the WTP, the more likely will the added benefits of SSM exceed its extra costs.

Potential benefits (or losses) of SSM refer to the increment (or decrement) in economic and environmental benefits obtained under standard practices, i.e., the differences between model performance under standard practices and SSM. Economic benefits are reported in terms of net income in dollars per acre. The environmental benefits can be inferred from herbicide indexes. Since the higher the indexes, the more friendly the control strategies are in terms of their environmental attributes, positive values for differences in net income and pesticide indexes indicate potential benefits of implementing SSM. Negative values imply costs.

The initial parameter settings for mean and K, the index of weed aggregation, were obtained by fitting a negative binomial distribution to the weed seed and seedling data from a West central Minnesota farmer's field. These parameters, coupled with the rank correlation matrices of weeds, were used to generate the weed density information for the subfields. The use of on-farm data helps ensure that simulated weed distributions resemble the degree of variation in weed densities and weed species mix in a field setting. Though there is no statistical basis to guarantee that the farmer's field is a representative farm, subsequent sensitivity analyses with varying levels of weed pressure and aggregation help guarantee that all probable field scenarios are represented.

Initially, the farmer's field was implicitly partitioned into ten subfields by generating ten sample vectors from the joint distribution of weeds. Each sample vector represents the weed density information for a subfield. Though the choice of ten subfields was arbitrary, simulation with higher number of subfields did not reveal any additional benefits. Also, the Kriged maps shown in Appendix 4 suggest that ten subfields closely approximate the number of management units in reality.

The ten subfields can be managed in either of two ways. Weed populations in the subfields can be controlled using standard practices based on the weed densities averaged over all subfields. Alternatively, SSM practices which match control strategy with the weed density in each subfield can be used. For evaluating the potential benefits of SSM, both methods were employed to facilitate the comparison of model recommendations under SSM to standard practices.

The procedure for simulating weed population information for each subfield involves considerable randomization. Also, since the simulation was based on the information obtained from a field, there is a need to explore model sensitivities and check the consistency of its recommendations from one replication to another. For this reason, weed densities of all subfields of a field were independently and repeatedly simulated ten times using the same parameters for the parent field. Model recommendations were compared across the replications to reveal noticeable differences among them. Results in Appendix 3 suggest that the multivariate generator produces fairly consistent estimates, as model recommendations compare favorably well from one replication to another. Nevertheless, the average of model recommendations of all replications was employed in assessing SSM overall performance.

The time horizon for simulating the potential benefits of SSM was set at four years. This time frame, which covers two full cycles of corn-soybean rotations, is long enough for the long run pattern of SSM benefits to be discernible. Extending this time perspective beyond four years requires a better insight into the biology of weed population and its dynamics than the current state of knowledge permits. Streams of net incomes within this time horizon were discounted to a present value using the real interest rate of 4%. This rate approximates the return on a risk-free asset in the absence of inflation. The present value of the cumulative net incomes was annualized to denote the potential average annual economic benefits of SSM over a four year period.

Two restrictions were imposed on the model runs to reflect management practices or recognize potential constraints of implementing SSM. One restriction deals with mechanical weed control. When weeds occur in patches, using a mechanical control strategy, such as a rotary hoe, for implementing SSM may pose a challenge. Often, weed patches appear in contorted, rather than regular strips. This makes it difficult to use mechanical controls on a site-specific basis. Therefore, mechanical weeding has been eliminated from potential strategies for SSM. The alternative is to use this method on the entire field irrespective of the pattern of weed distribution.

The second restriction limits the number of herbicide products that can be effectively mounted on a spray applicator in a field at a time. While this may be a trivial issue when weed pressure is low and weed species mix is relatively homogeneous, it can be a crucial factor in implementing SSM at high levels of weed pressures and patchiness as the tendency to increase the spectrum of herbicide products increases. For this reason, a maximum number of four different herbicide packages were allowed in the experiments.

Although these two restrictions have the tendency to lower the value of SSM, they do approximate the current practical realities of implementing SSM. When technology permits the relaxation of one or both restrictions, then the estimates of economic value of SSM in this study will represent lower bounds.

4.2. Value of Site-Specific Weed Management

Value of site-specific weed management refers to the improvement in expected profitability for model recommendations under SSM when compared to standard practices. Since MODWSIM predicts potential weed problems from seedbank density information, the model evaluates the potentials of SSM for both soil applied and post-emergence weed control decisions. This is a considerable improvement upon previous models (Wiles et al.; Thornton et al.; Brain and Cousens) that assess the worth of SSM for post-emergence control decisions only.

The simulation experiments were initially conducted for simulated subfields of a west central Minnesota farm. These initial parameter values are shown in Table 4.1. Mean seedbank densities range from 173 per squared meter for foxtails to 877 per squared meter for redroot pigweed. These seedbank densities are averages of the seed densities estimated by direct seed extraction from several soil cores in sampled plots. In general, these densities are below the average densities of viable seeds in western Minnesota (Forcella et. al, 1992). For this reason, the weed pressure is considered low for these initial parameters.

To examine the prospects of SSM practices under increasing weed pressures, the initial weed seed densities in Table 4.1 were doubled. This reparameterization makes the seedbank densities approach the average seed densities of weed species in western

Minnesota. Under this condition, the field is classified as being moderately weedy. Finally, for evaluating the potential of SSM under extreme weed pressures, the initial weed seed densities were multiplied by a factor of 5. The resultant weed seed densities are high but not unusual in Minnesota fields (Forcella et al., 1992). Model recommendations for these weed populations are considered as representing high weed-pressured fields.

As noted earlier, K values in Table 4.1 show the degree of weed aggregation. Having decided on the choice of a negative binomial as the appropriate distributional form, these K values were computed from seed extraction estimates per core. For weed seedlings, quadrat counts of weeds would have sufficed. These K values are close to the median values of K defined for most weed species (Wiles et al.; Brain and Cousens). Therefore, K values in Table 4.1 suggest that the field is moderately patchy.

To gauge the influence of varying weed dispersion on the strength of SSM strategies, the K values were also reparameterized. For each of the three categories of weed pressures considered, the value of SSM under low, medium and high degrees of weed patchiness was considered. This was accomplished by doubling, retaining and halving the K values given in Table 4.1, respectively.

Table 4.2 summarizes the economic parameters used for the simulation experiments. The same level of prices and costs shown in the Table was maintained for all simulations throughout the entire planning horizon.

For the simulation results, the economic component refers to the difference in net income under SSM and standard practices. This difference is given in terms of annualized

Table 4.1: Initial Settings of the Biological Parameters for the Simulation

Weed	Mean Weedseed density per m^{-2}	K	Rank's Correlation Matrix of Weed Species				
			Fox.	Lamb.	Pig.	Must.	Smart.
Foxtails	173	0.03	1.00				
Lambsquarters	733	0.13	0.72	1.00			
Pigweed	877	0.12	0.62	0.61	1.00		
Wild Mustard	218	0.04	0.92	0.69	0.60	1.00	
Smartweed	775	0.04	0.83	0.67	0.55	0.85	1.00

Parameter Values

Table 4.2: Initial Settings of the Economic Parameters for the Simulation

	Corn	Soybeans
Selling Price($/bu)	2.15	5.65
Other variable Costs($/acre)	126.15	62.70
Maximum yield(Bu/acre)	110	40
Discount rate	4%	4%

dollars per acre. The environmental component refers to changes in pesticide(herbicide) indexes of these two practices. For both economic and environmental benefits, values for the standard practice are deducted from its SSM counterparts. Therefore, positive values imply benefits, while negative values signify costs to SSM practices. Income trend values refer to the dollars per acre differences in the economic value of SSM practices between the first and the next time the crop appears in a corn-soybean rotation. Values shown are averages over all the ten replications of the simulation experiments considered. Since the time horizon for simulating the benefits of SSM was set at four years, income trends are appropriate for examining the patterns of these gains over time. If the tendency for weeds to approach uniform distribution increases with SSM practices over time, then one expects the benefits of SSM to be short-lived. The trend values may therefore be low or even negative. On the other hand, if weed distribution remains patchy with SSM practices, the benefits of SSM may persist with time and the trend values will be significant and positive. These factors have important ramifications in deciding whether to adopt SSM practices and invest in its technology.

Finally, figures shown in the parentheses are the paired difference t-statistics that were used to test if model performance under SSM is different from its performance under standard uniform management. In other words, they test if the values shown in the economic and environmental components are statistically different from zero at a given level of confidence for the underlying distribution.

4.2.1. Value of SSM Under Low Weed Pressures

Table 4.3 presents the simulation results under low weed pressures, i.e., for initial weed seed densities given in Table 4.1. The results are presented in three sections which are for low, medium and high patchiness in weed distributions. The results are also shown for two site-specific weed management options. The first option assumes that intra-field weed management strategies are adopted for both pre- and post-emergence control decisions. The second alternative considered the potential benefits of SSM for post-emergence control only. For post-emergence control only, three choices were considered for managing pre-plant weeds. These choices are: (i) routine mechanical weeding; (ii) use of pre-plant incorporated (PPI) or pre-emergence herbicides; and (iii) a choice of no control. However, results of the two most promising options are shown.

When patchiness in weed distribution is low, the results suggest that economic gains of SSM are minimal for both pre- and post-emergence weed control, particularly for corn. The economic gain of implementing SSM is higher in soybean fields than corn. Since economic benefits of SSM stem mainly from savings in weed control costs, soybeans impute higher value to SSM because herbicides for post-emergence weed control in soybeans, on average, are relatively more expensive than in corn.

The results in Table 4.3 also indicate that there is virtually no economic benefit to using SSM practices for pre-plant weed control (PPWC) at low weed aggregation in both crops. The modest economic gains come mainly from post-emergence weed control, particularly with routine mechanical weeding for PPWC. Trend values in the Table show that gains of SSM decline over time for low patchy fields. Under this condition, the

Table 4.3: Simulated Values of SSM under Low Weed Pressures

SSM Option	Average Annual Benefits of SSM					
	Corn			Soybeans		
	Economic Component ($/acre)	Income Trend ($/acre)	Environmental Component (Herb. ind.)	Economic Component ($/acre)	Income Trend ($/acre)	Environmental Component (Herb. ind.)
I. Low Weed Patchiness						
(A) For both pre & post	0.01	-2.10	0.02	1.94	-1.72	0.00
	(0.23)		(1.34)	(2.24)		
(B)<u>Post-emergence only</u>						
(i) Rotary hoe for pre-emergence	0.03	-1.74	0.04	2.52	-0.76	0.02
	(0.44)		(1.01)	(3.78)		(1.19)
(ii) No control option for pre-emergence	0.02	-1.31	0.03	1.11	-0.89	0.01
	(0.37)		(1.47)	(2.17)		(0.98)
II. Moderate Weed Patchiness						
(A) For both pre & post	0.30	-1.32	0.24	3.91	-1.18	0.11
	(1.35)		(15.08)	(13.71)		(12.06)
(B)<u>Post-emergence only</u>						
(i) Rotary hoe for pre-emergence	0.85	-1.52	0.29	4.41	-0.84	0.14
	(3.62)		(16.60)	(15.87)		(18.53)
(ii) No control option for pre-emergence	0.49	-1.55	0.25	3.73	-1.36	0.12
	(2.09)		(15.21)	(13.98)		(14.97)
III: High Weed Patchiness						
(A) For both pre & post	3.21	2.52	0.31	5.42	1.71	0.09
	(6.03)		(7.35)	(8.25)		(5.05)
(B)<u>Post-emergence only</u>						
(i) Rotary hoe for pre-emergence	2.91	0.66	0.44	6.37	0.69	0.18
	(10.02)		(39.68)	(20.71)		(12.08)
(ii) No control option for pre-emergence	4.19	3.16	0.45	7.28	2.41	0.17
	(5.56)		(43.15)	(13.38)		(34.24)

Paired-t difference statistics are in parentheses.

tendency for weeds to approach uniform distribution over time increases with SSM practices.

Economic gains of SSM for corn are not statistically different from zero at the 5% level under low weed aggregation. For soybeans, the economic benefits are significant at the 5% level under all options. For environmental benefits, herbicide index differences are not significant at the 5% under low weed patchiness in both crops. In other words, both the economic and environmental benefits of SSM are negligible when weeds appear to be uniformly distributed.

The middle section of the Table presents simulation results for medium weed aggregation. This scenario corresponds to the initial parameter settings for weed seed densities and K values given in Table 4.1. To a large extent, the results resemble the ones for low weed aggregation. Though there is a modest improvement in the economic gains of SSM for corn, the gains are not statistically significant at the 5% level, except for routine mechanical weeding. Trend values also indicate that the benefits of SSM wane over time as weeds tend to be evenly spread. However, the environmental benefits of SSM practices begin to show as patchiness in weed distribution increases. At medium weed aggregation, the herbicide indexes are all positive and significant. Also, the indexes are higher for corn than soybeans. Therefore , for corn, the greatest incentive to adopting SSM practice under low weed pressure stems from their environmental benefits.

The last section of the Table reports the potential benefits of SSM under high patchiness in weed distributions. For the simulations, the seedbank densities in Table 4.1 were retained but the K values were halved. As noted earlier, since weed patchiness increases as K tends to zero, this reparameterization makes the field more patchy in weed distribution, although the weed pressure is still considered low. The results show that economic benefits of SSM become more pronounced as weeds become more patchy in distribution, even at low weed pressure. Under this scenario, the economic gains are significantly different from zero for both crops and under all control options. Increased weed aggregation now makes SSM strategy for both pre-and post-emergence control significant, although the most optimal is still post-emergence site-specific management with no PPWC.

Environmental benefits of SSM under increased weed patchiness are also enhanced with increased aggregation. The differences in herbicide indexes are all significant at the 5% level and the values are higher than corresponding values under low or moderate weed aggregation. While the economic potential of SSM is brighter under soybeans, the environmental gains under corn also surpass that of soybeans. It is also informative to observe that herbicide treatment is not an optimal control option for pre-plant weeds under low weed pressures, irrespective of the extent of weed patchiness.

Another notable feature of high weed aggregation can be inferred from the trend of SSM benefits over time. It is a bit surprising to see that the trend values are positive which indicate that benefits of SSM now increase over time. Although one may expect benefits of SSM to disappear over time as intra-field weed management makes weeds more uniformly distributed, the dynamics of weeds that escape control in perpetuating the species may make patchy weed distributions a recurring phenomenon.

The results of these simulation experiments have some important ramifications. When weed pressure is low and weed distribution is relatively uniform or moderately patchy, benefits of SSM are modest and wane over time. This has implication for investing in SSM technology. Under these conditions, perhaps custom hiring , rather than capital investments in such technology, is the appropriate course of action, if the scale effect is ignored. On the other hand, when economic benefits from SSM increase over time, as it is the case for highly patchy fields, the prospects of recouping costs of investment in SSM technology seem rather bright. Therefore, investments in such technology, rather than custom hiring, can be a wise choice.

Finally, the results show that the bulk of economic gains comes from post-emergence weed control. Therefore, farmers can decide to limit the adoption of SSM practices to only post-emergence control. As mentioned earlier, since economic gains represent WTP for SSM technology, the strategy may only be economically feasible for soybeans at low weed pressures. However, corn fields use the largest amount of herbicides among U.S. crops and herbicide indexes impute substantial environmental gains to SSM practices when weeds are patchy in distributions. Consequently, some public support may be necessary to induce the use of SSM strategy in corn fields with low weed pressures but considerable patchiness in weed distributions.

4..2.2 Value of SSM under Moderate Weed Pressures

Simulation results under moderate weed populations are presented in Table 4.4. The outcomes show that there are modest gains from carrying out SSM practices at low level of weed aggregation. However, as weed pressure increases, routine mechanical weeding and routine herbicide treatment generate higher returns than when pre-plant weeds are not controlled.

The economic benefit of SSM in corn is not significant at the 5% level for low patchy fields. Also, the importance of pre-emergence control decisions is noticeable as the benefit now seems to be evenly split between pre- and post-emergence control, unlike under low weed pressures when the bulk of the economic gains is credited to only post-emergence SSM practices. For soybeans, the economic gains are all positive and significant at the 5% level and a sizeable proportion of the economic gains is still attributable to post-emergence SSM.

Trend values indicate that benefits increase over time only if SSM strategy is carried out for both pre- and post-emergence weed control. This seems at variance with a priori expectation of a trend toward enhanced uniform distribution of weeds under full practices of SSM over time. Compared to benefits of SSM under low weed pressures in Table 4.3, the increase in the magnitude of economic gains does not suggest that an increase in weed pressures exerts much influence on the potential benefits of SSM in soybeans when the degree of weed patchiness remains the same.

Environmental gains of SSM practices are now significant even at the low level of weed aggregation. Except for soybeans at low level of weed aggregation , the differences

Table 4.4: Simulated Values of SSM under Moderate Weed Pressures

	Average Annual Benefits of SSM					
SSM Option	Corn			Soybeans		
	Economic Component ($/acre)	Income Trend ($/acre)	Environmental Component (Herb. ind.)	Economic Component ($/acre)	Income Trend ($/acre)	Environm. Comp. (Herb.ind)
I. Low Weed Patchiness						
(A) For both Pre & Post Emergence Control	0.71	0.31	0.13	2.31	0.03	0.01
	(1.92)		(4.44)	(8.42)		(1.43)
(B)Post-emergence only						
(i) Rotary hoe for Pre	0.21	-2.11	0.19	1.92	-2.07	0.03
	(0.87)		(10.12)	(6.43)		(2.43)
(ii) No control option for Pre-emergence	0.34	-0.92	0.20	3.03	-0.57	0.05
	(1.29)		(11.40)	(17.38)		(3.27)
II. Moderate Weed Patchiness						
(A) For both Pre & Post	1.11	0.54	0.21	3.97	0.18	0.09
	(4.47)		(15.43)	(14.33)		(8.44)
(B)Post-emergence only						
(i) Rotary hoe for Pre	0.45	-1.42	0.26	3.94	-1.17	0.14
	(1.76)		(15.61)	(14.59)		(17.80)
(ii) Routine PPI/Pre-emergence herbicide for Pre	0.52	-0.87	0.28	5.42	-0.72	0.13
	(1.40)		(20.44)	(26.61)		(33.57)
III: High Weed Patchiness						
(A) For both Pre & Post	5.00	3.26	0.31	7.01	2.71	0.08
	(7.37)		(6.92)	(9.79)		(4.76)
(B)Post-emergence only						
(i) Rotary hoe for Pre	3.64	2.03	0.45	6.93	1.70	0.17
	(7.07)		(66.21)	(13.52)		(31.25)
(ii)Routine PPI/Pre-emergence herbicide for Pre	2.60	0.27	0.38	6.14	0.12	0.12
	(31.77)		(44.39)	(31.33)		(46.21)

Paired-t difference statistics are in parentheses.

in herbicide indexes are all significant at the 5% level for both crops and irrespective of the management options chosen. On average, the value of herbicide index differences for corn exceeds the one for soybeans. Compared to standard practices, this implies that higher environmental gains are derived from SSM practices in corn than soybeans.

Results for moderate level of weed aggregation in the mid-section of Table 4.4 show that the outcomes resemble the ones under low patchy fields. For corn, the economic benefits are also not significant at the 5% level, except for the SSM of both pre-plant and post-emergence weeds. The economic benefits are all positive and significant for soybeans at the 5% level. Trend values suggest that benefits of SSM may increase over time if the practice is used for both pre- and post-emergence control. However, it is doubtful if WTP for SSM practices is high enough in both crops to cover the additional cost of implementing SSM for both pre- and post-emergence control under low or medium weed aggregation.

With increased patchiness in weed distributions, environmental gains of SSM practices improve substantially. They are all positive and statistically different from zero at the 5% level. The final section of the Table presents results for high patchiness in weed distributions. The results indicate that both differences in net incomes and herbicide indexes are statistically different from zero in both crops and for all management options. For the first time, implementing SSM for both pre- and post-emergence weed control decisions clearly dominates partial use of SSM for post-emergence control alone. Income trend values indicate that this strategy is sustainable in the long run as benefits are increasing over time. Also, while a substantial proportion of economic gains can be credited to post-emergence SSM strategy, the gain from pre-emergence SSM is profound, especially for corn, thus strengthening the increased importance of SSM practices as weed pressure and patchiness mount.

However, the economic benefits of SSM for both pre-and post-emergence control are obtained at the expense of environmental gains. The strategy has the least increment in herbicide indexes among all options while routine mechanical weeding of pre-plant weeds is the most environmental-friendly. This suggests that partial implementation of SSM for only post-emergence weed control is probably a good choice for balancing profit motives with desirable environmental characteristics of weed control strategies under moderate weed pressures irrespective of the degrees of weed aggregation.

4.2.3. Value of SSM under High Weed Pressures

Finally, the prospect of SSM practices was examined in fields with high weed populations. As mentioned earlier, this was accomplished by increasing the seedbank densities in Table 4.1 by a factor of 5. Simulation results are shown in Table 4.5.

From the Table, economic gains of SSM also increase with higher weed populations but the increase is not commensurate with the rise in weed pressures. In fact, for soybeans, economic gains of SSM are fairly consistent across weed populations under low levels of weed aggregation. In both crops, full SSM practices for both pre- and post-emergence weed control are superior and economic benefits due to pre-emergence SSM strategies exceed benefits for post-emergence SSM control only.

Table 4.5: Simulated Values of SSM under High Weed Pressures

	Average Annual Benefits of SSM					
SSM Option	Corn			Soybeans		
	Economic Component ($/acre)	Income Trend ($/acre)	Environmental Component (Herb. ind.)	Economic Component ($/acre)	Income Trend ($/acre)	Environ. Comp. (Herb. ind.)
I. Low Weed Patchiness						
(A) For both Pre & Post	1.49	0.09	0.14	3.07	0.71	0.03
	(3.74)		(9.21)	(11.42)		(3.86)
(B)Post-emergence only						
(i) Rotary hoe for Pre-emergence	0.23	-0.39	0.17	1.87	0.14	0.07
	(2.19)		(11.93)	(5.09)		(13.43)
(ii) No control option for Pre-emergence	0.38	-0.65	0.16	1.98	0.22	0.07
	(2.44)		(10.15)	(10.33)		(11.67)
II. Moderate Weed Patchiness						
(A) For both Pre & Post	2.09	0.06	0.19	4.75	0.84	0.05
	(5.32)		(12.13)	(12.32)		(5.94)
(B)Post-emergence only						
(i) Rotary hoe for Pre	0.65	-0.46	0.22	2.53	0.18	0.11
	(4.15)		(17.77)	(6.68)		(15.26)
(ii) Routine PPI/Pre-emergence herbicide for Pre	0.67	-0.63	0.24	3.45	0.25	0.10
	(3.06)		(27.82)	(10.89)		(18.26)
III: High Weed Patchiness						
(A) For both Pre & Post	7.64	0.01	0.38	11.67	0.14	0.26
	(9.45)		(7.13)	(9.25)		(9.29)
(B)Post-emergence only						
(i) Rotary hoe for Pre	0.91	0.99	0.00	0.46	0.99	0.00
	(1.72)			(1.37)		
(ii)Routine PPI/Pre-emergence herbicide for Pre	0.01	0.02	0.01	0.03	0.04	0.00
	(0.05)		(2.60)	(1.18)		

Paired-t difference statistics are in parentheses.

Trend values under low weed aggregation show that benefits of SSM are fairly consistent over time. Environmental gains as typified by values of herbicide indexes are still positive and significant, but the values are far less than those under low and moderate weed pressures, showing that environmental gains of SSM decline as weed population increases.

Outcomes under moderate level of weed patchiness follow a similar pattern as recommendations under low aggregation. Both the environmental and economic benefits of SSM go up with increased weed patchiness. However, the WTP for SSM practices does not seem to be high enough to cover added costs of SSM technology.

Results obtained for model runs under high degrees of weed aggregation are more informative. As can be seen in the last section of Table 4.5, economic gains of SSM increase substantially for full adoption of SSM practices in both crops. At high level of weed populations and high degree of weed patchiness, control of pre-plant weeds becomes quite important and a more effective control is achieved through SSM practices. Since the potential for subsequent weed problems is reduced, economic gains from only post-emergence SSM practices have virtually disappeared and the bulk of these benefits is attributable to SSM practices for pre-emergence weed control. Hence, partial adoption of SSM strategy for only post-emergence control is not worthwhile in any of the crops. Incidentally, WTP for SSM practices may be high enough to make SSM practices economically feasible after paying for SSM costs. Trend values also suggest that the pattern of economic gains is fairly stable over time; a factor that may be conducive for adopting SSM practices and investing in its technology.

Environmental benefits of SSM practices are minimal in fields of high weed population and aggregation. The tendency to use highly toxic but effective herbicides on patchy subfields has offset the advantage of non-chemical usage in the remaining portion of the field. Interestingly, in densely populated, highly patchy fields when there is no benefit to the society whether the farmer practices SSM or not, farmers may not require any incentive to adopt SSM as the economic gains of such strategies may be high enough to cover potential costs. Also, it is instructive to note that though the society is not better off, the use of SSM strategies does not adversely affect the environment as the differences in the values of herbicide indexes, on average, are non-negative.

4.3 Comparing Optimal Strategies under Varying Conditions of Weed Pressure and Aggregation

The gains of SSM under varying degrees of weed populations and dispersion can be placed in proper perspective if one compares model recommendations under some base parameter values with recommendations under different states of weed diversity. Model recommendations in Table 4.3 for low weed pressure and aggregation will constitute this reference point.

Tables 4.6 and 4.7 summarize the results in Table 4.3 through Table 4.5 and present the net changes in model recommendations per acre as weed populations and aggregation change relative to recommendations for these base values for corn and soybeans, respectively. Specifically, the results show the dollar per acre change in net

Table 4.6: Effects of Changing Weed Populations and Dispersion on Benefits of SSM in Corn

		Weed Pressure					
		Low		Medium		High	
		$/acre	herbind	$/acre	herbind	$/acre	herbind
Weed Patchiness	Low	0.00	0.00	0.70	0.11	1.48	0.12
	Medium	0.29	0.22	1.10	0.09	2.08	0.17
	High	3.20	0.29	4.99	0.29	7.63	0.36

Table 4.7: Effects of Changing Weed Populations and Dispersion on Benefits of SSM in Soybeans

		Weed Pressure					
		Low		Medium		High	
		$/acre	herbind	$/acre	herbind	$/acre	herbind
Weed Patchiness	Low	0.00	0.00	0.77	0.01	1.53	0.03
	Medium	2.37	0.11	2.43	0.09	3.21	0.05
	High	3.88	0.09	5.47	0.08	10.13	0.26

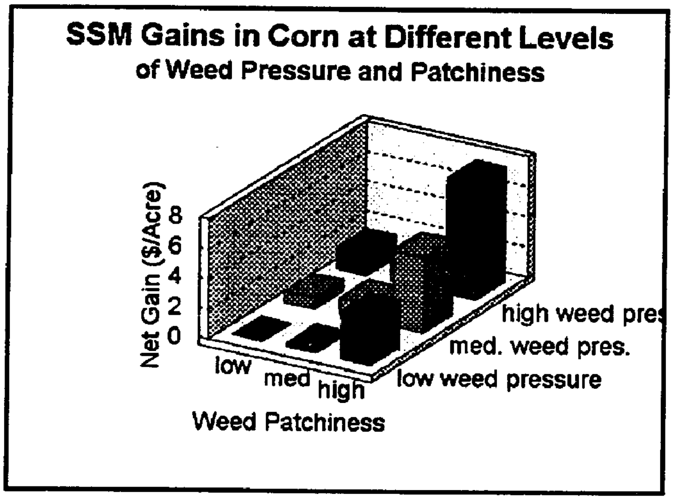
income and the change in herbicide indexes as weed populations and patchiness in weed distributions change. The graphical illustrations of these results are shown in Figure 4.1. The results given in Tables 4.6, 4.7 and Figure 4.1 were developed under the assumption of full SSM practices for both pre- and post-emergence weed control.

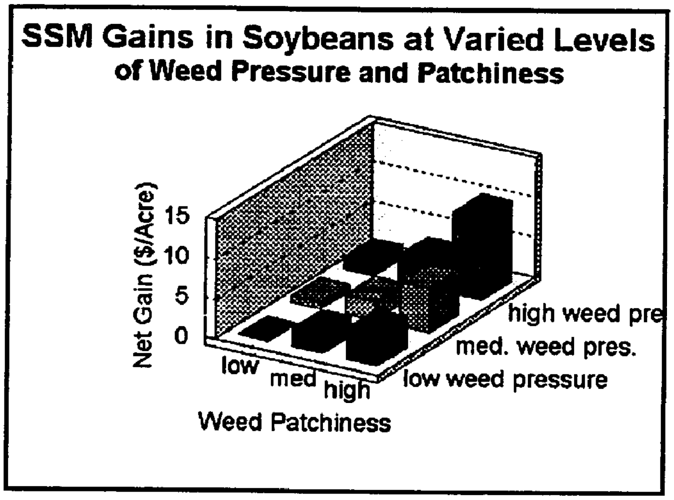
Results of the analysis suggest that the influence of rising weed populations on the economic potential of SSM is rather modest, but increasing patchiness in weed distributions improves the potential economic benefits of SSM considerably. At low level of weed aggregation, and as weed populations increase, there is an increase in the economic benefit of SSM but the change in economic returns is not high enough to induce SSM practices by itself, unless SSM practices are economically feasible for low patchy, low weed-pressured fields. For corn whose WTP for SSM practices is low for the reference recommendations, SSM practices may not be preferred at any level of weed pressures if weed aggregation is low.

This picture begins to change as weeds become more patchy in distribution. The results suggest that weed patchiness is the main driving force behind the economic merit of SSM practices. Economic benefits of SSM practices increase substantially as weeds become more clumped. Given a particular level of weed pressure, increased weed patchiness can induce the use of SSM strategy even when such practice is not feasible at lower level of weed aggregation.

While increasing weed aggregation is very crucial to the adoption of SSM practices, increasing weed populations fully complement growing weed patchiness to produce maximum economic benefit of SSM practices. Under considerably high degrees

Figure 4.1: Economic Value of SSM Information at Different Levels of Weed Pressure and Patchiness





of weed pressure and aggregation, the economic benefit of SSM strategy is high enough such that one is approaching a situation when the practice will be economically feasible, contingent upon the cost of SSM application.

Changing conditions of weed pressures and aggregation also influence the magnitude of environmental gains of using SSM practices. When weeds are uniformly spread, there is no environmental benefit from adopting SSM practices, irrespective of the degree of weed pressures. Conversely, the environmental benefits of SSM practices generally increase as weed patchiness rises, although there are few instances when these environmental gains disappear, especially in fields with considerable weed pressure. As noted earlier, in these instances, the choice of highly toxic herbicides to control weeds in densely populated subfields has overshadowed the benefits of low input use in other sections of the field.

On the strength of the simulation results, it seems as if both environmental and economic benefits of SSM practices are considerable under increasing weed patchiness, but economic gains under increasing weed pressures are modest, particularly if the increase in weed pressure is not accompanied by corresponding increase in weed aggregation. Therefore, on the strength of economic returns alone, it is questionable whether farmers will be willing to adopt SSM practices under the prevailing conditions, especially when the attendant risk and cost considerations are factored in.

However, given the potential of SSM practices for lowering environmental hazards of pesticide usage, modest financial incentives may be appropriate for inducing the adoption of this weed control strategy. These incentives can take various forms, such as direct financial subsidies, adequate funding of research for low-cost SSM technology and tax premiums that make herbicide users bear responsibility for the cost of herbicide usage.

V. DELAYED PLANTING STRATEGIES

Simulation experiments to assess the benefits and costs of delayed planting as a weed control instrument were conducted within a deterministic framework. In addition to weed control, information on delayed planting strategies can aid in sequencing field operations. Therefore, model runs were undertaken under varying degrees of weed populations, weed species mixes and varietal choice of corn hybrids. In this chapter, the assumptions governing the simulation experiments are first presented. Later, the simulation experiments are described. Finally, model results and their implications for delayed planting strategies as a weed control instrument are discussed.

5.1 Modeling Assumptions and Management Considerations

Modeling assumptions regarding crop yields, prices and input costs are similar to those presented in Chapter 4. However, the inclusion of varietal choice introduces two additional corn hybrids whose yield potentials are less than that of full season corn which is usually the standard hybrid. Potential yields of mid-season and short-season corn were set at 96 and 84 bushels per acre, respectively. These weed free yields represent the long run average maximum yields of these hybrids obtained from experimental fields in west central Minnesota.

Unlike SSM practices, no substantial cost outlay for acquiring new technology is envisaged for delayed planting strategies. However, there are institutional bottlenecks that could set a limit to the feasibility of such a strategy and the extent to which a farmer can delay planting. In addition to possible labor constraints, farmers willing to participate in crop insurance programs are expected to plant their crops within some specified periods of time. For corn and soybeans in Minnesota, planting of these crops should not extend beyond June 10 for the crops to be insurable. Zilberman et al. (p.28) draw attention to other agents whose functions impact on farmers production decisions. Among such agents are the bankers who now rely on ability of farmers to repay loans as a major criterion in loan decision making. To reduce instances of loan defaults and loans that result in bankruptcies, bankers often recommend the use of conservative production plans which may include restrictions on delayed planting. Also, production inputs such as fertilizers and pesticides often have a time window of application for such inputs to be effective. This window of application is relevant in deciding the extent of late planting. Considering all these factors, farmers were not allowed to delay planting beyond the early weeks of June in the simulation experiments. This period coincides with the time limit sets by crop insurance programs.

Simulation experiments were conducted for a number of conventionally tilled fields of either crop in corn-soybean rotation, continuous corn and mid- and short-season corn in rotation with soybeans. The choice of conventional tillage practices was made to reflect the dominant tillage system in Minnesota. Despite the attractiveness of conservation tillage practices, progress in switching from conventional to conservation tillage has been rather slow in Minnesota. For instance, Mirotchie (p.12) reported that about 82% and 74% of total corn and soybean acreage respectively, were under a conventional tillage system in Minnesota in 1982. Estimates from 1994 National Tillage Information Surveys of USDA Soil Conservation Service[2] put the total acreage under conventional tillage at 5.24 million, out of a total 6.8 million acres for corn in 1994. This is about 77%, or a difference of 5% over a 12-year period. For soybeans, 3.8 million acres or about 67% of total acreage were under a conventional tillage system in 1994. While the model can be modified to accommodate conservation tillage system as this practice becomes dominant, the impact of such switch in tillage systems on the potential of delayed planting strategy is not obvious.

In the simulated experiments, the base planting dates for corn and soybeans were set at April 28 and May 1, respectively. These represent early planting dates for these crops in Minnesota. Planting dates were successively increased for varying degrees of weed seed populations and weed mixes in order to determine planting date(s) that maximize net returns under the specified conditions. As mentioned earlier, model runs were undertaken for three corn hybrids and under varying conditions of weed pressures and species mixes. Results for full season corn, mid- and short season corn can identify hybrid varieties with the best potential for late planting.

A number of factors influence the choice of control strategies and the resultant net returns and environmental indexes. In addition to weed rivalry indicated by their competitive indices, timing of weed emergence also plays a role in deciding whether a weed species should be controlled and what control strategy to use. Furthermore, since the benefits of late planting stem mainly from the proportion of emerging weeds destroyed

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[2] Figures provided by David Breitbach of USDA Soil Conservation Service

during pre-plant tillage, timing of weed emergence is crucial to the realization of its gains. Weed emergence models described in Chapter 3 have shown that timing of seedling emergence partly depends on the weed species under consideration. Therefore, the weed species in the model were categorized into two broad groups, the early and late emerging weeds. Based on the timing of observed and simulated weed emergence levels, wild mustard, Pennsylvania smartweed and common lambsquarters are classified as early emergers, while foxtails and redroot pigweed are grouped as late emergers. Simulations under this broad grouping can identify weed species whose preponderance influences the optimality of late planting strategies. This information can aid farmers in sequencing field operations.

Finally, simulated model recommendations under the delayed planting option were compared with those obtained when planting is done in accordance with recommendations of the Extension Service. In Minnesota, suggested planting dates for these crops range from late April to early May. For the purpose of this comparison, recommended planting dates were fixed at May 1 and May 5 for corn and soybeans respectively; the limit of possible planting dates before any noticeable yield loss due to late planting sets in. Therefore, if optimal planting dates fall beyond first week of May for either crop, then delayed planting strategy has become a part of preferred weed management strategies. The differences in model performance when planting is delayed as compared to expected model performance for earlier planting dates impute value to delayed planting strategies.

5.2: Potential for Late Planting under Varying Weed Populations and Mixes

On the basis of expected benefits of delayed planting, the optimal planting date should increase with rising weed populations . Also, given the competitive indices of weeds, fields in which the early emerging weeds predominate are expected to exhibit a different potential for late planting when compared to fields in which late emerging weeds are prevalent. Simulation experiments in this section were specifically designed to reveal the prospects for late planting under these conditions. The weed seed densities used for the simulations are similar to those presented in Table 4.1, except for the foxtail seed densities which were set at 2000 per square meter. This balances the mix of grass and broadleaf weeds in the populations.

In addition to these initial weed populations, two other variations were used. These are in multiples of 0.25 and 4 of the weed seed densities. For this exposition, the three sets of weed populations in ratio 0.25:1:4 are categorized as having low, medium and high weed populations, respectively. Also, on the basis of the earlier categorization of weed species into early and late emerging types, a grouping of these weed seed densities into a 3-by-3 matrix combinations provides weed population information required for nine model runs. These model runs reflect virtually all possible effects of changing weed populations and weed species mixes on model recommendations and choice of delayed planting strategies. Results obtained from these simulations are presented in Tables 5.1 and 5.2.

Table 5.1: Values of Delayed Planting Strategies at Different Levels of Weed Populations and Mixes in Corn (Compared to May 1 Planting Date)

			Early Emergers (Relative Weed Populations)		
			Low	Medium	High
Late Emergers	Low	Planting Date	1-May	10-May	22-May
		Income($/acre)	82.48	74.11	62.37
		Δ income	0.00	14.30	64.27
		Herbicide Index	0.83	0.83	0.80
		Δ herb. Index	0.00	0.00	0.13
	Medium	Planting Date	7-May	13-May	23-May
		Income($/acre)	79.01	71.43	61.74
		Δ income	6.50	21.98	70.31
		Herbicide Index	0.83	0.83	0.80
		Δ herb. Index	0.03	0.03	0.13
	High	Planting Date	13-May	18-May	23-May
		Income($/acre)	66.81	64.37	59.05
		Δ income	37.88	46.25	85.97
		Herbicide Index	0.80	0.80	0.80
		Δ herb. Index	0.13	0.13	0.13

Low, Medium and High refer to multiples of 0.25, 1 and 4 of the base weed populations, respectively. The base weed populations are : foxtails 2000; lambsquarters 733; pigweed 877; wild mustard 218; and smartweed 775, all in weed seed densities per square meter. Early emergers are lambsquarters, mustard and smartweed. Late emergers are foxtails and pigweed. As an example, the mix of weed-seed densities for high populations of early-emerging but low populations of late-emerging weeds are:Foxtails 500; lambsquarters 2932;Pigweed 219;wild mustard 872; and smartweed 3100.

Table 5.2: Values of Delayed Planting Strategies at Different Levels of Weed Populations and Mixes in Soybeans (Compared to May 5 Planting Date)

			Early Emergers (Relative Weed Populations)		
			Low	Medium	High
Late Emergers	Low	Planting Date	5-May	10-May	21-May
		Income($/acre)	147.51	136.01	127.12
		Δ income	0.00	1.84	18.01
		Herbicide Index	0.78	0.78	0.73
		Δ herb. Index	0.00	0.05	0.16
	Medium	Planting Date	11-May	13-May	20-May
		Income($/acre)	135.49	130.25	126.59
		Δ income	3.45	7.20	29.43
		Herbicide Index	0.78	0.73	0.73
		Δ herb. Index	0.05	0.16	0.16
	High	Planting Date	18-May	21-May	22-May
		Income($/acre)	125.56	131.52	126.28
		Δ income	29.58	23.52	51.01
		Herbicide Index	0.73	0.73	0.73
		Δ herb. Index	0.16	0.16	0.16

Low, Medium and High refer to multiples of 0.25, 1 and 4 of the base weed populations, respectively. The base weed populations are : foxtails 2000; lambsquarters 733; pigweed 877; wild mustard 218; and smartweed 775, all in weed seed densities per square meter. Early emergers are lambsquarters, mustard and smartweed. Late emergers are foxtails and pigweed. As an example, the mix of weed-seed densities for high populations of early-emerging but low populations of late-emerging weeds are:Foxtails 500; lambsquarters 2932;Pigweed 219; wild mustard 872; and smartweed 3100.

The diagonal elements in these Tables show model performance under direct proportional changes in populations of early and late emerging weeds. The off-diagonal values are model performances when weed populations of late emerging weeds are inversely related to population of early emerging ones. The planting dates shown in the Tables are the optimal planting dates that maximize net returns under the stated conditions. The corresponding net incomes in dollars per acre at these optimal planting dates are also given. Δ income refers to the increment in net incomes over net incomes associated with fixed planting dates, i.e., May 1 for corn and May 5 for soybeans.

In evaluating the potential economic benefits of delayed planting strategies under increasing weed pressure, changes in net income, rather than the magnitude of net income, will be appropriate. With increasing weed populations, net incomes generally decline due to increasing crop yield losses from weeds that escape control. Therefore, Δ income denotes the economic value of late planting strategies. The herbicide index is the measure of environmental impact of choice control strategies. The change in herbicide index, Δ herb. index, which is the difference between the herbicide index under late planting strategies and fixed planting dates, imputes environmental values to delayed planting strategies.

The results show that imputed values of late planting are virtually nil at low pressures of both early and late emerging weeds in both crops. Therefore, farmers whose extent of weed pressure resembles the weed densities at low weed pressure would maximize returns from early plantings. However, delayed planting appears to be a feasible strategy as weed pressure intensifies. At moderate weed populations which are close to actual field conditions, delaying planting for a few days beyond the fixed planting dates is optimal in both crops. In fact, at high weed populations of either early or late emerging weeds in corn, simulation results suggest losses may be reported for early plantings. As a result, late planting may actually be the best strategy for optimizing net income. Fortunately, such extreme weed populations are rarely encountered in actual fields.

The off-diagonal values in Tables 5.1 and 5.2 suggest that the use of delayed planting as a weed control instrument is more attractive when there is a preponderance of early emerging weeds. For example, for corn in Table 5.1, the optimal planting date is May 22 at high populations of early emerging but low population of late-emerging weeds. On the other hand, the optimal planting date is May 13 for high populations of late emerging but low populations of early emerging weeds. Therefore, the preponderance of early emerging weeds may yield an extra window of about nine planting days for which planting can be delayed. Optimal planting dates for soybeans in Table 5.2 follow the same pattern, permitting up to an additional window of about three days for planting if population of early emerging weeds exceeds that of late emerging weeds.

The results suggest that the economic potential for delayed planting is higher in corn than in soybeans. This supports the earlier observation in Chapter 3 that soybeans are generally more sensitive to late planting than corn. This information has important implications in managing fields of heterogenous weed populations and weed species mixes.

Herbicide indexes are the measures of environmental impact of choice strategies under late planting. In general, environmental benefits of delayed planting strategies, as represented by their Δ herb. index, increase as weed populations rise. Since all the herbicide indexes are less than unity, optimal weed control at all levels of weed pressure involves some herbicide treatment. This is better illustrated in Appendix 6. Results in this Appendix show detailed simulated net incomes and herbicide indexes for all probable planting dates of corn which underlie some of the summary recommendations presented in Tables 5.1.

The results in Appendix 6 show that the optimal planting date is May 13 for corn under medium level of early and late emerging weeds. Although the need for herbicide use declines with increasing delay in planting, the control strategy at this optimal planting date involves herbicide use. For herbicide-free control of weeds in corn, planting has to be delayed till at least May 25. However, the corresponding loss in potential income of more than $8 per acre makes such strategies unattractive to farmers whose primary objective is profit maximization. Delayed planting strategy is therefore not an alternative to herbicide use at the optimal level of control.

Despite the fact that delayed planting strategy does not eliminate the need for herbicides, it is remarkable to observe that it eliminates use of pre-plant chemical treatments at all weed populations and weed species mixes. Rather, the use of either mechanical weeding or no control strategies is optimal depending on the extent of weed pressures. Mechanical and no control strategies have the most environmentally- friendly attributes among the treatments included in the model. Although results in Tables 5.1, 5.2 and Appendix 6 suggest that optimal control strategies under fixed planting dates sometimes coincide with the preferred control treatment under delayed planting strategies, model recommendations assuming a fixed planting date may sometimes involve the use of PPI/pre-emergence herbicides at high weed pressures. Delayed planting strategy may therefore be a promising tool for reducing the use of pre-emergence herbicides.

5.3: Delayed Planting and Varietal Selection

Full season corn, which requires between 110 and 115 days to mature, has the maximum yield potential for early planting. However, compared to its mid-season and short-season hybrids, it suffers the most when planting is delayed. To further investigate the impact of hybrid selections on the economic and environmental benefits of delayed planting strategies, simulation experiments were carried out for mid-season and short season corn, in addition to model runs for full season corn under a wide range of weed densities. Table 5.3 presents model recommendations as a function of planting dates at three discrete levels of weed pressure. These three levels are in 0.25:1:4 proportions of the base weed populations respectively.

In terms of planting dates that maximize net returns for each of the three corn hybrids, the results show that short-season corn is the variety whose planting can be most delayed, irrespective of the degree of weed pressures. This is followed by mid-season corn. As weed populations increase, further delay in planting offers an optimal path for farmers to maximize net returns, irrespective of corn hybrids grown.

Table 5.3: Value of Delayed Planting Strategies for Three Corn Hybrids

	Variety		
	Full season	Mid-season	Short season
Low Weed Populations			
Planting Date	1-May	8-May	27-May
Net Income($/acre)	82.48	57.22	41.08
Herbicide Index	0.83	0.87	1.00
Medium Weed Populations			
Planting Date	13-May	19-May	31-May
Net Income($/acre)	71.43	50.11	38.34
Herbicide Index	0.83	0.87	1.00
High Weed Populations			
Planting Date	23-May	27-May	6-Jun
Net Income($/acre)	59.05	40.11	33.73
Herbicide Index	0.80	0.83	0.87

Low, Medium and High refer to multiples of 0.25, 1 and 4 of the base weed populations, respectively. The base weed populations are : foxtails 2000; lambsquarters 733; pigweed 877; wild mustard 218; and smartweed 775, all in weed seed densities per square meter.

The environmental gains of planting mid-season and short-season varieties under delayed planting strategies are quite substantial when compared to full season corn. For mid-season corn, environmental indexes are generally higher than that of full season, which implies the use of less toxic herbicides. However, since each of these indexes is still less than unity, recourse to a mid-season hybrid under optimal planting strategies may not eliminate the need for post-emergence herbicides completely.

If environmental gains are the sole criterion for choosing delayed planting strategy, then short-season corn is definitely the best variety. Its planting can be delayed far enough to allow most weed seeds to have germinated. Since these weeds are destroyed by pre-plant tillage, the potential for subsequent weed problems is greatly reduced.
For this reason, environmental gains for short season corn are greatest for mild weed infestations under optimal path of delayed planting strategies. The use of post-emergence herbicides is only required when weed pressure is high, but the herbicides that are selected are still less toxic when compared to herbicide choices either under early planting of short-season or both early and late planting of mid- and full season corn.

Despite the environmental merit of short- and mid-season hybrids under delayed planting strategies, it is doubtful if any farmer will prefer these hybrids to full season corn under similar modeling conditions. A cursory glance at the magnitude of net incomes in Tables 5.3 shows that net incomes from full season corn consistently exceed corresponding incomes for short and mid-season varieties at all levels of weed populations. This implies the maximum yield potential of full season corn duly compensates for the corresponding loss in crop yields as planting is delayed, although full season corn is most sensitive to late planting. Without financial incentives to explicitly account for the differences in income, a switch to shorter season varieties is not envisaged. Financial incentives can even achieve better results if used to promote adoption of environmentally friendly strategies in full season corn, rather than encouraging late planting of mid- or short-season hybrids. However, breeding programs that increase yields of short-season varieties may be a step in the right direction.

5.4: Delayed Planting and Crop Rotation Practices

Crop rotation is an important component of a weed management program (Durgan et. al, p.5). Rotation practices affect the choice of feasible control strategies, and by extension, the potential of delayed planting strategies for weed control. An example is the use of atrazine, a restricted herbicide product. Atrazine is among the feasible control treatments in continuous corn, but its use is not permitted in a corn-soybean rotation because of its potential carryover effects on atrazine-sensitive crops such as soybeans. Table 5.4 shows the model performance for continuous corn and corn in corn-soybean rotations for two discrete levels of weed pressures. These two discrete levels of weed pressure are in multiples of 1 and 4 of the base weed seed populations shown in Table 5.1.

Results in Table 5.4 show that optimal planting dates for both rotational practices are virtually the same irrespective of the extent of weed pressures. Therefore, the choice of optimal planting dates is generally invariant to crop rotation practices at all weed pressures. The minor differences in net incomes and environmental indexes are

Table 5.4: Influence of Rotational Practices on Optimal Planting Dates

	Medium Weed Populations				High Weed Populations			
	Rotation		Continuous		Rotation		Continuous	
Planting Date	Income ($/acre)	Herb. index	Income ($/acre)	Herb. Index	Income ($/acre)	Herb. Index	Income ($/acre)	Herb. Index
28-Apr	31.67	0.80	32.30	0.67	-46.00	0.80	-46.92	0.56
1-May	49.45	0.80	50.76	0.67	-26.92	0.67	-27.46	0.56
4-May	52.47	0.80	52.21	0.67	-12.47	0.67	-12.41	0.56
7-May	61.30	0.80	60.99	0.67	13.57	0.67	13.50	0.56
10-May	63.97	0.80	65.89	0.67	26.90	0.67	27.71	0.56
13-May	71.43	0.83	70.64	0.67	39.83	0.67	39.39	0.67
16-May	66.10	0.83	65.37	0.83	46.00	0.67	45.49	0.67
19-May	65.52	0.83	67.49	0.83	51.64	0.80	53.19	0.67
22-May	63.81	0.83	65.72	0.83	55.34	0.80	57.00	0.67
25-May	63.15	1.00	62.83	1.00	56.37	0.80	56.09	0.67
27-May	63.49	1.00	63.17	1.00	55.91	0.80	55.63	0.67

Medium Weed Populations correspond to weed seed densities in the footnote of Table 5.1. High Weed Populations are these weed populations multiplied by 4.

due to differences in costs, toxicity and effectiveness of choice control strategies. However, the above results may be valid only within a static, deterministic framework.

In a dynamic setting, crop rotation promotes use of different types of herbicides on the same field over the years which prevents the buildup of difficult to control or herbicide resistant weeds (Durgan et al., p.5). Also, the patterns of competition between crops and weeds obviously affect the choice of herbicide products. The need for highly effective herbicides is minimal for crops that vigorously compete with weeds. Yenish et al. have found evidence of changing weed species mixes as rotation and tillage practices vary due to competitive patterns between weeds and crops and the different control strategies that such practices entail. For these reasons, it is reasonable to expect different potential for delayed planting strategies in a static setting when compared with outcomes of dynamic simulation experiments. Whether this divergence will be significant is yet to be determined.

VI. SUMMARY AND CONCLUSION

Growing concerns about possible health and environmental hazards of pesticides are responsible for the implementation of various measures, ranging from herbicide restrictions to use quotas, to regulate pesticide usage worldwide. However, the adverse effects of uncontrolled pest populations are well documented. In the United States alone, the annual value of crop yield losses from uncontrolled weed populations runs into several billions of dollars. These considerations are kindling interest in identifying control strategies that are both profitable and environmentally friendly.

The next wave of economic growth is expected from knowledge-based businesses (Davis and Botkin). This assertion is particularly relevant in pest management where bioeconomic models for optimal control strategies have proved useful in maximizing returns and curtailing herbicide usage. These models employ concepts of economic thresholds to recommend control strategies that are responsive to field conditions under the implicit assumption that weeds are evenly spread throughout the field. This contrasts with routine weed control which is the standard practice of most farmers. Although these models acknowledge that misapplication of herbicides can be counter-productive in terms of yield loss or high control costs, little consideration is given to environmental implications of herbicide use.

Recent emerging tools for pest management can provide the means of balancing the profit motive of pest control with environmental needs. One such instrument is site-specific weed management (SSM). SSM prescribes herbicide treatment for only the portion of a field infested by weeds, rather than the entire field. This intra-field weed management recognizes that the assumption of uniform weed distribution throughout the entire field may not be valid. The second tool that is increasingly becoming relevant is delayed planting strategy coupled with mechanical control weeds. By allowing weeds to emerge prior to planting, delayed planting reduces the need for herbicides as the bulk of potential weeds would have been eradicated during pre-plant tillage. Taken together, these weed control practices have the potential to reduce herbicide use and possibly enhance profit.

However, these emerging weed control tools also have their costs. SSM requires additional costs for obtaining the information and technology for implementation. Delayed planting generally reduces crop yields and can interfere with other field operations. Therefore, the broad objective of the study was to explore the costs and benefits of these tools for reduced input weed management. The specific objectives of the study were:

(i) To modify the dynamic bioeconomic model for the control of multiple weed species (Swinton; Swinton and King) for the effects of weed distribution, delayed planting and mechanical weed control on its decision rules;

(ii) to use simulation experiments to assess the potential economic and environmental benefits of managing for intra-field weed variability under varying weed populations, weed species mixes and dispersion;

(iii) to determine planting thresholds that balance the benefits of delayed planting strategy against its costs and describe the set of environmental and resource conditions under which delayed planting and mechanical weed control can become a part of preferred weed management strategies.

In the sections that follow, the conceptual basis for the study, model specification and validation are first presented. Next, the major findings of the simulation experiments to evaluate the net benefits of SSM and delayed planting strategies are indicated. Finally, directions for future research are suggested.

6.1: Conceptual Basis for the Study, Model Specification and Estimation

The study reviews the conceptual issues involved in weed management modeling. It demonstrates the impact of weed distribution patterns on estimated yield losses and expected income from weed control. Two methods of incorporating weed management models are discussed. These are the geostatistical techniques and simulation method.

Geostatistical interpolation technique known as Kriging is a suitable method for establishing how weeds are distributed in space. The resultant weed population maps offer an easy, practical step of using SSM. However, for evaluating the potential economic and environmental benefits of SSM in this study, the alternative simulation approach is employed. For the simulation method, intra-field weed management is accomplished through sub-division of a field into a discrete number of subfields such that weeds are evenly spread within each subfield but weed density may vary from one subfield to another. To obtain weed density information for these subfields, parameters of a negative binomial distribution which characterize weed species included in the model were used in generating variates of the distribution. To account for the nature of interdependency occurring among weed species, King's multivariate process generator was employed to recast variates into their random multivariable forms. Each set of interdependent random variables constitutes the seed density information for each subfield.

The thesis develops a model of delayed planting strategies in weed control. Late planting lowers yield, but the cost of achieving comparable effective level of weed control may be less for late planting than early planting. The model identifies planting dates for which economic benefits of cheaper weed control practices under late planting exceed or equal the negative benefits of yield loss. Under these conditions, model performance under delayed planting strategies will be superior to performance under standard practices of early planting.

Although the choice of optimal control strategies in this study is based on the magnitude of net incomes, due consideration is given to the environmental effects of the preferred weed management options. The study builds on the earlier work by Kovach et al. in developing herbicide indexes for evaluating the environmental impact of herbicide usage. This method recognizes the toxicological strength and application dosage of individual herbicide products in computing herbicide indexes. The method improves upon previous practices (Wiles; Swinton) of using only numerical loads to assess environmental impact of alternative control strategies.

The starting decision model for estimating the potential benefits of SSM and delayed planting strategies is WEEDSIM. This is a computer-based, dynamic bioeconomic weed management model which accommodates multiple weeds and control treatments. WEEDSIM identifies the optimal path of weed control treatments that maximizes net returns over a two-year time horizon. MODWSIM is an extension of WEEDSIM that incorporates SSM and delayed planting sub-models in its decision rules. MODWSIM employs information provided by the user on weed density information, crop prices and input costs to identify optimal strategies ranked on the basis of net returns for any specified finite number of years. Environmental indexes are provided to facilitate comparisons of alternative control strategies. MODWSIM identifies optimal strategies and compares model performance under standard practices to performance under SSM and delayed planting strategies. The differences, if any, in model performance impute value to these weed control instruments.

Considerable efforts are devoted towards estimating the biological parameters required for running the model. The input parameters that WEEDSIM share in common with MODWSIM were re-estimated due to availability of richer data set. Input parameters that are unique to MODWSIM were developed and validated. Although the parameter estimates are generally satisfactory, the quality of parameter estimates can be enhanced as better information on weeds and their population dynamics becomes available.

6.2 Potential Benefits of SSM

The potential benefits of SSM are examined under low, medium and high degrees of weed populations and aggregation. Weed populations are considered low if they fall below the average populations of the weed species in west central Minnesota. Weed populations that fall within or above this range are considered medium or high, respectively. Similarly, the degree of weed patchiness is classified as low, medium or high based on the magnitude of its estimated K. Previous values of K estimated for a wide range of weed species serve as a guide for the classification. The simulation experiments for evaluating the benefits were conducted within a dynamic but deterministic framework.

In general, weed patchiness, which is the compelling reason for implementing SSM, turns out to be the most important factor influencing the benefits of SSM practices. Simulation results show that economic and environmental benefits of SSM practices are almost nil at low weed pressures, particularly if weeds are uniformly distributed. As weeds become more clumped, there are minimal economic gains from SSM practices. At high level of weed aggregation, economic benefits of SSM are more visible. However, the main incentive to adopting SSM practices stems from its environmental benefits which are quite significant at low weed pressure for high patchy fields. In this situation, weeds are concentrated on some portions of the field such that herbicide application may not be necessary (or economically optimal) on the remaining segment of the field.

Simulations at moderate weed pressures which closely approximate Minnesota fields do not reveal substantial changes in SSM performance when compared to its benefits at low weed pressures. Economic and environmental benefits of SSM are still modest at low level of weed aggregation. However, as weeds become more patchy, the economic benefits appear significant and considerably higher than similar benefits under low weed pressures. On the other hand, the environmental benefits are also significant but less than benefits under low weed pressures. Since economic benefits of SSM denote WTP for SSM technology, it is doubtful if the strategy will be economically feasible at low and moderate levels of weed populations, irrespective of the degrees of weed patchiness. Under these conditions, the main advantage of SSM practices is the considerable environmental benefit but which, by itself, cannot induce farmers to accept the practices without some support.

The best economic returns to SSM practices are obtained under high degrees of weed pressure and aggregation. Implementing SSM practices under this condition may be economically attractive as the WTP for SSM technology appears high enough to pay for the potential costs of SSM practices. However, environmental benefits of SSM practices are not so clear-cut. Environmental gains of SSM practices may disappear in fields with high degree of weed pressure and patchiness if the effects of using toxic herbicides to control weeds in densely populated subfields offset the benefits of low input use in the remainder of the fields.

Finally, economic gains of SSM practices stem from savings in herbicide costs. Therefore crops whose herbicides are relatively more expensive will benefit more from SSM practices.

6.3 Delayed Planting Strategies

The difference between model performance when planting is delayed as compared to when timely planting is carried out in accordance with Extension Service recommendations imputes value to delayed planting strategies. Simulation analyses within a static, deterministic framework show that delayed planting can indeed be a primary tool for optimizing weed control and net income, rather than eliminating herbicide use.

When weed pressure is low, there is neither economic nor environmental benefit from late planting. However, as weed populations increase, these benefits are realized. Though the simulation results do not suggest that delayed planting strategy can substitute for herbicide use under optimal strategy for weed control, the environmental strength of late planting lies in its potential to reduce or eliminate the need for pre-emergence herbicides. Due to the fact that more pre-plant weeds emerge with delayed planting, the use of mechanical weeding for pre-plant weeds is a clearly superior strategy over herbicide treatment irrespective of the degree of weed pressures for all simulations under delayed planting strategies.

The influence of varietal hybrid selection on the strength of delayed planting strategies was also examined. Hybrid varieties requiring fewer days to mature are less sensitive to late planting than full season varieties. The environmental gains of using these varieties are significant, since the bulk of potential weeds are eliminated during pre-plant tillage. However, the greater tolerance of short-season varieties for late planting does not adequately compensate for their lower yield potentials when compared to full season varieties. Therefore, full season hybrids still remain the economically optimal varieties under delayed planting strategies.

Finally, simulation results suggest that the choice of optimal planting dates are invariant to crop rotation practices within a static framework. However, it is very likely that rotational practices will influence delayed planting practices in a dynamic setting.

6.4 Conclusion

The study showed that under suitable conditions, SSM and delayed planting strategies have the potential to enhance profit and reduce herbicide use. The practices are environmentally friendly, so the society is never worse off when compared to standard practices. However, the impact on profit is generally modest and it may not induce the adoption of these practices by farmers when cost and risk issues are considered. If the environmental gains of these tools are adjudged significant, then some public incentives may be needed to promote the use of these weed control strategies.

6.5 Suggestions for Future Research

Findings in this study have imputed some value to SSM and delayed planting strategies as weed control instruments. Under suitable conditions, SSM practices can be economically feasible such that the errors in weed control decisions based on the assumption of uniform weed distribution can be significant. This departs from simulation results reported by Wiles. Since these findings have important research and policy ramifications, field trials to validate these results will be an appropriate research effort. The design of such field trials can be similar to the on-going validation field trials of WEEDSIM recommendations in Morris and Rosemount, MN (Forcella, 1992).

Adoption of SSM practices depends in part on the availability of affordable SSM technology. The economic benefits of SSM practices denote the WTP for SSM technology since uniform cost is assumed for standard practices and SSM. At present, the cost of acquiring variable rate equipment and computer software for managing soil fertility is about $275,000, according to Cargill, a leading provider of such services (Walsh). For this reason, it is doubtful if SSM will be economically feasible if similar cost outlay is involved given the magnitude of its WTP under most conditions. As a result, future research into production of low-cost VRT deserves consideration. Since the use of SSM for weed control generally has less adverse effect on the environment as compared to standard practices, some public support for such research endeavors is in order.

Simulation experiments in this study are conducted within deterministic framework. In addition, the potential of delayed planting strategies is evaluated under a static environment. These assumptions represent an oversimplification of reality. An extension of this research is to examine the impact of farmers' risk attitudes on the benefits of these weed control instruments. The use of stochastic simulation within a whole-farm context will further approximate the real prospects of SSM and delayed planting strategies under field conditions.

The quality of model recommendations depends on the precision of the input parameters, especially the biological information. Often, the biological data employed for estimating these parameters are obtained from agronomic studies whose research objectives are sometimes at variance with the goals of bioeconomic modeling for weed management. As a result, the data may not be suitable for rigorous statistical estimation of input parameters or they can produce generally unsatisfactory estimates. Further research is needed to improve our understanding of the biology of these weed species and their dynamics. Relevant research should come up with data that permit more precise estimation of the parameters of crop-weed interference, weed seed production, germination, viability and mortality.

The delayed planting sub-model used a piecewise linear function of yield as a function of planting date which ignores other pertinent factors. In addition to planting date, an appropriate model needs to consider the influence of factors such as planting locations, varietal selection, frost and weather conditions. Research efforts in this area will definitely enhance the quality of model recommendations under delayed planting. Fortunately, interest is growing in this area of research. Swinton (p.172) alludes to some work of Eradat Oskoui and Voorhees in this direction. Also, Toichoa Buaha and Apland are currently developing models of crop yield as a quadratic function of planting dates, planting location and varietal selection. Such research efforts deserve support.

This study has considered only conventional tillage which is the dominant practice in Minnesota. In some states, e.g., Iowa, the use of conservation tillage is quite prominent. While one is not certain how a switch to conservation tillage practices will affect the prospects of SSM and delayed planting strategies as weed control instruments, it may be worthwhile to investigate how conservation tillage system impact the findings of this study.

Finally, public policy studies that investigate how the use of alternative policy options will influence the adoption of these weed control strategies are needed. These options which can include a ban on some herbicide products, tax on the use of herbicides, recourse to use quotas and permits will make pesticide users bear full social responsibility for pesticide use. In this era of anti-subsidy sentiments, these options provide a convenient way of inducing the use of more environmentally-friendly control strategies which otherwise would have remained on shelves due to their low economic returns.

APPENDICES

A.1. Listing of the MODWSIM Program Code[3]

```
' ***********************
' * Show Opening Screen *
' ***********************
CLS
SCREEN 0
COLOR 14, 1, 8
LOCATE 4, 1
"                    **************"
"                    *  MODWSIM  *"
"                    **************"

"                    by  Caleb  A. Oriade"
"           Department of Agricultural and Applied Economics"
"             University of Minnesota, St. Paul, MN 55108"
 "                   December, 1994

" MODWSIM is a modified version of WEEDSIM (Swinton and King, 1994)."
" WEEDSIM is a dynamic model that recommends optimal weed control"
" strategies for continuous corn and corn-soybeans rotations. The"
" recommendations are based on current year weed-seed and seedling"
" counts, and forecasts of weed problems in the succeeding years."
"  This modified model incorporates routines that:"
"      (1) permit site-specific weed management"
"      (2) assess delayed planting effects on weed control strategies and"
"      (3) give the indexes of herbicide impacts on the environment."


'*************************************************************


DEFINT I-N

' ****************
' * Declare Types *
' ****************
TYPE cfile
 cid AS INTEGER
 cname AS STRING * 8
```

---

[3] Being an extension of WEEDSIM, programming credit also goes to Drs Swinton and King.

```
    cprice AS SINGLE
    ccost AS SINGLE
    grate AS SINGLE
    yrmax AS SINGLE
    p1 AS SINGLE
    p2 AS SINGLE
    p3 AS SINGLE
    p4 AS SINGLE
    p5 AS SINGLE
    p6 AS SINGLE
    yl1 AS SINGLE
    yl2 AS SINGLE
    yl3 AS SINGLE
    yl4 AS SINGLE
    yl5 AS SINGLE
  END TYPE

  TYPE wfile
    wid AS INTEGER
    wname AS STRING * 8
    grate AS SINGLE
    sprod AS SINGLE
    erate AS SINGLE
    smrate AS SINGLE
  END TYPE


  TYPE tfile
    tid AS INTEGER
    tname AS STRING * 16
    tcost AS SINGLE
    hload AS SINGLE
    hindex AS SINGLE
  END TYPE

  TYPE ffile
  fid AS INTEGER
   year AS INTEGER
   crop1 AS INTEGER
   pldate1 AS INTEGER
   postdate1 AS INTEGER
   cultdate1 AS INTEGER
   wfy1 AS SINGLE
   crop2 AS INTEGER
```

```
 pldate2 AS INTEGER
 postdate2 AS INTEGER
 cultdate2 AS INTEGER
 wfy2 AS SINGLE
 cultcontrol AS SINGLE
 END TYPE

TYPE sfile
 preid AS INTEGER
 postid AS INTEGER
 netrev AS SINGLE
 revfy AS SINGLE
 eyield AS SINGLE
 hload AS SINGLE
 hindex AS SINGLE
END TYPE

'************************************
' * Declare Functions and Subprograms *
'************************************

DECLARE SUB GetCropInfo (ncrop, c() AS cfile)
DECLARE SUB GetWeedInfo (nweed, w() AS wfile)
DECLARE SUB GetSeedCts (id, nweed, scount() AS SINGLE)
DECLARE SUB GetWeedCts (id, nweed, wcount() AS SINGLE)
DECLARE SUB PrePostEval (i, j, ncrop, nweed, ntpre, ntpost, nepoint, nstrat, c() AS
cfile, w() AS wfile, f AS ffile, sct() AS SINGLE, tpre() AS tfile, tpost() AS tfile, preff()
AS SINGLE, poeff() AS SINGLE, prfeas() AS INTEGER, pofeas() AS INTEGER, _
compi() AS SINGLE, epoint() AS INTEGER, ecum() AS SINGLE, topstrat() AS sfile,
endsct() AS SINGLE)
DECLARE SUB GetPreTInfo (ntpre, tpre() AS tfile)
DECLARE SUB GetPostTInfo (ntpost, tpost() AS tfile)
DECLARE SUB GetTrFeasInfo (ncrop, ntpre, ntpost, prfeas() AS INTEGER, pofeas()
AS INTEGER)
DECLARE SUB GetEffInfo (ncrop, ntpre, ntpost, nweed, preff() AS SINGLE, poeff()
AS SINGLE)
DECLARE SUB GetCompInfo (ncrop, nweed, compi() AS SINGLE)
DECLARE SUB GetEmergeInfo (nweed, nepoint, epoint() AS INTEGER, ecum() AS
SINGLE)
DECLARE SUB NextYearEval (ncrop, nweed, ntpre, ntpost, nepoint, c() AS cfile, w()
AS wfile, f AS ffile, sct() AS SINGLE, tpre() AS tfile, tpost() AS tfile, preff() AS
SINGLE, poeff() AS SINGLE, prfeas() AS INTEGER, pofeas() AS INTEGER, compi()
AS  _SINGLE, epoint() AS INTEGER, ecum() AS SINGLE, topstrat AS sfile)
DECLARE SUB TStratUpdate (nstrat, topstrat() AS sfile, revty AS sfile)
```

```
DECLARE SUB PrintPostRecs (ncrop, nweed, ntpost, nstrat, c() AS cfile, w() AS wfile, f
AS ffile, wcount(), tpost() AS tfile, topstrat() AS sfile)
DECLARE FUNCTION Tabli (np, xval() AS INTEGER, yval() AS SINGLE, iarg)
DECLARE FUNCTION Ydpen (p1, p2, p3, p4, p5, p6, yl1, yl2, yl3, yl4, yl5, x AS
SINGLE)


' * Get Model Size and Type Information                *
' *  NCROP    number of crops                   *
' *  NWEED    number of weeds                    *
' *  NEPOINT  number of dates in the emergence Table      *
' *  NTPRE    number of PRE treatments              *
' *  NTPOST   number of POST treatments               *
' *  NSTRAT   number of strategies to save for reports    *
' *  NSFLD    number of subfields for each field         *
'*************************************************************

OPEN "inputfname" FOR INPUT AS #1
INPUT #1, mtype, ncrop, nweed, nepoint, ntpre, ntpost, nstrat, nsfld, nyear
CLOSE #1
mtype = 1

LOCATE 24, 1
PRINT "               Please wait while data files are being loaded.";

'*****************
' * Define Arrays *
'*****************

DIM crop(ncrop) AS cfile
DIM weed(nweed) AS wfile
DIM year(nyear) AS ffile
DIM tpre(ntpre) AS tfile
DIM tpost(ntpost) AS tfile
DIM prfeas(ncrop, ntpre) AS INTEGER
DIM pofeas(ncrop, ntpost) AS INTEGER
DIM preff(ncrop, ntpre, nweed) AS SINGLE
DIM poeff(ncrop, ntpost, nweed) AS SINGLE
DIM compi(ncrop, nweed) AS SINGLE
DIM ascount(nsfld, nweed) AS SINGLE
DIM awcount(nsfld, nweed) AS SINGLE
DIM scount(nweed) AS SINGLE
DIM wcount(nweed) AS SINGLE
DIM topstrat(nstrat) AS sfile
```

```
 DIM af(nsfld, nyear) AS ffile
 DIM f AS ffile
 DIM epoint(nepoint) AS INTEGER
 DIM ecum(nweed, nepoint) AS SINGLE
 DIM escount(nstrat, nweed) AS SINGLE

 '*************************
 ' * Read Model Parameters *
 '*************************

 CALL GetCropInfo(ncrop, crop())
 CALL GetWeedInfo(nweed, weed())
 CALL GetPreTInfo(ntpre, tpre())
 CALL GetEmergeInfo(nweed, nepoint, epoint(), ecum())
 CALL GetPostTInfo(ntpost, tpost())
 CALL GetTrFeasInfo(ncrop, ntpre, ntpost, prfeas(), pofeas())
 CALL GetEffInfo(ncrop, ntpre, ntpost, nweed, preff(), poeff())
 CALL GetCompInfo(ncrop, nweed, compi())

'**********************
' * Read Subfield Data *
'**********************
OPEN "Inpfname2" FOR INPUT AS #1
FOR i = 1 TO nsfld
 FOR y = 1 TO nyear
  INPUT #1, af(i, y).fid, af(i, y).year, af(i, y).crop1, af(i, y).pldate1, af(i, y).postdate1, af(i,
y).cultdate1, af(i, y).wfy1, af(i, y).crop2, af(i, y).pldate2, af(i, y).postdate2, af(i,
y).cultdate2, af(i, y).wfy2, af(i, y).cultcontrol
 NEXT y
NEXT i
CLOSE #1

OPEN "Inpfnme3" FOR INPUT AS #2
FOR i = 1 TO nsfld
 FOR j = 1 TO nweed
  INPUT #2, nid, wid, ascount(i, j)
 NEXT j
NEXT i
CLOSE #2

'*********************
' * Execution Section *
'*********************
'************************************
```

```
' Loop Statement for Recommending
' Strategies from 1 to n subfields
' ************************************

 FOR ISFLD = 1 TO nsfld

 FOR j = 1 TO nweed
  scount(j) = ascount(ISFLD, j)
 NEXT j

FOR iy = 1 TO nyear
f = af(ISFLD, iy)
CLS

'****************************************
'* Screen Statement While Evaluating    *
'*         Strategies               *
'****************************************

LOCATE 7, 16
 PRINT "Bioeconomic Weed Management Program in Progress"
  LOCATE 8, 15
 PRINT "Please wait while strategies are being evaluated.";
  LOCATE 9, 20
  PRINT " (c) MODWSIM3: Caleb A. Oriade, 1994"

' ********************************************
' * Evaluate Strategies for Current Subfield *
' ********************************************

 FOR i = 1 TO nstrat
  topstrat(i).preid = 0
  topstrat(i).postid = 0
  topstrat(i).netrev = -999999
  topstrat(i).revfy = -999999
  topstrat(i).eyield = -999
  topstrat(i).hload = 9999
  topstrat(i).hindex = 9999
 NEXT i
 FOR i = 1 TO nstrat
  FOR K = 1 TO nweed
  endsct(k) = escount(i, k)
NEXT K
NEXT i
```

```
  IF (mtype = 1) THEN
   FOR i = 1 TO ntpre
    FOR j = 1 TO ntpost
     IF ((prfeas(f.crop1, i) <> 0) AND (pofeas(f.crop1, j) <> 0)) THEN
      CALL PrePostEval(i, j, ncrop, nweed, ntpre, ntpost, nepoint, nstrat, crop(), weed(),
f, scount(), tpre(), tpost(), preff(), poeff(), prfeas(), pofeas(), compi(), epoint(), ecum(),
topstrat(), endsct())
     END IF
    NEXT j
   NEXT i
END IF
'***************************
' * Direct output to a file *
'***************************

  OPEN "outfile1" FOR APPEND AS #1
  PRINT #1, "Recommendations for subfield:";
   PRINT #1, USING "####"; f.fid
   PRINT #1, "pldate:";
   PRINT #1, USING "##"; f.pldate1
   PRINT
   PRINT #1, "Current crop: ";
   PRINT #1, USING "\      \"; crop(f.crop1).cname;
   PRINT #1, "   Next year crop: ";
   PRINT #1, USING "\      \"; crop(f.crop2).cname
   PRINT
   PRINT #1, " Weed               Seed Count"
   FOR i = 1 TO nweed
    PRINT #1, USING "\      \"; weed(i).wname;
     PRINT #1, "           ";
     PRINT #1, USING "##########"; scount(i)
   NEXT i
   PRINT
   PRINT #1, "Soil Applied       Expected POST    Net Revenue   HerbIndex      Exp.
Yield"
  FOR i = 1 TO nstrat
   PRINT #1, USING "\            \"; tpre(topstrat(i).preid).tname;
   PRINT #1, "   ";
    PRINT #1, USING "\            \"; tpost(topstrat(i).postid).tname;
    PRINT #1, " ";
    PRINT #1, USING "#######.##"; topstrat(i).revfy;
    PRINT #1, "   ";
    PRINT #1, USING "#######.##"; topstrat(i).hindex;
    PRINT #1, "  ";
```

```
    PRINT #1, USING "#######.#"; topstrat(i).eyield
   NEXT i
   PRINT
   PRINT
 CLOSE #1

  OPEN "outfile2" FOR APPEND AS #2
   FOR i = 1 TO nstrat
     PRINT #2, USING "####"; f.fid;
     PRINT #2, USING "####"; f.pldate1;
     PRINT #2, USING "######.##"; topstrat(i).revfy;
     PRINT #2, USING "####.##"; topstrat(i).hindex;
    PRINT #2, USING "######.#"; topstrat(i).eyield
   NEXT i
  CLOSE #2


FOR K = 1 TO nweed
scount(k) = endsct(k)
 NEXT K

  NEXT iy

NEXT ISFLD

' ***************
' * End Program *
' ***************

CLS

END

SUB GetCompInfo (ncrop, nweed, compi() AS SINGLE)
 OPEN "compi.dat" FOR INPUT AS #1
 FOR i = 1 TO ncrop
  FOR j = 1 TO nweed
   INPUT #1, cid, wid, compi(i, j)
  NEXT j
 NEXT i
 CLOSE #1
END SUB

SUB GetCropInfo (ncrop, c() AS cfile)
```

```
 OPEN "crops.dat" FOR INPUT AS #1
 FOR i = 1 TO ncrop
  INPUT #1, c(i).cid, c(i).cname, c(i).cprice, c(i).ccost, c(i).grate, c(i).yrmax, c(i).p1,
c(i).p2, c(i).p3, c(i).p4, c(i).p5, c(i).p6, c(i).yl1, c(i).yl2, c(i).yl3, c(i).yl4, c(i).yl5
 NEXT i
 CLOSE #1
END SUB

SUB GetEffInfo (ncrop, ntpre, ntpost, nweed, preff() AS SINGLE, poeff() AS SINGLE)
 OPEN "preff1.dat" FOR INPUT AS #1
 FOR i = 1 TO ncrop
  FOR j = 1 TO ntpre
   FOR K = 1 TO nweed
    INPUT #1, icrop, jtreat, kweed, preff(i, j, k)
   NEXT K
  NEXT j
 NEXT i
 CLOSE #1
 OPEN "poeff.dat" FOR INPUT AS #1
 FOR i = 1 TO ncrop
  FOR j = 1 TO ntpost
   FOR K = 1 TO nweed
    INPUT #1, icrop, jtreat, kweed, poeff(i, j, k)
   NEXT K
  NEXT j
 NEXT i
 CLOSE #1
END SUB

SUB GetEmergeInfo (nweed, nepoint, epoint() AS INTEGER, ecum() AS SINGLE)
 OPEN "epoint.dat" FOR INPUT AS #1
 FOR i = 1 TO nepoint
  INPUT #1, epoint(i)
 NEXT i
 CLOSE #1
 OPEN "ecum.dat" FOR INPUT AS #1
 FOR i = 1 TO nweed
  FOR j = 1 TO nepoint
   INPUT #1, wid, ecum(i, j)
  NEXT j
 NEXT i
 CLOSE #1
END SUB
```

```
SUB GetPostTInfo (ntpost, tpost() AS tfile)
 OPEN "tpost.dat" FOR INPUT AS #1
 FOR i = 1 TO ntpost
  INPUT #1, tpost(i).tid, tpost(i).tname, tpost(i).tcost, tpost(i).hload, tpost(i).hindex
 NEXT i
 CLOSE #1
END SUB

SUB GetPreTInfo (ntpre, tpre() AS tfile)
 OPEN "tpre.dat" FOR INPUT AS #1
 FOR i = 1 TO ntpre
  INPUT #1, tpre(i).tid, tpre(i).tname, tpre(i).tcost, tpre(i).hload, tpre(i).hindex
 NEXT i
 CLOSE #1
END SUB

SUB GetSeedCts (id, nweed, scount() AS SINGLE)
 FOR i = 1 TO nweed
  INPUT #2, nid, wid, scount(i)
  IF (nid <> id) THEN
   PRINT ("The subfield ID's do not match for seed counts.  SFID: ");
   PRINT USING "####"; id;
   PRINT USING "  NID: ####"; nid
  END IF
 NEXT i
END SUB

SUB GetTrFeasInfo (ncrop, ntpre, ntpost, prfeas() AS INTEGER, pofeas() AS
INTEGER)
 OPEN "prfeas.dat" FOR INPUT AS #1
 FOR i = 1 TO ncrop
  FOR j = 1 TO ntpre
   INPUT #1, icrop, itreat, prfeas(i, j)
  NEXT j
 NEXT i
 CLOSE #1
 OPEN "pofeas.dat" FOR INPUT AS #1
 FOR i = 1 TO ncrop
  FOR j = 1 TO ntpost
   INPUT #1, icrop, itreat, pofeas(i, j)
  NEXT j
 NEXT i
 CLOSE #1
END SUB
```

```
SUB GetWeedCts (id, nweed, wcount() AS SINGLE)
 FOR i = 1 TO nweed
  INPUT #3, nid, wid, wcount(i)
  IF (nid <> id) THEN
   PRINT ("The subfield ID's do not match for weed counts.  SFID: ");
   PRINT USING "####"; id;
   PRINT USING "  NID: ####"; nid
  END IF
 NEXT i
END SUB

SUB GetWeedInfo (nweed, w() AS wfile)
 OPEN "weeds.dat" FOR INPUT AS #1
 FOR i = 1 TO nweed
  INPUT #1, w(i).wid, w(i).wname, w(i).grate, w(i).sprod, w(i).erate, w(i).smrate
 NEXT i
 CLOSE #1
END SUB

SUB NextYearEval (ncrop, nweed, ntpre, ntpost, nepoint, c() AS cfile, w() AS wfile, f AS
ffile, sct() AS SINGLE, tpre() AS tfile, tpost() AS tfile, preff() AS SINGLE, poeff() AS
SINGLE, prfeas() AS INTEGER, pofeas() AS INTEGER, compi() AS SINGLE, _
epoint() AS INTEGER, ecum() AS SINGLE, topstrat AS sfile)
 DIM harweed(nweed)
 DIM cume(nepoint)
 topstrat.netrev = -9999999.99#
 FOR i = 1 TO ntpre
  FOR j = 1 TO ntpost
   IF ((prfeas(f.crop2, i) <> 0) AND (pofeas(f.crop2, j) <> 0)) THEN
    y = 0
    FOR K = 1 TO nweed
     FOR l = 1 TO nepoint
      cume(l) = ecum(k, l)
     NEXT l
     harweed(k) = sct(k) * w(k).erate
     wkill = harweed(k) * (Tabli(nepoint, epoint(), cume(), f.pldate2))
     emerge = harweed(k) * (Tabli(nepoint, epoint(), cume(), f.postdate2)) - wkill
     wkill = wkill + emerge * preff(f.crop2, i, k)
     emerge = emerge * (1 - preff(f.crop2, i, k))
     wkill = wkill + emerge * poeff(f.crop2, j, k)

     '*********************************************
     ' * The following statements model cultivation *
     '*********************************************
```

```
        emerge = harweed(k) * (Tabli(nepoint, epoint(), cume(), f.cultdate2)) - wkill
        wkill = wkill + emerge * f.cultcontrol
        harweed(k) = harweed(k) - wkill


' *** Note that weeds have been reduced to reflect cultivation. ***
        harweed(k) = harweed(k) * .1
        y = y + compi(f.crop2, k) * harweed(k)
      NEXT K
  pd2 = f.pldate2
  dploss = Ydpen(c(f.crop2).p1, c(f.crop2).p2, c(f.crop2).p3, c(f.crop2).p4, c(f.crop2).p5,
c(f.crop2).p6, c(f.crop2).yl1, c(f.crop2).yl2, c(f.crop2).yl3, c(f.crop2).yl4, c(f.crop2).yl5,
pd2) * .01
  y = (y * c(f.crop2).yrmax) / (c(f.crop2).yrmax + y)
  awfy2 = f.wfy2 * (1 - dploss)
  y = (1 - y) * awfy2

      rev = y * c(f.crop2).cprice - c(f.crop2).ccost - tpre(i).tcost - tpost(j).tcost
      IF (rev > topstrat.netrev) THEN
        topstrat.preid = i
        topstrat.postid = j
        topstrat.netrev = rev
        topstrat.eyield = y
        topstrat.revfy = revfy
        topstrat.hload = tpre(i).hload + tpost(j).hload
        topstrat.hindex = tpre(i).hindex + tpost(j).hindex
      END IF
    END IF
   NEXT j
  NEXT i
END SUB

SUB PrePostEval (i, j, ncrop, nweed, ntpre, ntpost, nepoint, nstrat, c() AS cfile, w() AS
wfile, f AS ffile, sct() AS SINGLE, tpre() AS tfile, tpost() AS tfile, preff() AS SINGLE,
poeff() AS SINGLE, prfeas() AS INTEGER, pofeas() AS INTEGER, compi() _
AS SINGLE, epoint() AS INTEGER, ecum() AS SINGLE, topstrat() AS sfile, endsct()
AS SINGLE)

'
*************************************************************************
***
' * This procedure evaluates preemergence strategies.  Its parameters are:  *
' *    J        :  number of the current strategy                    *
```

```
'*   NCROP      : number of crops in the model                 *
'*   NWEED      : number of weeds in the model                 *
'*   NTPRE      : number of preemergence treatments            *
'*   NTPOST     : number of postemergence treatments           *
'*   NEPOINT    : number of points on the emergence curve      *
'*   C()        : array of crop information records            *
'*   W()        : array of weed information records            *
'*   F          : record of field information                  *
'*   SCT()      : array of seed counts for the current field   *
'*   WCT()      : array of weed counts for the current field   *
'*   TPRE()     : array of preemergence treatment records      *
'*   TPOST()    : array of postemergence treatment records     *
'*   PREFF()    : array of preemergence efficacy levels        *
'*   POEFF()    : array of postemergence efficacy levels       *
'*   PRFEAS()   : array of preemergence feasibility indicators *
'*   POFEAS()   : array of postemergence feasibility indicators *
'*   COMPI()    : array of competitive indices                 *
'*   EPOINT()   : array of dates in emergence tables           *
'*   ECUM()     : array of cumulative emergence levels         *
'*   TOPSTRAT() : array of top strategy records                *
'
************************************************************************
***

 DIM hweed(nweed)
 DIM hseed(nweed)
 DIM cume(nepoint)
 DIM revtp AS sfile
 DIM revny AS sfile
 DIM pd AS SINGLE

 rev = -c(f.crop1).ccost - tpre(i).tcost - tpost(j).tcost
 hload = tpre(i).hload + tpost(j).hload
 hindex = tpre(i).hindex * tpost(j).hindex
 y = 0
 FOR K = 1 TO nweed
  FOR l = 1 TO nepoint
   cume(l) = ecum(k, l)
  NEXT l
  hweed(k) = sct(k) * w(k).erate
  wkill = hweed(k) * (Tabli(nepoint, epoint(), cume(), f.pldate1))
 emerge = hweed(k) * (Tabli(nepoint, epoint(), cume(), f.postdate1)) - wkill
  wkill = wkill + emerge * preff(f.crop1, i, k)
  emerge = emerge * (1 - preff(f.crop1, i, k))
```

```
      wkill = wkill + emerge * poeff(f.crop1, j, k)

      '************************************************
      ' * The following statements model cultivation *
      '************************************************

      emerge = hweed(k) * (Tabli(nepoint, epoint(), cume(), f.cultdate1)) - wkill
      wkill = wkill + emerge * f.cultcontrol
      hweed(k) = hweed(k) - wkill
      y = y + compi(f.crop1, k) * hweed(k)
    NEXT K
    pd = f.pldate1
    dploss = Ydpen(c(f.crop1).p1, c(f.crop1).p2, c(f.crop1).p3, c(f.crop1).p4, c(f.crop1).p5,
  c(f.crop1).p6, c(f.crop1).yl1, c(f.crop1).yl2, c(f.crop1).yl3, c(f.crop1).yl4, c(f.crop1).yl5,
  pd) * .01
    y = (y * c(f.crop1).yrmax) / (c(f.crop1).yrmax + y)
    awfy1 = f.wfy1 * (1 - dploss)
   y = (1 - y) * awfy1

   FOR K = 1 TO nweed
     hseed(k) = (1 - w(k).erate - w(k).smrate) * sct(k) + hweed(k) * w(k).sprod
   NEXT K

   '**********************
   ' * Update net revenue *
   '**********************

   rev = rev + y * c(f.crop1).cprice
   revfy = rev
   '*************************************************************
   ' * Calculate net revenue and herbicide load for second year *
   '*************************************************************

   CALL NextYearEval(ncrop, nweed, ntpre, ntpost, nepoint, c(), w(), f, hseed(), tpre(),
  tpost(), preff(), poeff(), prfeas(), pofeas(), compi(), epoint(), ecum(), revny)

   '*******************************************************************
   ' * Calculate two-year net revenue and update TOPSTRAT, if needed *
   '*******************************************************************

   rev = rev + (revny.netrev / 1.04)
   IF (rev > topstrat(nstrat).netrev) THEN
     revtp.preid = i
     revtp.postid = j
```

```
    revtp.netrev = rev
    revtp.revfy = revfy
    revtp.eyield = y
    revtp.hload = hload
    revtp.hindex = hindex
    FOR K = 1 TO nweed
    IF hseed(k) > 0 THEN
    endsct(k) = hseed(k)
    ELSE
    endsct(k) = 0
    END IF
    NEXT K
    CALL TStratUpdate(nstrat, topstrat(), revtp)
  END IF

END SUB

SUB PrintPostRecs (ncrop, nweed, ntpost, nstrat, c() AS cfile, w() AS wfile, f AS ffile,
wcount(), tpost() AS tfile, topstrat() AS sfile)
 LOCATE 12, 1
 OPEN "RECOMEND.OUT" FOR APPEND AS #1
  PRINT #1, "Postemergence recommendations for subfield: ";
  PRINT #1, USING "###"; f.fid
  PRINT
  PRINT #1, "Current crop: ";
  PRINT #1, USING "\       \"; c(f.crop1).cname;
  PRINT #1, "    Next year crop: ";
  PRINT #1, USING "\       \"; c(f.crop2).cname
  PRINT
  PRINT #1, " Weed            Seedling Count"
  FOR i = 1 TO nweed
   PRINT #1, USING "\       \"; w(i).wname;
   PRINT #1, "            ";
   PRINT #1, USING "##########"; wcount(i)
  NEXT i
  PRINT
  PRINT #1, "POST Application    Net Revenue    Herb Index  Exp. Yield"
  FOR i = 1 TO nstrat
   IF (topstrat(i).postid > 0) THEN
    PRINT #1, USING "\               \"; tpost(topstrat(i).postid).tname;
    PRINT #1, "   ";
    PRINT #1, USING "#######.##"; topstrat(i).netrev;
    PRINT #1, "   ";
    PRINT #1, USING "#######.##"; topstrat(i).hindex;
```

```
    PRINT #1, "  ";
    PRINT #1, USING "#######.#"; topstrat(i).eyield
   END IF
  NEXT i
  PRINT
  PRINT
  CLOSE #1
 END SUB

FUNCTION Tabli (np, xval() AS INTEGER, yval() AS SINGLE, iarg)
 IF (iarg <= xval(1)) THEN
  Tabli = yval(1)
 ELSEIF (iarg >= xval(np)) THEN
  Tabli = yval(np)
 ELSE
  i = 2
  WHILE (iarg > xval(i))
   i = i + 1
  WEND
  Tabli = yval(i - 1) + (iarg - xval(i - 1)) * ((yval(i) - yval(i - 1)) / (xval(i) - xval(i - 1)))
 END IF
END FUNCTION

SUB TStratUpdate (nstrat, topstrat() AS sfile, revty AS sfile)
 i = 1
 WHILE (topstrat(i).netrev > revty.netrev)
  i = i + 1
 WEND
 IF (i = nstrat) THEN
  topstrat(i) = revty
 ELSE
  FOR j = 1 TO (nstrat - i)
   topstrat(nstrat - j + 1) = topstrat(nstrat - j)
  NEXT j
  topstrat(i) = revty
 END IF
END SUB
```

```
FUNCTION Ydpen (p1, p2, p3, p4, p5, p6, yl1, yl2, yl3, yl4, yl5, x)
'   ************************************************
'   *       Ydpen Function                     *
'   * This function penalizes yield for delay in    *
'   * planting. The estimates of % yield loss were   *
'   * provided by Professor  Dale Hicks of Agronomy  *
'   * Department, University of Minnesota          *
'   * ***********************************************
IF x - p1 <= 0 THEN
Ydpen = 0
ELSEIF x - p1 > O AND x - p2 <= 0 THEN
Ydpen = yl1 * (x - p1) / (p2 - p1)
ELSEIF x - p2 > O AND x - p3 <= 0 THEN
Ydpen = yl1 + ((yl2 - yl1) * (x - p2) / (p3 - p2))
ELSEIF x - p3 > O AND x - p4 <= 0 THEN
Ydpen = yl2 + ((yl3 - yl2) * (x - p3) / (p4 - p3))
ELSEIF x - p4 > O AND x - p5 <= 0 THEN
Ydpen = yl3 + ((yl4 - yl3) * (x - p4) / (p5 - p4))
ELSEIF x - p5 > O AND x - p6 <= 0 THEN
Ydpen = yl4 + ((yl5 - yl4) * (x - p5) / (p6 - p5))
ELSE
Ydpen = 100
END IF
END FUNCTION
```

```
'***********************************************
'  PROGRAM FOR AGGREGATING OVER ALL SUBFIELDS
'  This program aggregates net returns, herbicide
' and expected yields over a specified number of
' subfields and years
'**********************************************
CLS
SCREEN 0
COLOR 14, 1, 8
LOCATE 3, 4

PRINT "    ****************************************************"
PRINT "          PROGRAM FOR AGGREGATING OVER ALL SUBFIELDS"
PRINT "        This program is suitable for aggregating net returns, "
PRINT "          herbicide indexes and expected yields over a "
PRINT "           specified number of subfields and years"
PRINT "            (c)  Caleb A. Oriade, 1994   "
PRINT "   *****************************************************"

lflag = 1
DO WHILE (lflag = 1)
PRINT
INPUT "What is the name of the input data file? ", Addfile$
INPUT "What do you want to call the output data file? ", Outfile$
INPUT "How many subfields do you want to aggregate? ", nsfld%

REDIM netrev(nsfld%, nyear%) AS SINGLE
REDIM hindex(nsfld%, nyear%) AS SINGLE
REDIM yield(nsfld%, nyear%) AS SINGLE
REDIM NR(nyear%) AS SINGLE
REDIM hi(nyear%) AS SINGLE
REDIM yld(nyear%) AS SINGLE

OPEN Addfile$ FOR INPUT AS #1
FOR i = 1 TO nsfld%
  FOR j = 1 TO nyear%
INPUT #1, iid, j, netrev(i, j), hindex(i, j), yield(i, j)
  NEXT
NEXT
CLOSE #1

FOR j = 1 TO nyear%
NR(j) = 0
hi(j) = 0
```

```
 yld(j) = 0
  FOR i = 1 TO nsfld%
  NR(j) = NR(j) + netrev(i, j)
  hi(j) = hi(j) + hindex(i, j)
  yld(j) = yld(j) + yield(i, j)
  NEXT
 NEXT

 OPEN Outfile$ FOR OUTPUT AS #1
  IMAGE1$ = "YEAR  NETREV  HERBIND  EXPYLD"
  IMAGE2$ = " ###   ####.##  #.##    ###.##"
  PRINT #1, IMAGE1$
  FOR j = 1 TO nyear%
 NR(j) = NR(j) / nsfld%
 hi(j) = hi(j) / nsfld%
 yld(j) = yld(j) / nsfld%
 PRINT #1, USING IMAGE2$; j; NR(j); hi(j); yld(j)
  NEXT
  CLOSE #1

  LOCATE 24, 1
  PRINT "        Do you want to aggregate over another set of subfields? (Y/N) ";
  INPUT ; "", flag$
  IF ((flag$ = "y") OR (flag$ = "Y")) THEN
   lflag = 1
  ELSE
   lflag = 0
  END IF

LOOP



 END
```

```
CLS
SCREEN 0
COLOR 14, 1, 8
LOCATE 3, 4

PRINT "    ****************************************************"
PRINT "         PROGRAM FOR MODIFYING SEED POPULATIONS"
PRINT "      This program is suitable for reparameterinzing weed seed "
PRINT "      populations. In  this version, the output is written to a "
PRINT "                           file                  "
PRINT "            (c)  Caleb A. Oriade, 1994   "
PRINT "   *****************************************************"

lflag = 1
DO WHILE (lflag = 1)
PRINT
INPUT "What is the name of the input data file? ", Addfile$
INPUT "What do you want to call the output data file? ", Outfile$
'INPUT "By what factor do you want to multiply seed count? ", num!
INPUT "How many subfields are in the model? ", nsfld
INPUT "How many weed species are in the modelt? ", nweed


REDIM sfld(nsfld, nweed) AS INTEGER
REDIM weed(nweed) AS INTEGER
REDIM ascount(nsfld, nweed) AS SINGLE
REDIM scount(nsfld, nweed) AS SINGLE

OPEN Addfile$ FOR INPUT AS #1
FOR i = 1 TO nsfld
 FOR j = 1 TO nweed
  INPUT #1, sfld(i, j), j, ascount(i, j)
 NEXT j
NEXT i
CLOSE #1

FOR i = 1 TO nsfld
 FOR j = 1 TO nweed
  scount(i, j) = ascount(i, j) * num!
 NEXT j
NEXT i

OPEN Outfile$ FOR OUTPUT AS #1
FOR i = 1 TO nsfld
```

```
  FOR j = 1 TO nweed
 PRINT #1, sfld(i, j); j; scount(i, j)
  NEXT j
NEXT i
 CLOSE #1

  LOCATE 24, 1
  PRINT "        Do you want to run the program for another data set? (Y/N) ";
  INPUT ; "", flag$
  IF ((flag$ = "y") OR (flag$ = "Y")) THEN
   lflag = 1
  ELSE
   lflag = 0
  END IF

LOOP

 CLS

 END
```

A.2: Listing of Program Code for NEGBIN, a Program for simulating Negative Binomial Variates

```
'**************************************************************************
***
'              This Version                    August 30, 1994
'                        NEGBIN
' Program NEGBIN generates negative binomial variables distributed
' NB(m,k), where m is the mean and K is an index of patchiness.
'
' NB variates are generated from gamma and Poisson random variates,
' following the 2nd procedure on p. 106 in R.Y. Rubinstein, "Simulation
' and the Monte Carlo Method", NY: Wiley, 1981.
' Gamma r.v.'s are generated using the GS acceptance-rejection algorithm
' on p. 256 of A.M. Law & W.D. Kelton, "Simulation Modeling and Analysis,"
' NY: McGraw-Hill, 1982 (1st ed.), which is suited to G(a,b) r.v.'s where
' a < 1.

'************************
'Show Opening Screen
'*************************


CLS
SCREEN 0
COLOR 14, 1, 8
LOCATE 3, 1
PRINT
PRINT "                    NEGBIN"
PRINT
PRINT "                       by"
PRINT "                 Scott M. Swinton"
PRINT "               Michigan State University"
PRINT "                      and"
PRINT "                 Caleb A. Oriade"
PRINT "              University of Minnesota"
PRINT
PRINT "  Program NEGBIN generates negative binomial variables distributed"
PRINT "  NB(k,m), where m is the mean and K is an index of patchiness.  Up to"
PRINT "  8000 NB random variates may be generated at a time. The algorithm may fail to
PRINT"work properly for very small values of K and large values of m.
PRINT"  The variates are sortedin ascending order out of which a specified number of
PRINT"variates canbe drawn using a  systematic procedure. This Process permits the
PRINT"interdependent random variables to be drawn using the process developed by King
PRINT"(1979)"
```

```
PRINT "   This batch version uses an input file provided by the user. The input file
"PRINT " contains the parameters of negative binomial distribution, weed identifiers,"
PRINT "  initial seed and number of random variates desired."
PRINT"




'****************
'Declare type
'****************
TYPE parfile
wid AS INTEGER
wname AS STRING * 8
mean AS SINGLE
K AS SINGLE
n AS INTEGER
seed AS INTEGER
END TYPE


'***********************
'Read Model Parameters
'***********************
INPUT "How many  weed species do you want to simulate their variates?", nweed%

DIM w(nweed%) AS parfile

OPEN "Inputfile" FOR INPUT AS #1
FOR i = 1 TO nweed%
INPUT #1, w(i).wid, w(i).wname, w(i).mean, w(i).K, w(i).n, w(i).seed
NEXT i
CLOSE #1

FOR i = 1 TO nweed%
n = w(i).n
K = w(i).K
seed = w(i).seed
m = w(i).mean
NEXT i

'************************
'Execution Section
'************************
```

```
'***************************
'Loop Statement for n weeds
'***************************
FOR iweed = 1 TO nweed%
Temp$ = w(iweed).wname
Temp$ = Temp$ + ".out"


RANDOMIZE (seed)
'$DYNAMIC
REDIM x#(n), nb%(n), nebi%(101)
'Generate gamma(a,1) random variates, denoted x#(i).  (x#() is double-precision).
'
alpha = K
beta = 1
b = (EXP(1) + alpha) / EXP(1)
i% = 1
DO
 x#(i%) = -1
 u1 = RND
 u2 = RND
 p = b * u1
 IF p > 1 THEN
  y = -LOG((b - p) / alpha)
  IF u2 <= y ^ (alpha - 1) THEN x#(i%) = y
 ELSE
  y = p ^ (1 / alpha)
  IF u2 <= EXP(-y) THEN x#(i%) = y
 END IF
 IF x#(i%) <> -1 THEN i% = i% + 1
LOOP WHILE i% < n + 1

'  Generate NB(k,m) r.v.'s using Poisson procedure, p. 103 of Rubinstein
'  NB: k/m = p/(1-p) must be inverted.
'
OPEN Temp$ FOR OUTPUT AS #1
q = m / K
FOR i% = 1 TO n
 x#(i%) = x#(i%) * q
 a# = 1
 j% = 0
step3:
 a# = RND * a#
 IF a# < EXP(-x#(i%)) THEN
```

```
    nb%(i%) = j%
    ELSE
    j% = j% + 1
    GOTO step3:
  END IF
  WRITE #1, nb%(i%)
NEXT i%
CLOSE #1



'**********************************
'Procedure to sort Variates in
'ascending order using the bubble
' sort method
'**********************************

OPEN Temp$ FOR INPUT AS #1
 CONST FALSE = 0, TRUE = NOT FALSE
 limit% = n
 DO
 Swaps% = FALSE
 FOR i% = 1 TO (limit% - 1)
 IF nb%(i%) > nb%(i% + 1) THEN
 SWAP nb%(i%), nb%(i% + 1)
 Swaps% = i%
 END IF
 NEXT i%
 limit% = Swaps%
 LOOP WHILE Swaps%
 CLOSE #1

'**********************************
'Write the sorted variates to a file
'**********************************

 OPEN Temp$ FOR OUTPUT AS #1
 FOR i% = 1 TO n
 WRITE #1, nb%(i%)
 NEXT i%
CLOSE #1

'****************************************
'Use Table look-up approach for choosing
```

```
'variates  of CDFs . Selected variates
'are then written to a text file.
'****************************************

OPEN Temp$ FOR INPUT AS #1
nebi%(1) = 0
FOR v% = 2 TO 101
nebi%(v%) = nb%((v% - 1) * 10)
NEXT v%
CLOSE #1

 OPEN Temp$ FOR OUTPUT AS #1
 FOR v% = 1 TO 101
  WRITE #1, nebi%(v%)
  NEXT v%
 CLOSE #1



NEXT iweed

'***********************
' End of Program
'***********************

CLS

END
```

A3. Sample Model Recommendations for Ten Replicated Field from the Same Weed Population Parameters

A: CORN /SOYBEANS

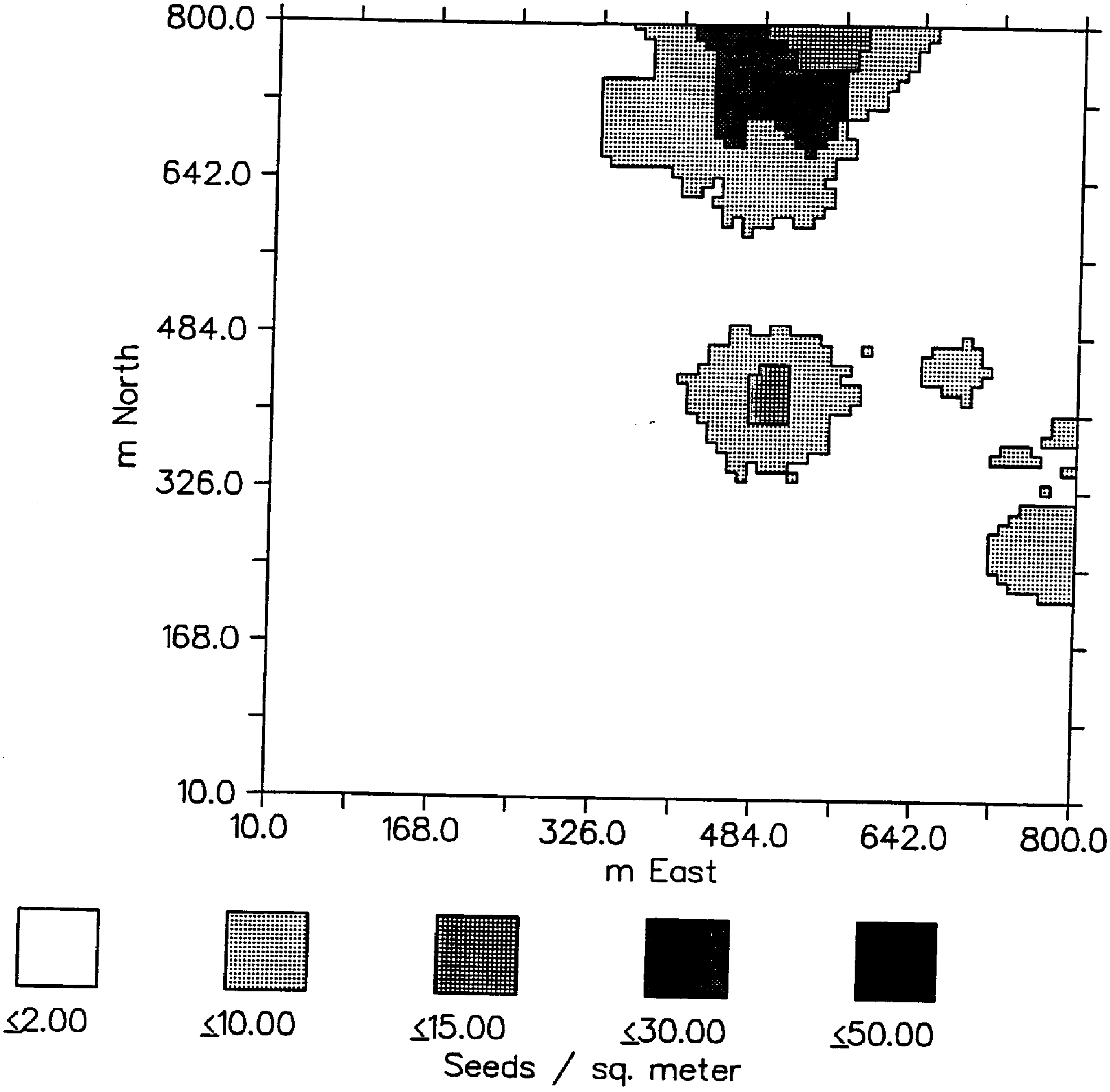
YEAR	NET RETURNS($/ACRE)			HERBICIDE INDEXES			EXP. YIELD(BU/ACRE)		
	SSM	STD	DIFF	SSM	STD	DIFF	SSM	STD	DIFF
1	71.1	69.69	1.41	0.7	0.44	0.26	94.05	93.31	0.74
2	136.37	131.07	5.3	0.87	0.78	0.09	36.24	35.91	0.33
3	74.71	71.19	3.52	0.7	0.44	0.26	95.72	94.01	1.71
4	138.2	131.29	6.91	0.84	0.78	0.06	36.83	35.95	0.88
1	65.03	64.22	0.81	0.58	0.44	0.14	91.59	91.2	0.39
2	133.22	129.96	3.26	0.83	0.78	0.05	35.98	35.72	0.26
3	67.62	65.81	1.81	0.58	0.44	0.14	92.8	91.92	0.88
4	135.1	131	4.1	0.8	0.78	0.02	36.45	35.91	0.54
1	90.93	89.25	1.68	0.72	0.44	0.28	103.27	103.39	-0.12
2	149.61	145.5	4.11	0.91	0.78	0.13	38.69	38.84	-0.15
3	90.62	91.15	-0.53	0.66	0.44	0.22	103.28	104.26	-0.98
4	149.14	146.48	2.66	0.89	0.78	0.11	38.76	39.01	-0.25
1	74.32	73.25	1.07	0.65	0.44	0.21	95.26	94.83	0.43
2	135.56	131.28	4.28	0.87	0.78	0.09	36.03	35.9	0.13
3	73.48	73.62	-0.14	0.64	0.44	0.2	95	95.15	-0.15
4	135.03	131.44	3.59	0.8	0.78	0.02	36.44	35.93	0.51
1	93.06	91.08	1.98	0.77	0.44	0.33	103.15	102.98	0.17
2	150.77	144.7	6.07	0.96	0.78	0.18	38.08	38.22	-0.14
3	92.59	92.51	0.08	0.71	0.44	0.27	103.11	103.65	-0.54
4	149.6	145.99	3.61	0.89	0.78	0.11	38.3	38.45	-0.15
	B: SOYBEAN/CORN								
1	135.25	131.51	3.74	0.87	0.78	0.09	36.05	36	0.05
2	74.24	72.47	1.77	0.7	0.44	0.26	95.51	94.61	0.9
3	138.7	133.11	5.59	0.87	0.78	0.09	36.65	36.28	0.37
4	76.4	72.35	4.05	0.7	0.44	0.26	96.52	94.55	1.97
1	133.85	131.4	2.45	0.85	0.78	0.07	35.88	35.99	-0.11
2	67.13	67.47	-0.34	0.58	0.44	0.14	92.57	92.7	-0.13
3	134.93	132.84	2.09	0.8	0.78	0.02	36.42	36.22	0.2
4	69.68	68.31	1.37	0.58	0.44	0.14	93.75	93.1	0.65
1	135.66	132.5	3.16	0.87	0.78	0.09	36.05	36.11	-0.06
2	75.07	75.33	-0.26	0.59	0.44	0.15	95.79	95.79	0
3	136.59	133.38	3.21	0.83	0.78	0.05	36.58	36.28	0.3
4	76.24	74.69	1.55	0.58	0.44	0.14	96.45	95.63	0.82
1	151.78	147.86	3.92	0.89	0.78	0.11	38.69	38.73	-0.04
2	92.52	91.79	0.73	0.61	0.44	0.17	102.97	103.18	-0.21
3	150.88	147.64	3.24	0.89	0.78	0.11	38.53	38.69	-0.16
4	90.48	91.12	-0.64	0.61	0.44	0.17	102.03	102.88	-0.85

APPENDIX 4[4]

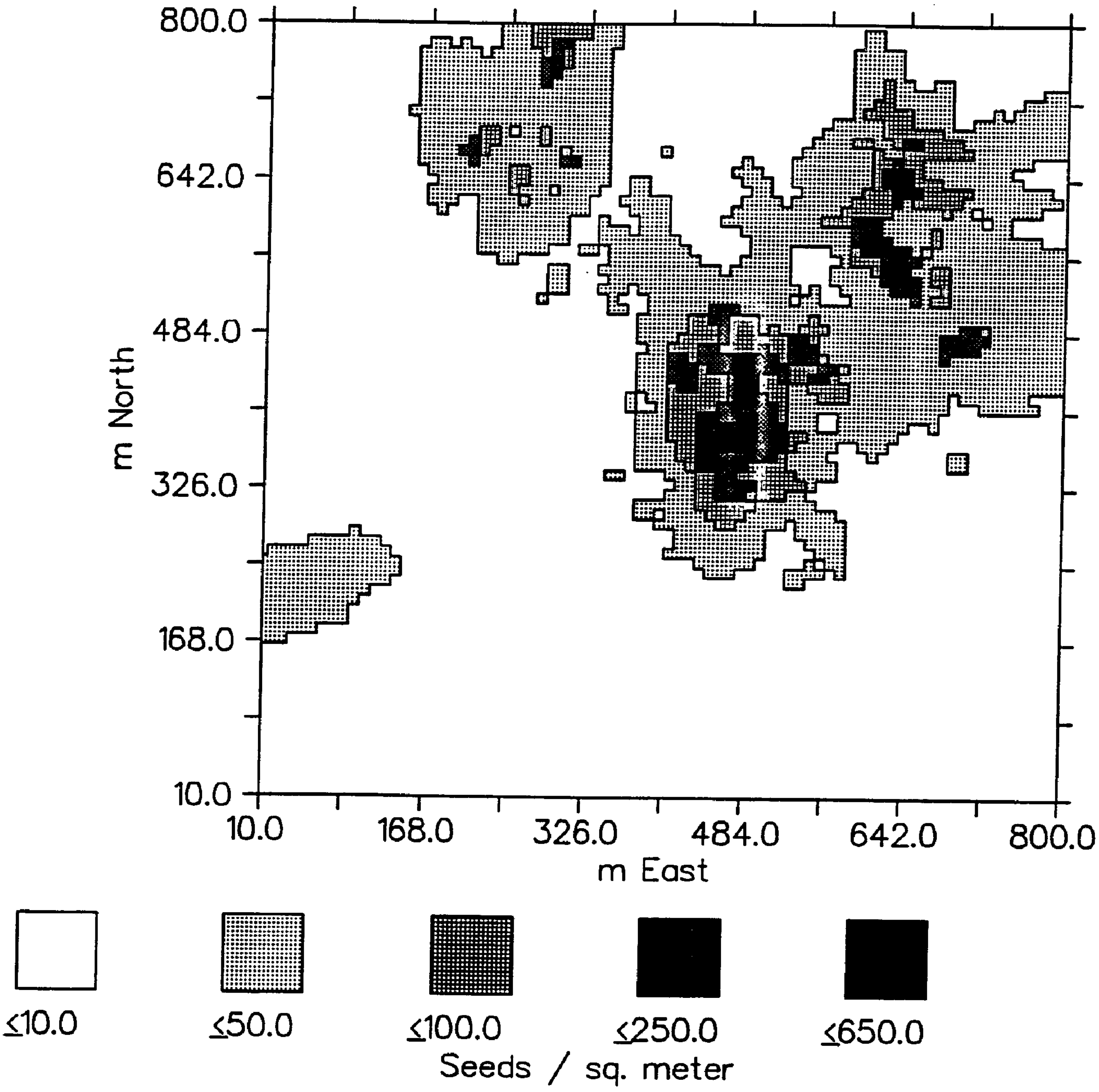
---

[4] The weed population maps in this appendix were generated by Dr. James Barbour of USDA-ARS Soil Conservation Service, Morris, MN with the aid of a computer software, the geostastical software for environmental sciences (GS+2).

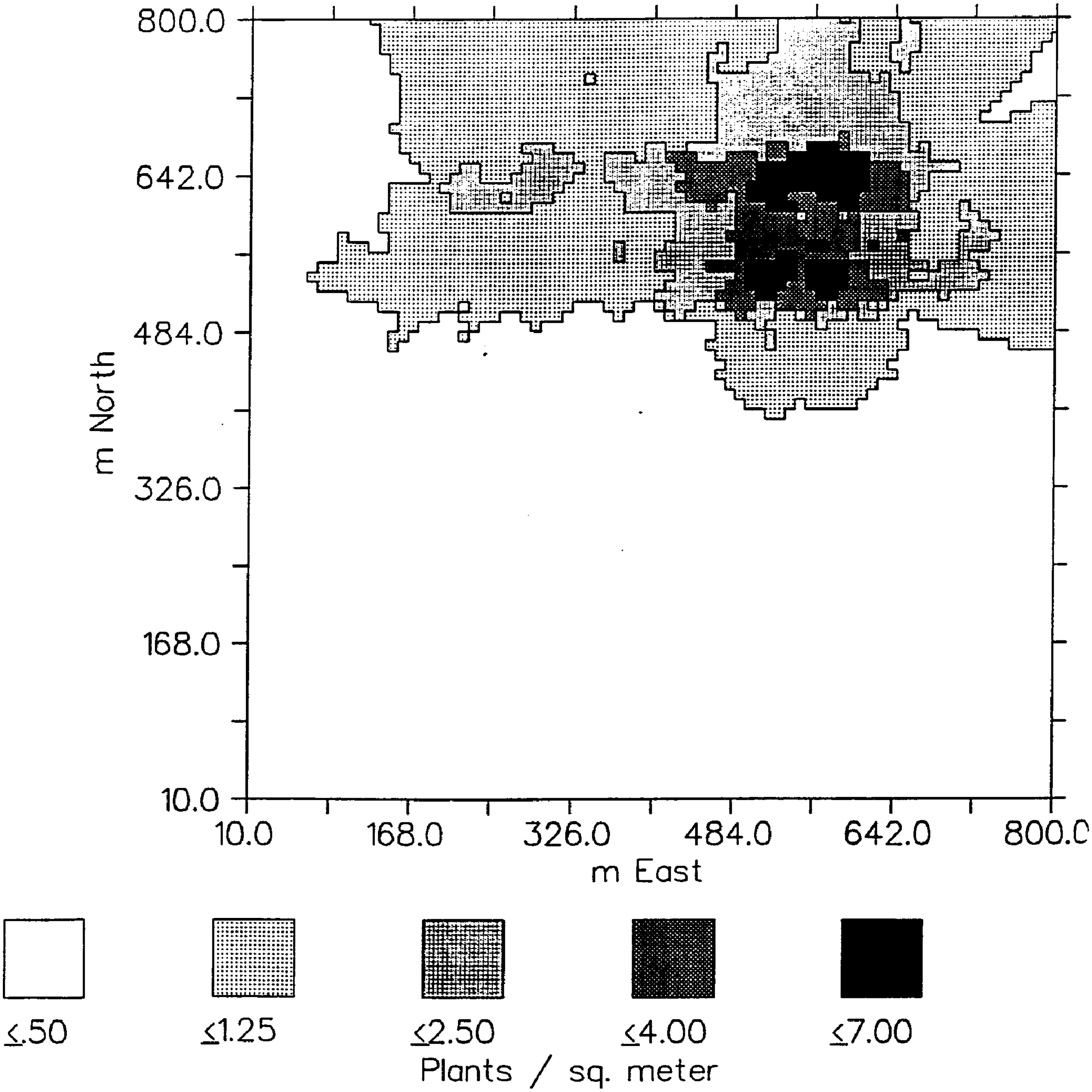
Appendix 4.1: A Weed-Seed Population Map for Foxtails in a west central Minnesota Farm



Appendix 4.2: A Weed Population Map for Common Lambsquarters in a west central Minnesota Farm



Appendix 4.3: A Weed Population Map for Redroot Pigweed in a west central Minnesota Farm



Appendix 5: Estimating the Emergence Model

To estimate the emergence model given in (3.4), i.e.:

$$X_{interv} = \sum_{i=1}^{interv.} \beta_{i-1} \frac{GDD_{i-1}}{CGDD_{i-1}} S_{i-1} D_{i-1} \qquad \text{(A5.1)}$$

then let's denote

$$\frac{GDD_{i-1}}{CGDD_{i-1}} S_{i-1} D_{i-1} \quad by \quad P_{i-1} \qquad \text{(A5.2)}$$

for a specified average scouting interval (interv.) of say, 4 days, the number of weed seedlings that are counted on the scouting day is the sum of daily seedling emergence in all the days since the day the previous scouting was done, i.e.:

$$X_4 = \sum_{i=1}^{4} X_i \qquad \text{(A5.3)}$$

and:

$$X_4 = \beta_0 + \beta_1 P_3 + \beta_2 P_2 + \beta_3 P_1 \qquad \text{(A5.4)}$$

Similarly, if the scouting interval has been 3 days, then:

$$X_3 = \beta_0 + \beta_1 P_2 + \beta_2 P_1 \qquad \text{(A5.5)}$$

Therefore, the estimable form of the model for average interv. of four days is:

$$X_4 = \beta_0 + \beta_1 (P_3 + P_2 + P_1) + \beta_2 (P_2 + P_1) + \beta_3 P_1 \qquad \text{(A5.6)}$$

Appendix 6: Expected Net Incomes and Herbicide Indexes at all Probable planting Dates of Corn (Full-season

	Medium		Low		High	
Planting Date	Net Income ($/acre)	Herbicide Index	Net Income ($/acre)	Herbicide Index	Net Income ($/acre)	Herbicide Index
	Early* 1, late*1		Early*0.25, late*0.25		Early*4, late*4	
28-Apr	31.67	0.80	82.09	0.83	-46.00	0.80
29-Apr	35.80	0.80	82.23	0.83	-40.95	0.80
30-Apr	40.14	0.80	82.37	0.83	-35.32	0.80
1-May	49.45	0.80	82.48	0.83	-26.92	0.67
2-May	49.78	0.80	82.03	0.83	-25.24	0.67
3-May	50.54	0.80	81.96	0.83	-19.21	0.67
4-May	52.47	0.80	81.79	0.83	-12.47	0.67
5-May	55.29	0.80	81.62	0.83	-4.88	0.67
6-May	58.22	0.80	81.23	0.83	3.72	0.67
7-May	61.30	0.80	80.53	0.83	13.57	0.67
8-May	62.17	0.80	79.82	0.83	17.72	0.67
9-May	63.06	0.80	79.11	0.83	22.16	0.67
10-May	63.97	0.80	78.39	0.83	26.90	0.67
11-May	65.05	0.80	77.67	0.83	32.13	0.67
12-May	66.16	0.80	76.95	1.00	37.74	0.67
13-May	**71.43**	**0.83**	76.22	1.00	39.83	0.67
14-May	66.17	0.83	75.52	1.00	41.81	0.67
15-May	66.14	0.83	74.81	1.00	43.87	0.67
16-May	66.10	0.83	74.11	1.00	46.00	0.67
17-May	66.07	0.83	73.39	1.00	48.21	0.67
18-May	66.04	0.83	72.66	1.00	50.50	0.67
19-May	65.52	0.83	71.93	1.00	51.64	0.80
20-May	65.01	0.83	71.04	1.00	53.47	0.80
21-May	64.41	0.83	70.01	1.00	54.39	0.80
22-May	63.81	0.83	69.79	1.00	55.34	0.80
23-May	63.21	0.83	69.76	1.00	59.05	0.80
24-May	62.35	0.83	69.61	1.00	56.34	0.80
25-May	63.15	1.00	69.46	1.00	56.37	0.80
26-May	63.63	1.00	69.26	1.00	56.03	0.80
27-May	63.49	1.00	69.06	1.00	55.91	0.80

Early*1, late*1 refers to the base weed seed densities in Table 5.1.

BIBLIOGRAPHY

Ahrens, J.H. and Dieter, U. "Computer Methods for Sampling Gamma, Beta, Poisson and Binomial Distributions." Computing 12(1974):223-246

Auld, B.A., Menz, K.M., and Tisdell, C.A. Weed Control Economics. London: Academic Press, 1987.

Auld, B. A. and C. A. Tisdell. "Influence of Spatial Distribution on Weeds on Crop Yield Loss." Plant Protection Quarterly 3,2(1988):81.

Ball, D. A. and Miller, S.D. "Weed Seed Population Response to Tillage and Herbicide Use in 3 Irrigated Cropping Sequences." Weed Science 38(1990):511-517

Belsey, D. A., Kuh, E., and Welsch, R.E. Regression Diagnostics- Wiley Series in Probability and Mathematical Statistics, John Wiley and Sons, 1980.

Bliss, C.I and Fisher, R. A. "Fitting the Negative Binomial Distribution to Biological Data" Biometrics (1955):176-200.

Brain, P. and R. Cousens. "The Effect of Weed Distribution on Predictions of YieldLoss." Journal of Applied Ecology 27(1990):735-742.

Carlson, Gerald A. "Risk Reducing Inputs Related to Agricultural Pests." In Risk Analysis for Agricultural Production Firms: Information Requirements and Policy Issues, Department Of Agricultural Economics, Paper AE-4573, University of Illinois, Urbana-Champaign, IL, 1984.

Chandler, J. M., Hamill, A. S. and Thomas, A. G. "Crop Losses Due to Weeds in Canada and the United States". Special Report of the Losses Due to Weeds Committee, Weed Science Society of America, IL., May 1984.

Cousens, Roger. "A Simple Model Relating Yield Loss to Weed Density." Annals of Applied Biology 107(1985):239-252.

Crook, T.M. and Renner, K.A. " Common Lambsquarters: Competition and Time of Removal in Soybeans." Weed Science 38(1990):358-364.

Davis, S. and Botkin J. " The Coming of Knowledge-Based Business." Harvard Business Review . September-October, 1994:165-170

Doyle, C. J. "Mathematical Models in Weed Management" Crop Protection 10(1991):432-443.

Durgan, B. R., J. L. Gunsolus, R. L. Becker, and A. G. Dexter. Cultural and Chemical Weed Control in Field Crops-1994. Bulletin AG-BU-3157-S, Minnesota Extension Service, University of Minnesota, 1994.

Egley, G. H. and William, R. D. " Decline of Weed Seeds and Seedling Emergence over 5 Years as Affected by Soil Disturbances." Weed Science 38(1990):504-510

Fackler, P. L. "Modeling Interdependence: An Approach to Simulation and Elicitation." American Journal of Agricultural Economics 73(1991):1091-1097.

Feder, Gershon. "Pesticides, Information, and Pest Management under Uncertainty." American Journal of Agricultural Economics 61(1979):97-103.

Fernholz, Carmen. "A Matter of Degrees." The New Farm 15,3(1993):20+.

Forcella Frank. "Seedling Emergence Model for Velvetleaf." Agronomy Journal 85(1993):929-933.

Forcella, F., Wilson, R.G., Renner, K.A., Dekker, J., Harvey, R.G., Alm, D.A., Buhler, D.D. and Cardina, J. "Weed Seedbanks of U.S. Corn Belt: Magnitude, Variation, Emergence and Application." Weed Science 40(1992):636-644

Forcella F., Eradat-Oskoui K. and Wagner, S. W. "Application of Weed Seedbank Ecology to Low Input Crop Management" Ecological Applications 3:1(1993):74-83.

Forcella, Frank and Wyse, D. " The NCR-157 Pesticide Index via Reformulation of the EIQ Field Use Rating" Unpublished Working Paper, Dept. of Agronomy and Plant Genetics, University Of Minnesota (1993)

Fuller, E., B. Lazarus. and L. Cariggan. "What to Grow in 1993: Crop Budgets for Soil Area 4." Minnesota Extension Service AG-FS-0937-a. University of Minnesota, 1993.

Gianessi, LP. and Puffer, C. "Herbicide Use in the United States." Quality of Environment Division, Resources for the Future, Washington D.C. April 1991.

Greene, William H. Econometric Analysis. Second Edition, New York, Macmillan Publishing Company. 1993. P222-225, 314-341.

Gunsolus, J.L. "Mechanical and Cultural Weed Control in Corn and Soybeans" American Journal for Alternative Agriculture Vol.5,No.3(1990):114-119.

Hardman, L. L. and J. L. Gunsolus. "Corn Growth and Development and Information for Replant Decisions." Minnesota Extension Service,AG. FO 5700-c, 1991a, University of Minnesota.

Hardman, L. L. and J. L. Gunsolus. "Soybean Growth and Development and Information for Replant Decisions." Minnesota Extension Service, AG. FO 5701-c, 1991b, University of Minnesota.

Harris, S. K. "Interference and Seed Production by Common Lambsquarters (Chenopodium album) in Soybeans (Glycine max)." Weed Science 38(1990):113-118.

Harvey, S.J and Forcella F. "Vernal Seedling Emergence Model for Common Lambsquarters (Chenopodium album)" Weed science 41(1993): 309-316.

Headley, J.C."Defining the Economic Threshold." In Pest Control Strategies for the Future. National Academy of Sciences,Washington, DC, 1972.

Hicks, D. H. "How Early Should Corn be Planted" Crop News No. 96, Agronomy and Plant Genetics, Minnesota Extension Service, University of Minnesota, 1992

Hicks, D.R. and Peterson, R. H. "Date of Planting Corn." Agronomy Fact Sheet No. 23, Agricultural Extension Service, University of Minnesota, 1978.

Hoar, S. K., Blair, A., Holmes, F.F., Boysen, C.D., Robel, R.J., Hoover, R., Fraumesi, Jr. J.F. "Agricultural Herbicide Use and Risk of Lymphonoma and Soft Tissue Sarcoma" Journal of the American Medical Association: 256(1986):1141-1147

Hughes, Gareth "Spatial Heterogeneity in Yield-Weed Relationships for Crop Loss Assessment" Crop Research vol 29, No. 2(1989):87-94.

Judge, G.G., Hill, R.C., Griffiths, W.E., Lutkepohl, H. and Lee, T-C. Introduction to the Theory and Practice of Econometrics. 2nd. Edition. John Wiley & Sons, 1988

Kelton W.D. and Law, A. M. Simulation Modeling and Analysis. McGraw Hill Book Co., NY, 1982 pp171-257

King Robert P. " Operational Techniques for Applied Decision Analysis under Uncertainty." Ph.D. dissertation, Department of Agricultural Economics, Michigan State University, 1979.

King, R. P.,Lybecker, D.W., Schweizer, E.E and Zimdahl, R.L. "Bioeconomic modeling to simulate Weed Control Strategies for Continuous Corn (Zea mays)." Weed Science 34(1986):972-979.

King, R. P.,Lybecker, D.W., Regmi A., and Swinton, S. M. "Bioeconomic Models of Crop Production Systems: Design, Development and Use" Review of Agricultural Economics Vol 15, No. 2(1993):389-401.

Kovach, J., Petzoldt, C., Degni, J. and Tette, J. " A Method to Measure the Environmental Impact of Pesticides." New York Food and Life Sciences Bulletin, New York State Agric. Experiment Station, Geneva, Bulletin N139, 1992.

Lichtenberg, Eric and Zilbermann, David. "The Econometrics of Damage Control: Why Specification Matters." American Journal of Agricultural Economics 68(1986): 261-273.

Lybecker, D.W., King R.P.,Schweizer, E.E and Zimdahl, R. L. "Economic Analysis of two weed management systems for two cropping rotations." Weed Science 32(1984): 90-95.

Lybecker, D.W., Schweizer, E.E and King, R.P. "Weed Management Decisions in Corn Based on Bioeconomic Modeling." Weed Science 39(1991): 124-129.

Marra, Michele C. and Carlson A. G. "An Economic Threshold Model for Weeds in Soybeans (Glycine max)." Weed Science 31(1983): 604-609.

Marshall, E. J. P. "Field Scale Estimates of Grass Weed Populations in Arable Land." Weed Research 28(1988):191-198.

Marx, D. B. and Thompson K.C. "Practical Aspects of Kriging." Arkansas Experiment Station Bulletin 903, 1987.

Mirotchie, M. "Comparative Economic Analysis of Conventional and Reduced Tillage Systems for Corn and Soybean Production in SouthEast Minnesota" Unpublished M.S Thesis, University of Minnesota, 1984 (p.12)

Moffitt, L. J., C. D. Hall, and D. C. Osteen. "Economic Thresholds under Uncertainty with Application to Corn Nematode Management." Southern Journal of Agricultural Economics 16(1984): 151-157.

Mortensen D. A., G. A. Johnson, and L. J. Young. "Weed Distribution in Agricultural Fields." Paper presented at Soil Specific Crop Management Conference, University of Minnesota, April 14-16, 1992.

Mulder, T.A. and Doll, J.D."Reduced Input Corn Weed Control: The Effect of Planting Date, Early Season Weed Control, and Row Crop Cultivar Section." Journal of Production Agriculture Vol 7(1994):256-260.

Nielsen, E.G. and Lee, L.K. "The Magnitude and Costs of Groundwater Contamination from Agricultural Chemicals: A National Perspective." Natural Economics Division, USDA-ERS Staff Report, AGES 870318, 1987.

Olson, D.K. and Eidman, V.R."A Farmer's Choice of Weed Control Method and the Impacts of Policy and Risk." Review of Agricultural Economics 14(1992): 125-137.

Olson, D.K., Nordquist, D.W., Talley, D.E., Christensen, J., Weness E.J., and Fales, A.P. " 1993 Annual Report of south western Minnesota Farm Business Management Association" Staff Paper P94-15, Department of Agricultural and Applied Economics, University of Minnesota, July 1994. p.19

Osteen C. and Szmedra P. "Agricultural Pesticide Use Trends and Policy Issues." Agricultural Economic Report No 622. U.S.Department of Agriculture, Washington, D.C., 1989.

Pannell, D. J. "An Economic Response Model of Herbicide Application for Weed Control." Australian Journal of Agricultural Economics 34(1990): 223-241.

Pannell, D. J. "Pests and Pesticides, risk and risk aversion." Agricultural Economics 5(1991):361-384.

Pindyck, R. S. and Rubinfeld, D. L. Econometric Models and Economic Forecast. Second Edition, McGraw-Hill, NY 1981.

Raskin, Rob and Cochran, M. J. "Interpretations and Transformations of Scale for the Pratt-Arrow Absolute Risk Aversion Coefficient: Implications for Generalized Stochastic Dominance." Western Journal of Agricultural Economics 11(1986): 204-210.

Regmi, Anita. "The value of Information in Integrated Pest Management of Corn Rootworm and European Corn Borer in Minnesota." Unpublished Ph.D Thesis, University of Minnesota, 1990.

Robison, L. J. and Barry, P. J. The Competitive Firm's Response to Risk. New York: Macmillan, 1987.

Rocheford T. R. , Sammons, D. J. and Baenziger, P. S. "Planting date in relation to Yield and Yield Components of Wheat in the Middle Atlantic Region" Agronomy Journal 80(1988):30-34.

Rubinstein, R. Y. Simulation and the Monte Carlo Method. Wiley, NY , 1981 p 106+

Schreiber, M. M. " Influence of Tillage, Crop Rotation and Weed Management on Giant Foxtails (Setaria faber) Population Dynamics and Corn Yield" Weed Science 40(1992):645-653.

Seeley, M. W., Spoden, G.J. and Schrader, C.A. "C.A.W.A.P-Crop Season Climatic Data." Unversity of Minnesota Agricultural Extension Services Research Locations.Minnesota Extension Service Publication No AG-BU-2291. Various Years.

Seymour, R. M., Skaggs, R. W. and Evans R.O. "Predicting Crop Yield Response to Planting Date Delay" Transactions of the ASAE Vol 35, No. 3(1992):865-869.

Swinton, Scott Mitchell. "A Bioeconomic Model for Weed Management in Corn and Soybean." Unpublished Ph.D Thesis, University of Minnesota, 1991.

Swinton, S. M. and R. P. King. "A Bioeconomic Model for Weed Management In Corn and Soybean." Agricultural Systems 44(1994): 313-335.

Taylor, C. R. and O. R. Burt. "Near-Optimal Management Strategies for Controlling Wild Oats in Spring Wheat." American Journal of Agricultural Economics 66(1984):50-60.

Thompson, J. F., Stafford, J. V. and Miller, P. C. H. "Potential for Automatic Weed Detection and Selective Herbicide Application" Crop Protection 10(1991): 254-259.

Thornton, P. K., Fawcett, R. H., Dent, J. B. and Perkins, T. J. "Spatial Weed Distribution and Economic Thresholds for Weed Control" Crop Protection 9(1990):337-342.

Upton, G.J.G. and Fingleton, B. Spatial Data Analyis by Example, Vol. 1: Point Pattern and Quantitative Data. Chichester, NY, Wiley, 1989.

Walsh, James " A Hard-Drive Harvest" World and Nation: A Star Tribune Supplement, February, 1995. PP 6-8.

Wiles, L. J. "A Decision Analytic Investigation on the Influence of Weed Spatial Distribution on Post-emergence Herbicide Decisions for Soybeans (Glycine max)." Unpublished Ph.D thesis, North Carolina State University, Raleigh NC. 1991. 143pp.

Wiles, L.J., Wilkerson, G. G., and Gold, H. J. "Value of Information about Weed Distributions for Improving Post-emergence Control Decisions" Crop Protection 11(1992a):547-554.

Wiles, L.J., Wilkerson, G. G., Gold, H. J. and Coble H.D. " Modeling Weed Distribution For Improved Post-Emergence Control Decisions." Weed Science 40(1992b):546-553

Wolf, D. D. and Edmisten, K. L. " Late Season Alfalfa Plantings: Conventional Vs. No-Till Methods." Crop Science 29(1989):170-175

Wossink, G.A. and Renkema, J. A. "Economic Modeling of Integrated Plant Production." Invited Paper Presented at International Congress, Plant Production on the Threshold of a New Century, Wageningen, The Netherlands, June 1993.

Yenish, J. P., Doll, J. D. and Buhler, D.D. " Effect of Tillage on Vertical Distribution and Viability of Weed Seed in Soil." Weed Science 40(1992):429-439.

Zilbermann, D., Sunding, D., Dobler, M., Campbell, M., and Manale, A. "Who Makes Pesticide Use Decisions: Implications for Policy Makers" in Pesticide Use and Produce Quality-Proceedings of a Workshop sponsored by Agricultural and Food Marketing Consortium, Farm Foundation, 1994

Zimdahl, R. L. "Weed-Crop Competition: A Review." International Plant Protection Center, Corvallis, Oregon, 1980.