

An assessment of the use of site-specific weed control for improving prediction-based management decisions and automating on-farm research
by Edward Charles Luschei

A dissertation in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Land Resources and Environmental Sciences
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Abstract:
Prediction of the competitive effect of a weed on a crop has generally been accomplished by extrapolating the results of small-plot experiments. I investigated the potential of site-specific technologies to improve the predictability of competitive response to chemical inputs by combining the concepts of management and experiment. The spatial distribution of wild oat (Avena fatua L.) was mapped in four north-central Montana study sites in spring wheat production. Two herbicide treatment strategies, site-specific and broadcast, were applied in a large-scale block design and contrasted using site-specific yield data. I found that the proportion of the field requiring treatment determined the short-term profitability of site-specific weed management. I also determined that site-specific on-farm research was feasible but experiments could not distinguish treatment effects unless the effects were relatively large, primarily because the resolution of the current generation of yield monitors is poor. Using supplemental quadrat count data, I parameterized a relationship describing the competitive effect of wild oat on wheat using the site-specific yield data. I suggest that creating locally parameterized stochastic functions may improve the accuracy of input response prediction over regional small-plot experiments because of field-specific effects, which are not calibrated by regional small plot experiments.

I examined the potential of improving small-plot study predictions by adding precipitation to weed-crop impact model structure. When using simulated small-plot competition study data and March through May precipitation, I found that the threshold (value of weed control) could not be predicted accurately, even when we had knowledge of the correct structural form of the weed-crop competitive relationship.

I also investigated the importance of weed demography in weed control decisions and developed an analytical approximation of the long-term economic threshold based on the growth rate of the weed with and without control. I suggest that site-specific weed management and on-farm studies may offer a means to estimate demographic model parameter distributions.

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APPROVAL

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This dissertation has been read by each member of the dissertation committee and has been found to be satisfactory regarding content, English usage, format, citations, bibliographic style, and consistency, and is ready for submission to the College of Graduate Studies.

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ABSTRACT

Prediction of the competitive effect of a weed on a crop has generally been accomplished by extrapolating the results of small-plot experiments. I investigated the potential of site-specific technologies to improve the predictability of competitive response to chemical inputs by combining the concepts of management and experiment. The spatial distribution of wild oat (*Avena fatua* L.) was mapped in four north-central Montana study sites in spring wheat production. Two herbicide treatment strategies, site-specific and broadcast, were applied in a large-scale block design and contrasted using site-specific yield data. I found that the proportion of the field requiring treatment determined the short-term profitability of site-specific weed management. I also determined that site-specific on-farm research was feasible but experiments could not distinguish treatment effects unless the effects were relatively large, primarily because the resolution of the current generation of yield monitors is poor. Using supplemental quadrat count data, I parameterized a relationship describing the competitive effect of wild oat on wheat using the site-specific yield data. I suggest that creating locally parameterized stochastic functions may improve the accuracy of input response prediction over regional small-plot experiments because of field-specific effects, which are not calibrated by regional small plot experiments.

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I also investigated the importance of weed demography in weed control decisions and developed an analytical approximation of the long-term economic threshold based on the growth rate of the weed with and without control. I suggest that site-specific weed management and on-farm studies may offer a means to estimate demographic model parameter distributions.

PROLOGUE

I believe that it would be worth trying to learn something about the world even if in trying to do so we should merely learn that we do not know much. This state of learned ignorance might be a help in many of our troubles. It might be well for all of us to remember that, while differing widely in the various little bits we know, in our infinite ignorance we are all equal.

—K. Popper

An applied science thesis such as this one must strike a balance between testing and applying scientific principles. The majority of research in weed science has been very applied, focusing primarily on technologies (e.g. herbicides, cultivation techniques) and factors related to short-term objectives within a management plan. Ecological studies, for example seed longevity in the seed bank, have most often been reported as purely ecological case studies without consideration of how to apply information to general management strategies.

The gap between ecological and applied weed research in large part reflects the experimental methods and types of models used in ecological studies. Hypothesis testing methodology (e.g. demonstrating that a seed mortality rate depends on environment) provides ecological information without having any direct link to application, except to suggest that perhaps some factor or suite of factors should be included in predicting seed fate over time. However interesting the ecological relationships, the inclusion of additional complexity in modeling efforts aimed at prediction of future effects must be

balanced with our ability to discern those relationships within the complexity of ecological systems.

This thesis will explore the possibility of merging our concepts of science and management in the arena of weed research. I demonstrate that we currently have the capability to make production fields into laboratories by conducting a large-scale investigation on the economic advantage of site-specific weed control. The work suggests that GPS-based technologies can perhaps allow *farmers* to conduct replicated studies and consequently compare different management strategies.

I also demonstrate how site-specific data (e.g. spatial information about crop yield) can be used for addressing questions beyond treatment comparisons. Supplemental data on weed densities are analyzed in conjunction with yield maps to provide estimates of the weed impact for individual fields. I claim that such local estimation can provide a way to compile (over time) a distribution of parameters for a stochastic impact model. Probabilistic predictions can then be made using Monte-Carlo techniques.

Beyond providing an example establishing that combining management and experiment is feasible, I studied some of the difficulties and limitations of using small-scale experiment station research to make predictions. The well-documented dependence of competitive impact on many environmental factors necessitates modeling impact variability in order to extrapolate relationships. I therefore investigated what improvement in prediction accuracy might be achieved by combining moisture data with small-plot weed-crop competition studies.

Impact studies can provide useful information about the economic importance of a weed and conditions under which control is going to lead to a net economic gain, but these considerations cannot be divorced from the long-term objective of controlling weed populations. I investigate how to include considerations of weed demography and environmental stochasticity in decision-making by analyzing published data on barnyardgrass demography and impact. The potential importance of demography in decision-making highlights another advantage of on-farm studies. There is probably more variability in weed habitat characteristics than competitive processes, and therefore assembling on-farm parameter distributions of weed growth rate may provide the greatest increase in predictive power.

A large part of my graduate career has been spent attempting to draw connections between the world of mathematical theory and observations, first in physics, then in ecology and finally in agricultural systems. I hope that the broad perspective this diversity of training provides will be useful in both clarifying issues and establishing the relevance of ecological studies to the management of weeds.

CHAPTER 1

INTRODUCTION

Agricultural production has traditionally managed inputs according to mean field conditions. A small number of soil samples obtained across large areas were lumped or averaged to set fertilizer recommendations; pesticide decisions were established by quick and often qualitative surveys of pest populations. Social, political and technological changes have tended to increase the scale of farm operations, and therefore decrease the potential of an individual farmer to effectively manage particular areas of their farm (NRC 1997).

With decreasing gross returns, rising input costs and mounting awareness of off-target effects, producers have ever-increasing incentive to conserve on expensive chemical applications. Yet reduction of inputs can result in an unacceptable increase in the variability of crop response. Improved decision-making is needed to target inputs to those sections of farms or fields where they are most effective. Effective targeting requires: (1) establishing the conditions, e.g. soil properties or pest spectrum, within particular sections of a field and (2) optimally allocating resources in accordance with those conditions.

A great deal of research at the sub-field scale has gone into determining how to optimally sample soils in order to produce quality nutrient maps. Spatial statistics are increasingly employed to interpolate measurements to areas where they were not quantified (Wollenhaupt et al. 1997). Yield monitors can relate crop production back to specific locations within the field (Pierce et al. 1997). Real-time sensors are being

developed to detect pests or soil properties (Sudduth et al. 1997). Low and high altitude remote sensing data are being analyzed and related back to sub-field scale conditions (Moran et al. 1997). Others are examining the prospects of multispectral digital imagery (Pearson et al. 1994, Moran et al. 1996, Lamb 1998).

As research and technological innovations improved the quality and detail of information about sub-field conditions, engineers developed the means to efficiently apply spatially variable input rates. Variable rate technologies (VRT) are frequently used to dispense fertilizers or pesticides in amounts tailored to local conditions. Computer technologies have been created to control VRT systems, catalog sensor data and display maps of soil or pest information. Yet, the acquisition of spatial information and the technology to strategically deploy inputs is of no avail unless knowledge of how to manage under those local conditions is available.

Farmers regularly make production decisions, and their experience influences future decisions. As Woiwood (1993) observed, every year hundreds of thousands of agricultural experiments take place. Observation and intuitive appraisal do not, however, always lead to better decision-making. The time lag between chemical application and results, the large amount of land under management and the complexity of the agroecosystems are all capable of causing misinterpretations and bias in informal human decision-making (Einhorn 1980).

On-farm Research

On-farm experimentation attempts to remove some of the bias involved in using experience or intuition in decision-making. By conducting research in the same field or under conditions where production-scale equipment is used, on-farm research is capable of producing results that closely approximate the conditions under which predictions are actually needed (Gotway-Crawford et al. 1997, Spaner et al. 2000).

In general, on-farm research has many advantages. Farmers trust the results from larger scale experiments (Rzewnicki et al. 1988) whereas many are skeptical about small-plot experiments (Thompson 1986). Participatory on-farm research also fosters an exchange of ideas between researchers and producers (Wuest et al. 1999) and can maintain research activity while research budgets are shrinking (Spaner et al. 2000). Other advantages cited by Lockertz (1987) include: specific conditions may occur on-farm that do not occur on experiment stations, on the former more land is available and constraints involved with real production situations are represented. Rzewnicki et al. (1988) contrasted the experimental error from on-farm experiments under several different conditions (size of equipment, level of producer involvement) and found that the experimental error in on-farm research was well within levels tolerated by agricultural researchers.

While the advantages of on-farm research are numerous, there are also disadvantages. If experimental fields are far apart, researchers may spend a great deal of time traveling. The additional care required collecting research data might not be a priority for the farmer who is operating under many constraints, particularly during

sowing or harvest. Although the producer is generally responsible for agronomic practices, and therefore fewer research resources are consumed than in an equivalent experiment station study, the chance of a lost plot or experiment on the farm scale *may* make on-farm research more risky.

The use of management events as experiments is sometimes called "adaptive management" (Walters 1986, Haney and Power 1996, McLain and Lee 1996) and mirrors the appealing philosophy of "leaning by doing" (Walters and Holling 1990). Not only does site-specific technology have the potential to provide feedback on management via the automated collection of the results of management efforts (Petersen et al. 1993), but it may also facilitate the on-farm experiment process (Shroder and Shnug 1995).

Site-Specific Weed Management

The value of accurate prediction or inference is certainly not sufficient to fund an army of researchers to collaborate with producers for on-farm research on every field. In order to make such research feasible, some automation of the research process must take place. Site-specific technology offers just such an opportunity.

The use of global positioning system technology in the farming operation is becoming increasingly frequent (NRC 1997). Yield monitors are standard on many combines and the spatial placement of inputs (e.g. fertilizers and pesticides) holds the promise of improving the economic returns of producers and decreasing the off-target effects of chemicals (Pierce and Nowak 1999). Variable rate technology, which allows

for tailoring the specific quantity of input to location, may further improve the benefits (Felton et al. 1991).

As many weeds are distributed in restricted areas of fields (Colliver et al. 1996, Marshall 1988, Mortensen et al. 1993) there is potential savings in applying herbicides only where they are needed (Felton et al. 1991, Johnson et al. 1995, Christensen et al. 1996, Colliver et al. 1996, Rew et al. 1997). The opportunity provided by spatial variation in weed density/abundance (Johnson et al. 1997, Mortensen et al. 1998) has stimulated the investigation of methods to measure and infer the spatial distribution of weeds (Cardina et al. 1995, Johnson et al. 1995, Christensen et al. 1996, Heisel et al. 1996, Johnson et al. 1996, Rew et al. 1996, Williams et al. 1998). Simulation techniques have been used to explore the potential benefits of site-specific weed management (Maxwell and Colliver 1995, Oriade et al. 1996, Paice et al. 1998).

While there are certainly savings to be made by forgoing herbicide use altogether in areas where there are no weeds, the production of density maps allows for the possibility of optimal rate (e.g. Pannell 1990) or density threshold (Coble and Mortensen 1992) methods. Gotway-Crawford et al. (1997) note that the soundness of the principle of site-specific management is almost "self-evident", however, what is not self-evident is whether enough is known to identify what amount of inputs specific areas require. Agricultural systems are complex and can be driven by factors that are stochastic and entirely unknown at the time decisions are made. Furthermore, the relationship between inputs and crop performance is often subject to variation that arises from our lack of ability to describe interactions among the inputs, environment, and crop. Excitement

about the potential benefits of site-specific management must be balanced by the increased information overhead in knowing *how* to manage on small spatial scales.

Perhaps one of the most promising aspects of site-specific technology is that it provides a way to improve farm profits, reduce polluting inputs and create information that can be used to improve our knowledge of the interrelationships between the environment and crop. By combining the concepts of management, experiment, and learning, the university researcher has the potential to contribute to producer management decisions in a very relevant way, potentially helping remove some of the psychological biases involved in intuiting crop responses to the environment (pests, weather, etc) and to inputs.

Prediction of Weed Impact

MacDonald and Smith (1993) assert that more precise forecasting can allow reduction of agrochemical inputs with little loss in efficacy, but how do we go about making more precise forecasts? The economic efficiency of weed management can be improved by either reducing unnecessary use of inputs or improving the relationship between cost and efficacy. The distinction is between the quantity and the quality of control measures. Both approaches deserve investigation, but we will consider perhaps the most basic decision, whether control needs to be exercised at all at a particular location.

The framework within which we analyze the necessity of management contrasts the value of production with and without control measures. If we consider the intensity

of the weed infestation to be the most likely indication of when control is warranted, we can define a density above which control measures are required. This is usually called the economic injury level (EIL) and sometimes called the economic threshold (ET) when it considers the single-year economic impact of the weed (Coble and Mortensen 1992). The weed density threshold is called the economic optimum threshold (EOT, Cousens 1987) when it considers multi-year effects.

Norris (1999) and Swanton (1999) provide recent history and issues in the study of thresholds in weed science. Lindquist and Knezevic (2001) discuss the current state of quantitative weed impact studies. Both ET and EOT strategies rely on predicting the value of weed control, which depends on a multitude of factors.

Many researchers have noted the importance of the relative time of emergence of the crop and weed on estimation of competitive impact (O'Donovan et al. 1985, Cousens et al. 1987, Blackshaw 1993, Dieleman 1996). Mortensen and Coble (1989) found that soil moisture influenced the competitive effect of Cocklebur (*Xanthium strumarium* L.). Soil factors can also contribute to variation, for example, soil texture (Firbank et al. 1990) or pH (Weaver and Hamill 1985). Other cropping system factors undoubtedly impact competitive effects of weeds on crop yield and quality: crop planting date, variety, density, residue, tillage, row spacing, rotation and fertilizer placement. O'Donovan (1996) suggests that attempting to untangle this complexity may be a "pipe dream".

Given the many potential influences on the outcome of competition, how are we to predict impact, and thereby the necessity of control, for sub-field areas in reduced input conditions? What's more, the many sources of variation in weed-crop interactions

pale in comparison to the potential uncertainties in long-term weed demographics (Firbank 1993a).

Future impacts have been addressed by attempting to model the population dynamics of the weed (Cousens 1986, Cousens and Mortimer 1995). Life-history models have been constructed for many weed-crop combinations and the models can then be used to predict, in combination with weed impact models, the long-run effects of forgoing control implementation (e.g. Maxwell and Colliver 1995, Bussan and Boerboom 2001a, 2001b).

The use of deterministic models for this purpose has met with massive dissatisfaction. In part, the dissatisfaction arises because the "noise" in demographic processes overwhelms the "signal" and prediction error may be very large (Firbank et al. 1985, Cousens 1995). In part, the dissatisfaction stems from the same psychology as general input decision-making wherein different decision makers may have different preferences for "risk" (Pannell 1995) or for variability in results.

Prediction of the economic or pest population consequences of forgoing control does not necessarily entail ignoring risk. The use of stochastic models, or models containing parameters arising from distributions, can include variability in the outcome of a strategy and thereby allow for a comparison of strategies. By allowing the decision maker to penalize potential variability in the outcome of a strategy, some of the frustration with demographic model performance can be removed. Shea and Possingham (2000) provide historical background on the use of "stochastic dynamic programming" for applied management. However, the use of stochastic models is not without its own

set of problems (Firbank 1993a). For example, how are we to integrate information from experts and current or past data to estimate the joint *distribution* of parameters? It is here where classical statistics are of little use and different methodologies are necessary, e.g. Bayesian theory (Hilborn and Mangel 1997).

Limitations of Small-Scale Competition Experiments

The traditional methods of studying agronomic practices involve small-scale trials on research farms distributed across regions. Their locations were intended to represent or typify environmental conditions that occur over the regions. New crop varieties or cropping system practices were tested at the experiment stations, which facilitated the transfer of technologies developed at research institutions to producers. When the management strategy is one where local variation is overwhelmed by input application, the effective similarity between an experiment station and a farmer's field may be quite large and this may result in high predictability of the response of the crop to the input. Perhaps rainfall, temperature, or general soil properties are primarily responsible for what variation remains in realized crop yield. These factors may be relatively constant over large spatial scales. However, when managing smaller areas with more variability between management areas and with smaller quantities of inputs, the notion that we can extrapolate small-scale studies over hundreds of miles becomes tenuous (Maxwell 1999).

There are several components of variation and the design must address all of them. An investment in estimating one source of variation may not be applicable to the estimation of variability on a different spatial or temporal scale. Firbank (1993a) has

criticized his own small-scale competition studies (Firbank et al. 1984, Firbank and Watkinson 1985) on the basis that "...the statistical population being sampled... is restricted to one part of one field of randomly dispersed plants in one season." Even within cereal fields in a small geographic region, the value of the estimates is questionable. We must not mistake subsampling for replication (Eberhardt and Thomas 1991).

The additive design competition experiment also presupposes that we want to remove environmental correlates of weed abundance when determining the relationship between the weed and crop. We create independence between weed density and environment by ensuring any weed density (treatment) might have occurred with any particular plot (randomization). Weed density/presence, however, may have ecological associations with particular environments (Dale et al. 1965, Dale et al. 1992, Dieleman et al. 2000) and the competitive relationship between weed and crop is also likely to be a function of the environment (Weaver and Hamill 1985, Mortensen and Coble 1989, Firbank et al. 1990). The correlation of occurrence and competitive effect may significantly bias estimates made under traditional randomized designs. The problem is not that the design is inherently flawed, merely that it addresses a different question than that with which the decision maker is concerned.

Beck (1997) stresses, "in science we seek not only to develop theories and hypotheses, but also to define the domain in which they provide explanatory or predictive value." This is particularly important when establishing credible claims of predicting the (indirect) response of crops to weed population management.

Needless to say, decisions must be made. Social, political and economic trends have provided incentive for justifying input use. Technology has given us the means to adjust or tailor the amount of inputs applied. For weed management, it is up to weed scientists to provide the methodology to determine how to utilize information to improve the efficiency of weed population control.

Two Broad Objectives of Modeling

There are two primary objectives of modeling: (1) to understand or gain insight into a phenomenon and (2) to accurately predict for decision-making (Caswell 1976). For many scientific endeavors, particularly in the physical sciences, the two objectives might be one and the same. However, for systems as complicated as agroecosystems, the two objectives may require very different approaches.

Scientific attempts to *understand* complex phenomenon have many potential benefits. Generalities may be discovered that aid in making better decisions (i.e. "rules of thumb"). The form of functional or structural relationships may be derivable without making specific claims to the generality of parameter estimates. Furthermore, if modeling of a complex system is "successful", the model can be extrapolated (used wherever the independent variables are known). Some have issued cautions regarding the tractability of understanding ecological complexity, for example, Egler (1977) states, "Ecosystems are not only more complex than we think, they are more complex than we can think."

Given the complexity of the apparently simple system, reliably predicting impact has proven difficult. We are often left with the question of how to determine the domain in which single factor studies provide explanatory or predictive value. Unfortunately, due to the great expense of field research, such questions are rarely answerable. With some success, attempts have also been made to use predictors that integrate the effects of growth factors. By integrating the causes of variation in growth instead of modeling them separately, the domain in which a relationship can provide accurate predictions may be improved. Examples of the use of integrative predictors include: the leaf area index (Kropff and Spitters 1991), and plant volume (Bussler 1995). In order to be useful for prediction, however, we must be able to estimate these predictors inexpensively prior to the time when decisions are to be made.

Constructing models that include the processes responsible for variation has seductive appeal (Kropff 1993). Even though a model that directly includes processes has many potential uses, it does not follow that it is necessarily better at predicting than less complex counterparts, particularly if measurements of the additional predictor variables are not readily available. Hilborn and Mangel (1997) eloquently describe the relationship between modeling and the scientific method and state with regard to decision-making, "It is in this realm that models have the most to offer in terms of practical application, but also where the greatest potential danger lies."

The proliferation of fast, inexpensive, computers in combination with increasing quantities of information, has led to an explosion in both the number and complexity of models. Much debate has ensued in agronomy concerning the appropriate role and

significance of complex "mechanistic" or process-based models (DeCoursey 1992, Boote et al. 1996, Monteith 1996, Passioura 1996, Sinclair and Seligman 1996). Passioura (1996) notes that the debate exists because of confusion between the two objectives of modeling. Barnett et al. (1996) used several crop growth simulation models and weather data to attempt to predict a great deal of historical yield data from England. The results are alarming; at best predictions were uninformative, at worst, uninformative and biased.

On-farm experimentation, automated by site-specific technologies, offers an alternative to both extrapolation of small-plot studies and complicated systems models that suffer from huge data requirements.

CHAPTER 2

IMPLEMENTING AND CONDUCTING ON-FARM WEED RESEARCH WITH THE USE OF GPS

Summary

The adoption of precision technologies that spatially register measurements using global positioning systems (GPS) greatly facilitates conducting large-scale on-farm research. On-farm experiments that utilize producer equipment include testing variations in agronomic practices that occur in situations where we want to predict the effect of inputs on yield. The domain of inference for such on-farm studies therefore more closely matches that desired by applied researchers. To investigate the feasibility of on-farm research using GPS, a study was conducted to evaluate the potential benefit of site-specific weed management. The study utilized producer maintained field-scale equipment on four Montana farms in dryland spring wheat production. Paired site-specific and whole-field herbicide treatment areas were established in 0.9-1.9 ha blocks using consultant weed maps and a geographic information system (GIS). Yield was unaffected by herbicide treatment strategy (site-specific or broadcast). Minimal detectable yield differences were evaluated for the experimental design (0.2 T ha^{-1}). Net returns increased when the percentage of field infested by wild oat decreased. Visual ratings of wild oat density taken at harvest indicated no difference in wild oat control between treatments in two of four site-years. This research suggests that producer owned

equipment can be used to compare treatments, but the accuracy and subsequent power of such comparisons are likely to be low.

Introduction

A great deal of work has been conducted over the past decade investigating the potential economic and environmental benefits of site-specific weed management (Johnson et al. 1997). As Gotway-Crawford et al. (1997) state, site-specific management is "based on an almost self-evident philosophy with which few agriculturalists would argue." Clearly it does not make sense to spray herbicides where weeds are not present. However, uncertain knowledge of weed distribution, the limitations in performance and reliability of technologies, and the uncertainties in short and long term effects of management decisions, make adoption of site-specific technologies less than obvious. In order to evaluate site-specific weed management so that the evaluation includes all of the uncertainty faced in real production situations, we need to use on-farm research.

On-farm research offers many advantages over experiment station or laboratory experiments. On-farm studies are cost effective, foster mutual learning between researchers and producers (Spaner et al. 2000, Wuest et al. 1999), and allow for inference of treatment effect without extrapolation (Gotway-Crawford et al. 1997, Rzewnicki et al. 1988).

Technologies associated with precision agriculture such as crop yield monitors, variable rate application equipment, and geographic information system (GIS) software, provide a means to automate the on-farm experimental process. Inputs can be applied

strategically so as to gain information on site-specific crop response to input treatments. By collecting spatially referenced crop yield information in conjunction with the controlled placement of inputs, the causes of yield variation can be investigated (Gotway-Crawford 1997, Schroder and Schnug 1995). Inclusion of additional spatial data layers, e.g. soil or environment data, may also improve response modeling and result in better decision making (Cook and Adams 1998) and understanding (Johnson et al. 1997). Spatial coincidence provides information about correlative relationships. However, to insure correlations are causal rather than spurious, it is necessary to study a large number of sites or apply treatments to different areas of a field in an unbiased manner (e.g. some form of randomized design).

Weed spatial variation offers the potential for more cost and input efficient weed management (Johnson et al. 1997, Mortensen et al. 1998). This possibility has been investigated via measurement of weed density distribution by spatial sampling (Christensen et al. 1996, Heisel et al. 1996, Rew et al. 1996, Williams et al. 1998), sampling in conjunction with interpolation (Johnson et al. 1995), or simulation (Maxwell and Colliver 1995, Oriade et al. 1996, Paice et al. 1998). The use of simulation to examine different management strategies is a low-cost alternative to field experimentation provided the model used is realistic. However, the trend toward increased adoption of site-specific technologies makes it possible to experimentally validate findings of simulation, or analyses based on weed density frequency distributions, by directly measuring system response to different treatment strategies. Some authors have called for on-farm case studies to confirm economic assessments of

precision technology (Pratley and Lemerle 1998). To our knowledge, no other on-farm, field-scale, weed control experiments have been attempted that use producer owned equipment to compare spatial application strategies.

Heisel et al. (1997) tested a decision algorithm for patch spraying (DAPS) that allowed for the use of variable herbicide dose. The authors experimentally demonstrated a reduction in herbicide use of 59% by comparing different treatments (site-specific spray, broadcast spray, no spray) within replicated, randomized blocks on one 4 ha field. Their results document no increase in at-harvest weed coverage in the DAPS treatment relative to the broadcast treatment. Further whole-field studies (Heisel et al.1999) were conducted using DAPS. The whole-field studies confirm the potential reduction of herbicides, however the whole-field experiments use a single application strategy (DAPS) over the entire field.

As an alternative to comparing the outcomes of "black box" application strategies for evaluating site-specific weed control, Williams et al. (1998) compared weed count frequencies distributions before and after implementing site-specific weed control. The authors demonstrated substantial herbicide reduction without significant alteration of weed count frequencies.

Most theoretical analyses indicate cost savings from the use of precision technologies are likely to be small (Christensen and Walter 1995, Olesen 1995, Oriade et al. 1996). Models allowing for variable herbicide rate application, thresholds, or multi-year optimization based on population simulation have shown greater potential economic benefits than applying herbicides based on presence/absence of weeds (Heisel et al. 1996,

Maxwell and Colliver 1995). These theoretical investigations need to be augmented by on-farm, field-scale studies that compare different treatment strategies. On-farm experimentation provides a means to validate the outcomes of theoretical models and ultimately the value of precision technology to the producer.

The objectives of this research were: (1) to examine the feasibility of using precision technologies and spatially referenced data to implement, conduct and evaluate on-farm weed research; 2) compare net returns of broadcast versus site-specific herbicide application; and 3) to test the usefulness of a simple economic model to quantify the relative advantage of patch spraying.

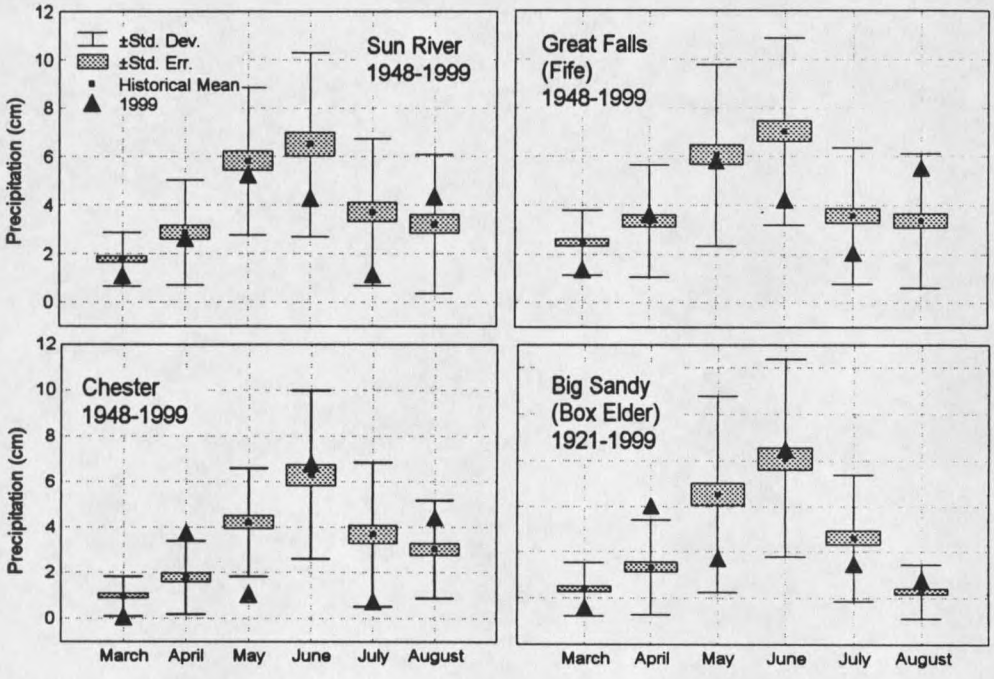


Figure 2.1. Historical and 1999 precipitation for study sites.

Materials and Methods

Field studies were conducted in 1999 on four fields in Sun River, Fife, Box Elder and Chester, Montana. Fields selected were historically seeded to a small grain, had a history of *A. fatua* infestation, and were harvested by combines equipped with a differential global positioning system (DGPS) and a yield monitor. *A. fatua* infestation varied greatly between sites (29-93% of the field area was infested as estimated from the consultant mapping procedure described below). Field information is presented in Table 2.1. Historical and 1999 growing season precipitation are shown by month in Figure 2.1.

Table 2.1. Site information for the four sites in the study. Plot and total areas are shown as well as number of replicates, type of yield monitor, and percentage of field infested and sprayed.

Site	Area[a]			Reps	Yield Monitor	Infested	Sprayed
	Total	BC	SS				
	——— ha ———					— % —	— % —
Sun River	16.2	0.82	0.93	8(12)	RDS Ceres 2	93	95
Fife	28.3	0.91	1.02	13	AFS	50	59
Box Elder	21.1	0.65	0.76	12	RDS Ceres 2	30	46
Chester	12.1	0.41	0.50	12	Agleader	29	40

[a] Total field area (Total), average area of the broadcast herbicide treatment area (BC) and average area of the site-specific herbicide treatment area (SS)

Some of the fields contained minor infestations of broadleaf weeds. The Sun River, Fife and Box Elder sites contained Kochia (*Kochia scoparia*) and the Box Elder site was also infested with Russian Thistle (*Salsola iberica*). In each field, the producers treated the broadleaf infestations as if the experimental fields were no different from any other field on their farm. The experimental study focused on the site-specific treatment of *A. fatua* because it is such a widespread problem in dryland cereal production, there are few POST herbicide options, and all options are relatively expensive.

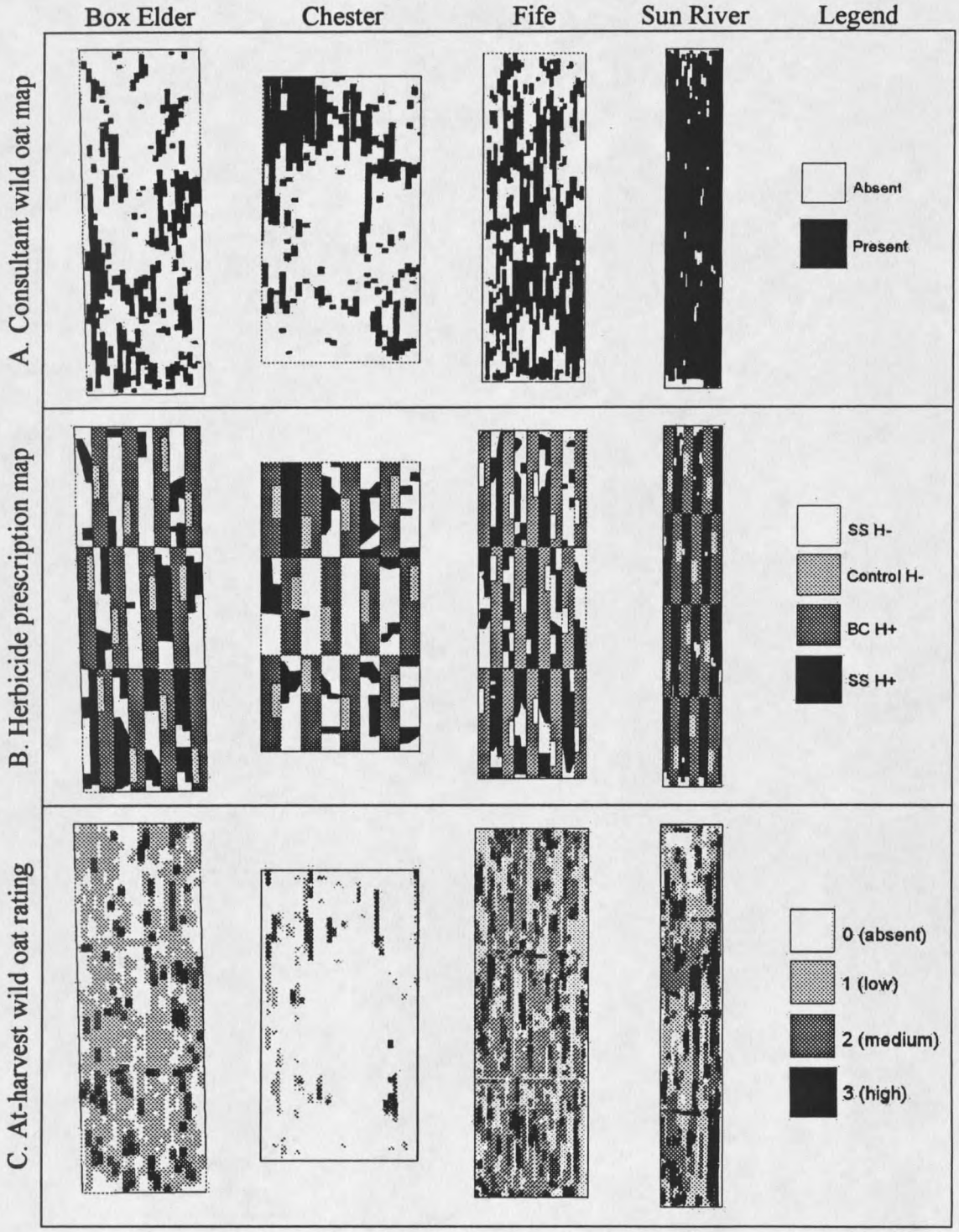
A crop consultant mapped *A. fatua* patches on all study sites during the 2-6 leaf stage of *A. fatua*. Weed mapping was accomplished using an all-terrain vehicle equipped with a DGPS and a computer[1] that performs real-time differential correction and location marking. The consultant surveyed the field for *A. fatua* by toggling a switch between two possible settings (representing presence and absence) while driving back and forth across the field on parallel 9.2 m wide transects (swaths). The computer automatically recorded the position of the switch every second. The positions marked as present (weed infested) were then made into 9.2 m wide weed "patches" with GIS software (Figure 2.2, top row of graphics).

Each field was subdivided into 12 to 14 replications. Four replicates were discarded from the analysis at the Sun River site due to sprayer malfunction. Replications contained a broadcast (label rate) *A. fatua* herbicide treatment and a site-specific *A. fatua* herbicide treatment. The entire plot area was sprayed with herbicide in the broadcast treatment.

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[1] Ashtech Ag Navigator, Model RDAC, Magellan Corp., 469 El Camino Real, Santa Clara, CA. 95050.

Figure 2.2. Consultant weed maps, experimental herbicide prescription maps and at-harvest wild oat infestation ratings for the four study fields.



Only the areas mapped by the consultant as infested with *A. fatua* were sprayed in the site-specific herbicide treatment (Figure 2.2, middle row of graphics). The experiment also included a no-spray treatment embedded within the broadcast application. This treatment was included for a companion study (Luschei et al. 2000). The experimental herbicide application was accomplished by creating a "prescription" map using a GIS. Each treatment was approximately 32 m wide (2 sprayer boom widths) and length varied by field. The plot sizes for each field are given in Table 2.1.

A sprayer equipped with a computer[1], DGPS and a rate controller[2] was used to apply the herbicide according to the prescription map. Herbicides and surfactants were applied at the recommended label rates. Imazamethabenz was applied at 0.34 kg ai ha^{-1} with 0.25%v/v NIS at the Sun River site. Fenoxaprop was applied at 0.093 kg ai ha^{-1} at the Fife site. Tralkoxydim was applied at 0.20 kg ai ha^{-1} with 0.5% v/v NIS and 1.7 kg ha^{-1} ammonium sulfate at the Chester and Box Elder sites. All herbicides were applied in water at 125 L ha^{-1} through 8003 spray nozzles spaced 76.2 cm apart on a boom placed 76.2 cm above the plant canopy traveling at 8.05 km/h. Herbicides were applied 2 to 3 d after *A. fatua* was mapped.

Fields were harvested with producer maintained combines equipped with yield monitors and GPS (Table 2.1). The producers calibrated the yield monitors according to manufacturer protocol. In the case of Sun River, the volumetric sensor in combination with low yields produced an erratic correlation between grain weight and monitor readings. The adjustment of a "calibration number" to compensate for this difference

[2] Mid-Tech TASC 6300, Midwest Technologies, Inc., 2733 E. Ash, Springfield, IL. 62703.

was frequently impossible. This error resulted in an underreporting of yields by the monitor of 40% of the average yield as weighed at the truck scale.

Prior to harvest, one header-width was cut with a combine from the end of each replicate perpendicular to layout of the plots. This generated a 20 m wide strip that had no wheat between replicates to allow for compensation of "lag" (time delay for grain to pass from the header to yield sensor) on the yield map. Further processing of yield data followed procedures outlined in Moore (1997). Yield data was removed from the data set if points were within 5 m of plot boundaries. Data was also deleted if it occurred in areas already harvested, or on corners where the combine speed or direction was changing substantially. Values were moisture corrected to 13.5% (Pierce et al. 1997).

A. fatua infestation levels were visually estimated at harvest from the combine by a researcher using a DGPS in combination with a computer[1] (Figure 2.2, bottom row of graphics). *A. fatua* was rated into 4 categories: none, low, medium, and high which corresponded to 0, 0 to 10, 10 to 50, and 50 to 100% cover by *A. fatua*, respectively. The same researcher rated all fields. Whole plot estimates of yield and weed density at-harvest were calculated by averaging all yield and *A. fatua* at-harvest rating values that occurred within a plot.

There are many techniques for utilizing the spatial aspect of information to improve accuracy in the comparison of treatment effects (Gotway-Crawford et al. 1997, Long 1998, Mulla et al. 1990, Scharf and Alley 1993). A simple alternative that removes (but does not allow the estimation of) spatial variation is a paired comparison test. To compare the efficacy and profitability of site-specific versus broadcast *A. fatua*

management, a paired t-test was used to analyze the distribution of differences in yield, net profit, and at-harvest *A. fatua* infestation. Feasibility of conducting on-farm research using the precision technology currently available to farmers was examined by determining the power (probability the design would have correctly rejected the null hypothesis if the "true" treatment difference were greater than or equal to the observed difference) and minimal detectable difference (the magnitude of mean difference that would be required before the test would be significant) for the design and analysis implemented in this research.

The profitability of site-specific versus whole-field *A. fatua* management was investigated with a simple economic model. For the full-field and patch-spray strategies, the net return was calculated:

$$NR = \hat{y} \cdot (1-\delta) \cdot p - ((c_{herb} \cdot \gamma) + (c_{tech} \cdot \beta) + c_{other}) \qquad (2.1)$$

Where $\hat{y}$ is the expected weed-free yield, δ is the proportional yield loss due to the treatment, p is the crop price, c_{herb} is the herbicide cost, γ is the proportion of the field targeted (sprayed), c_{tech} is the cost of the technology (includes the cost of obtaining the weed map and rental of extra sprayer technology), β is 0 for the broadcast treatment and 1 for the site-specific (patch) spray treatment, and c_{other} is all other costs (e.g. husbandry). The difference in net returns between the broadcast and precision spray treatments can be calculated:

$$\Delta_{NR} = NR_{SS} - NR_{BC} = -\hat{y} \cdot p \cdot \delta + c_{herb}(1-\gamma) - c_{tech} \qquad (2.2)$$

When net return is equal between broadcast and precision spray ($\Delta = 0$), the percentage of field targeted is:

$$\gamma = 1 - \frac{c'_{tech}}{c_{herb}} = 1 - \frac{(c_{tech} + \hat{y} \cdot p \cdot \delta)}{c_{herb}} \quad (2.3)$$

The proportion of the field targeted that results in a threshold (indifferent, Δ=0) net return can thus be predicted by the size of the effective technology cost (c'_{tech}) relative to the herbicide cost. The effective technology cost is the sum of direct costs (mapping, technology spray costs) and the value of lost yield due to weed escapes resulting from inaccurate herbicide application. It follows that if the value of lost yield due to escapes in site-specific herbicide treatment exceeds the difference between herbicide cost and direct technology costs, then site-specific spraying will never increase net return over broadcast. It is essential to measure yield differences between patch and broadcast herbicide application in experimental evaluation of precision weed control.

Economic parameters were: p = grain price = \$114 T^{-1}, c_{other} = non-weed control costs = \$123.55 ha^{-1}, c_{herb} = herbicide cost = \$44.48 ha^{-1}, c_{tech} = mapping (\$9.89 ha^{-1}) and additional technology application (\$2.47 ha^{-1}) costs = \$12.36 ha^{-1}. This technology cost represents the price charged for these services in Montana in 1999.

Results and Discussion

Net return of site-specific management improved as the percentage of the field requiring treatment decreased (Tables 2.1 and 2.2). As net return is a variable calculated directly from yield and constant economic parameters, this follows directly from the

economic model (Equation 2.1). The mapping and technology application fee costs associated with hiring a consultant and custom herbicide application were \$12.36 ha^{-1} making the break-even targeted percentage 72% (calculated from Equation 2.2, assuming no adverse yield impact resulting from herbicide or weed escapes and a weed control cost of \$44.48 ha^{-1}). The Sun River site was 95% treated and displayed no advantage of site-specific over broadcast treatment (Table 2.2). This result is consistent with the economic model (Equation 2.3). The Fife site was 59% treated and did not show an advantage to site-specific treatment because a negative impact on wheat yield caused by *A. fatua* escapes reduced the break-even targeted percentage to 56% (Equation 2.3). The Box Elder and Chester sites had improvements of \$14.21 ha^{-1} and \$20.00 ha^{-1} with targeted percentages of 46% and 40% respectively. These results were significant and consistent with Equation 2.3

The precision treatment did not influence *A. fatua* control in two of four fields (evaluated with mean at-harvest *A. fatua* ratings), though the tests had low power (Table 2.3). Both broadcast and site-specific herbicide treatments produced similar wheat yields. The minimum detectable difference of the design, with $\alpha = 0.1$ and $(1-\beta) = 0.8$, was approximately 0.2 T ha^{-1} at each site.

Yield differences between treatments are therefore likely to be smaller than 0.2 T ha^{-1} (8-30% of the average yields of the various fields). While this level of sensitivity (inability to judge differences smaller than 0.2 T ha^{-1} as significant) may be insufficient to provide comfort to weed management decision-makers, it is common in many agricultural studies (Cousens and Marshall 1987) that neglect consideration of design

Table 2.2. Means and standard deviations of the within-replicate differences in yield, net return and at-harvest wild oat rating between site-specific and broadcast herbicide applications for each of the four study sites.

Site	Relative Yield		Relative Net Return		Relative AHR	
	$\bar{d}$	s	$\bar{d}$	s	$\bar{d}$	s
	—— T ha^{-1} ——		—— \$ ha^{-1} ——		—— (0-3) ——	
Sun River	0.08	0.19	-3.20	21.33	0.03	0.46
Fife	-0.06	0.19	-0.59	25.17	0.39 *	0.15
Box Elder	0.02	0.20	14.21 *	21.56	0.24 *	0.29
Chester	0.04	0.17	20.00 *	21.52	-0.02	0.21

[a] $\bar{d}$ = Estimate of the mean of within replicate differences of response variable (site specific - broadcast value), s = estimate of standard deviation of within replicate differences.

power when interpreting treatment differences.

These results highlight the importance of assessing whether the use of site-specific weed control compromises control efforts and/or causes a yield impact. Any decreases in control would serve to add to future costs and increase the effective technology costs. This would in turn depress the breakeven targeted percentage in Equation 2.3. The logic is analogous to the manner in which consideration of future impacts depresses the value of the economic threshold.

The measurements obtained from yield monitors are potentially influenced by many sources of error (Pierce et al. 1997). Although this uncertainty directly influences our capacity to draw conclusions from site-specific data, the nature of these sources of

Table 2.3. Experimental design power and minimum detectable difference for the observed difference between yield, net return and wild oat at-harvest infestation rating.

Site	Reps	Yield		Net Return		At-Harvest Rating	
		mdd	Power	mdd	Power	mdd	Power
		— T/ha —		— $/ha —		— 0-3 —	
Sun River	8	0.24	0.22	26.52	0.12	0.57	0.10
Fife	13	0.19	0.21	24.55	0.10	0.15	0.99
Box Elder	12	0.20	0.11	21.89	0.49	0.29	0.65
Chester	12	0.17	0.16	21.85	0.74	0.21	0.11

error has not been the subject of much study. Moore (1997) performed the most comprehensive study to date and concluded that our knowledge of the error associated with point estimates of yield from yield monitors was severely lacking. Previously, attention has been focused on assessing the accuracy of yield estimates over large areas. While this may provide comfort to those interested in comparing large-scale treatments (e.g. variety trials), it is a hindrance to those seeking to use the information in a more surgical way. Researchers attempting to develop relationships between different spatial layers (e.g. soil properties or weed densities) or the impact of different inputs, need to know how much of the variation in the relationships are measurement error as opposed to variation caused by biological and chemical processes.

Use of data generated by precision farming raises several data quality and management issues. Some measurements made by the yield sensor are clearly erroneous (e.g. where the combine is turning or changing speed). Moore (1997) estimated that 37% of the data from his trials needed to be censored. Some harvest monitors automatically remove measurements that meet "outlier" criteria. While outlier removal may improve

the smoothness of maps and decrease human processing time, it complicates the scientific use of such data where indiscriminant outlier removal is not acceptable practice.

In our study we sought a balance between the number and size of replicate plots such that we would minimize the error associated with the estimate of within-treatment yield. The two primary measurement errors associated with a yield monitors are the "lag" where there is a relatively consistent delay of grain moving from header to sensor, and "redistribution" where the movement of grain to the sensor takes a variable amount of time. The use of "true zeros", cutting out specific portions of the crop before the main combining operation, allowed for correction of the lag effect (for those units that do not automatically correct for lag) and an estimate of plot size necessary to minimize the impact of the redistribution effect. Others (Pierce et al. 1997) have commented that the redistribution effect is important for "short" time intervals (5 –15 s), which corresponds to a distance of 7-21 m for a combine traveling at 5 km h^{-1}.

The influence of grain redistribution on the plot size necessary to minimize the error in yield measurement is worthy of much more detailed study as it is potentially dependent on many factors (e.g. level of yield, time of day or moisture level, presence of weeds, etc.). The power of statistical tests to detect differences could be increased if the plot size in the on-farm experiment were decreased without increasing measurement error in yield. Increased statistical power is needed to improve our ability to test hypotheses in field scale research. In this study, the minimum detectable yield difference of the design represented a substantial proportion of the mean yield.

Despite the fact that we cannot attribute variation in yield to that caused by measurement error or intrinsic yield variability, the use of precision technology resulted in less herbicide being applied. The extent of the reduction was a function of the degree to which the field was mapped as infested. The consultant presence/absence ratings were made at a spatial scale of 9.2 m, whereas the maximum resolution of targeted spraying was 16 m (1 sprayer boomwidth). The inability to target weeds at the scale of the weed map increased the proportion of area sprayed in the site-specific treatments between 2-16%. This difference represents the potential gain of finer-scale precision herbicide application. However, attempted high-resolution targeting brings with it greater potential risk of misapplication and escapes.

Accurate evaluation of the cost-effectiveness of precision technologies is hampered by low power in the determination of yield impacts that might indirectly ensue from use of the technology. This experimental design power could be increased by increasing the number of replicates or by reducing the variation in the estimates of treatment yield. A better understanding of errors associated with point estimates of yield would allow for increased replication by reducing plot size.

In the present study, the use of precision technology to administer a field-scale experiment and test hypotheses with data gathered by producer maintained equipment was successful. Given the increasing number of combines equipped with yield monitors, increased adoption of on-farm experimentation will greatly strengthen the researcher's capacity to make statements about treatment differences without the uncertainty of long distance extrapolation of experiment station results. As engineers continue to improve

the functioning of the technology, including estimation of point error, agricultural experimentation will be enabled at an appropriate scale for inferring local results. Previously this scale of research was prohibitively expensive.

On-farm weed research into application strategies other than broadcast will be more easily executed as the GIS applications and rate controller technologies improve. Given sufficient automation, producers may be able to conduct on-farm experimentation and analysis without direct involvement of academic researchers. Furthermore, although we tested only binary (no spray or 1X rate) spatial spray strategies (or decision rules) in this study, the methodology is general enough to accommodate comparison of any spray strategy. For instance, the effect of including a reduced rate buffer area around areas mapped as infested could be investigated. If methods are developed to generate inexpensive weed density maps from remote sensing, real-time sensors or an understanding of weed demographics, then strategies based on that information (e.g. use of thresholds or density optimized rates) could be experimentally compared.

CHAPTER 3

PARAMETERIZING WEED INTERFERENCE MODELS WITH SITE SPECIFIC DATA

Summary

Interference models can be parameterized on the field scale with weed seedling and crop yield data. Local parameterization attempts to reduce the noise in observed relationships by removing large-scale spatial variation. This process is made economically feasible by the increasing availability of site-specific yield data. As detailed information on weed spatial distribution is expensive to collect, a procedure that utilizes crop consultant scouted weed maps calibrated with quadrat sampling data was developed. The results of parameterization using calibrated consultant maps and interpolated quadrat counts were compared for five site-years of data from north-central Montana. The economic consequences of different weed control strategies were investigated using relationships derived from the two methodologies.

Introduction

Many weeds are distributed in patches or restricted areas of fields (Colliver et al. 1996, Marshall 1988, Mortensen et al. 1993). In these instances, applying control measures over the entire field may be unnecessary, as targeting application of herbicides to weed patches may increase net returns (Colliver et al. 1996, Felton et al. 1991, Heisel et al. 1996, Johnson et al. 1995, Rew et al. 1996). Until the day when accurate automated

weed detection systems are available, applying herbicides or any other input-based weed management tactic to an entire field will remain substantially less complicated than deciding which parts of the field require treatment.

The simplest method for determining which area of a weed-infested field to spray is to use the subjective judgment of a producer or a crop consultant. Judgment can either be rendered on a whole field basis with a subjective 'visual threshold' (Cousens 1987), or spatially encoded in a map based on an observer detection threshold.

A large literature exists on more complicated attempts to quantify and formalize various definitions of weed control thresholds. Most of these efforts depend on estimating density in a field or patch. Cousens (1987) noted that such efforts are beset with difficulties associated with sampling and its expense. The cost of acquiring detailed quantitative information on weed abundance is large and prohibitive for any purpose other than research. Colliver et al. (1996) compared accuracy and cost of weed density sampling by interpolated quadrat count, perimeter mapping and at-harvest weed abundance rating. Perimeter mapping was the most economical alternative because of the large amount of time required to sample spatial distribution with quadrats.

Statistical interpolation procedures have been investigated extensively (e.g. Cardina et al. 1995, Johnson et al. 1996) in the hopes that additional information on weed abundance could be extracted from sparse sampling schemes. Unfortunately, the spatial scale of correlation is often variable and too small to create accurate density maps without expensive, cost prohibitive, intensive sampling.

Interest and research on the subject of quantified thresholds has dwindled, yet any decision to forgo control measures in sections of a field uses an unknown detection threshold. The effect of gathering spatial information with a (perhaps variable) detection threshold may be assessed a posteriori by quadrat sampling. By creating a distribution of weed density counts in the areas mapped weeds present or weeds not present, the scout's classifications can be calibrated. When the field is sectioned into a grid, the proportion of each grid cell that occurs in each classification type (weeds present, weeds not present) can be assessed. Weed density within a cell is then calculated as the proportion weighted sum of the means of each class. This calibrated consultant map (CCM) process combines the accuracy of quadrat samples and the efficiency of the scouting map to generate an affordable weed map. The accuracy of the map is determined by the sampling process and relies on the interpolated areas being sufficiently large relative to size of the sampling quadrat and the range of spatial correlation of the weed.

The availability of a low-cost weed density map in conjunction with a yield map provides a basis for the parameterization of yield response models to assess management strategies. A large number of modeling techniques have been employed to predict yield response to inputs (e.g. Cook and Adams 1998), particularly in the area of nutrient management where interpolation is an effective remedy for sparse sampling. Modeling techniques for predicting crop response to various inputs or limiting conditions (e.g. pests, drought) have been theoretical in nature (e.g. growth simulation or mechanistic models) or phenomenological (e.g. regression, neural-network, AI, fuzzy clustering)

(Cook and Adams 1998). Whatever modeling framework is chosen, the problem remains of estimating parameters and (for stochastic processes) their probability distributions.

The complex nature of plant growth in relation to biotic and abiotic factors limits (in space and time) the accuracy of parameter distributions estimated for phenomenological relationships. This has been shown repeatedly for the case of weed interference (e.g. Lindquist et al. 1996). One of the most promising uses for data generated by precision farming operations is the potential to parameterize phenomenological models at a particular site. The hope is that, by removing large-scale regional variability, the parameter distributions for the model parameters will correctly assess prediction accuracy on that site and the predictive power will be usably high.

Once a model has been developed, it can be used in the context of a decision system (e.g. Christensen et al. 1996). Heisel et al. (1997, 1999) reported substantial savings using the decision-algorithm-for-patch-spraying (DAPS) system (Christensen et al. 1996). The success of such efforts depends on accuracy of the weed map, yield response model, and spatial control measures.

In order to use data from precision farming operations to improve the accuracy of local yield response models, elements of experimental design must be incorporated into precision application of inputs. This method of on-farm experimentation has become promoted as a way to add value to the precision technology and improve our (albeit phenomenological) understanding of yield response (Schroder and Schnug 1995, Cook and Adams 1998). Application of herbicides should be randomized with respect to presence and absence of weeds, however this is difficult to implement because producers

are uncomfortable with large weedy areas being left untreated. While this conflict of objectives poses a problem for conventional analytical techniques, more sophisticated analysis approaches, such as a Bayesian framework, allow for such unbalanced designs.

The goal of this paper is to model yield response to weed density as an example of how precision technologies can be used to generate locally parameterized models. The analysis will utilize data collected on four Montana farms where on-farm experiments were conducted. The specific objectives are to (1) relate crop yield to weed density on two different spatial scales, (2) investigate what spatial scale of analysis is most promising, (3) contrast the effect of two different yield interpolation procedures in this analysis, and (4) demonstrate the usefulness of locally derived yield relationships for estimating cost effectiveness of different management strategies.

Materials and Methods

Field studies were conducted on one field in 1998 in Fife, MT (F-98) and on four fields in 1999 in Sun River (SR-99), Fife (F-99), Box Elder (BE-99) and Chester (C-99), Montana. These fields were historically seeded to small grain, had a history of wild oat, and were going to be harvested by combines equipped with a GPS and yield monitors. Wild oat infestation level varied greatly between sites (25-93% by field as estimated from the consultant mapping procedure described below). Field size ranged from 12.1 – 28.3 ha.

Weed density mapping procedures

Wild oat quadrat density sampling was accomplished 1-4 days before the consultant mapping procedure. Fields were mapped on a 20 m grid with a 0.28 m^2 rectangular quadrat. Sample points were geo-referenced with a GPS. Although this sampling scheme covered less than 0.1 % of the total field area, it required approximately 300 man-hours to complete (~ 8 minutes per sample).

A crop consultant mapped wild oat patches at each study site during the 2-6 leaf stage of wild oat. Wild oat mapping was accomplished using an ATV equipped with a Trimble DGPS and an Agnavigator. The consultant marked the presence/absence of wild oat while driving transects spaced every 9.2 m. The tagged points were made into 9.2 m wide rectangular weed "patches" with GIS software.

Weed treatments, yield data collection and processing

The fields were divided into treatment blocks that consisted of a broadcast herbicide treatment, site-specific herbicide treatment and no-spray controls. Experimental design was chosen to facilitate an economic comparison between treatments (Luschei et al., 2001). The design was encoded as a prescription map with a GIS.

A sprayer equipped with an Agnavigator, GPS and a MidTech Tasc 6300 rate controller was used to apply the herbicide according to the prescription map. Herbicides and surfactants were applied at the recommended label rates (see Luschei et al., 2001 for details). Herbicides were applied 2 to 3 days after the consultant created the perimeter map of the weed.

The fields were harvested with producer maintained combines equipped with yield monitors and GPS. The Sun River and Box Elder sites used RDS Ceres 2 monitors, Fife used AFS and Chester used Agleader 2000. Yield monitors were calibrated by the producers according to manufacturer protocol.

In the case of Sun River, the grain flow was often too low to be appropriately calibrated. The volumetric sensor in combination with low yields produced an erratic correlation between grain weight (as determined by individual truck weights) and monitor readings. As a result, the estimated yield for the entire field was 40% smaller than the average yield as weighed at the truck scale.

Two adjacent combine passes were made perpendicular to the direction of harvesting, effectively cutting the field into quarters. These "true zero" areas were used to positionally correct for the time it took grain to pass from the header to the yield sensor (i.e. grain lag). Further processing of yield data followed procedures outlined in Moore (1997). Points were deleted if they occurred in areas already harvested, on a corner, or were anomalous in other ways. Yield values were moisture corrected to 13.5%.

Analysis

Two different spatial scales were chosen for analysis: the spray boom and the quadrat. As these scales roughly correspond to the different scales on which information was collected, they minimize the 'measurement' error caused by interpolation of yield (for the spray boom or decision scale) or weed density (for the quadrat scale). In both analyses, a sample point/area was classified as sprayed or not sprayed. The yield response model was parameterized separately for each classification.

The decision scale analysis was accomplished by tiling the field in a 16 x 16 m cellular grid. Cells were removed from the analysis if they: intersected the "true-zero" harvested regions or had between 25 and 75 % of the cell area sprayed. If the area sprayed was less than 25% of a cell it was classified as not-sprayed and above 75 % it was classified as sprayed.

Yields were estimated for each cell as the arithmetic average of all yield points within a cell. Spatial correlation between weed quadrat counts was weak to non-existent and at most one count was taken within a cell. Therefore, interpolation or estimates of mean density were inappropriate. A calibrated consultant map (CCM) procedure was therefore developed to estimate weed density on that scale.

Quadrat counts were tagged as "in" or "out" of the consultant patch. Mean values were calculated for the resulting distributions $(\overline{x}_0, \overline{x}_1)$ where x_0 corresponds to weed densities that occur outside of a patch and x_1 corresponds to values occurring within a patch. The percentage of each cell mapped as "in" a patch (p_1) was then calculated and a weed density assigned to the cell:

$$x = p_0 \cdot \overline{x}_0 + p_1 \cdot \overline{x}_1 = (1 - p_1) \cdot \overline{x}_0 + p_1 \cdot \overline{x}_1 \qquad (3.1)$$

The resulting paired values of yield and weed density were subjected to a standard linear maximum-likelihood estimate of an intercept and slope for each of the sprayed and unsprayed areas. The decision scale relationship was used to estimate a yield in each cell under a whole field spray (H+), whole field no-spray (H-) and a site specific application (SS) strategy. One-year whole field net returns were calculated by summing the returns in each cell:

$$\pi_T = \sum_{cells} \pi_i = \sum_{cells} \left[y(x_i) \cdot p - \beta_i \cdot c_{herb} - \delta \cdot c_{tech} \right] - c_{other} \qquad (3.2)$$

Where y(x) is yield as a locally parameterized function of weed density, p is the grain price, \$114 ha^{-1}, c_{herb} is the herbicide cost, \$44.48 ha^{-1}, β is the proportion of the cell sprayed, c_{tech} is the technology cost applicable for site-specific strategy, \$12.36 ha^{-1}, (including mapping and application), δ=1 for the site-specific analysis and 0 otherwise, and c_{other} is other costs, \$123.55 ha^{-1}, (e.g. husbandry).

The second method of analysis was conducted on the scale of the quadrat. As yield monitors average over a combine header width (~10 m), values were assigned to quadrat counts by interpolating with "inverse distance weighting" (IDW, power 2) over a radius of 5 m. Points were removed from the analysis if they fell on edges of treatments or in "true-zero" areas. Resulting pairs of yield and weed densities were fit to a linear response model as described above. To investigate the importance of the yield interpolation procedure, the quadrat scale analysis was redone using local averaging (16 x 16 m) to assign yields to quadrat counts.

Results and Discussion

The CCM method parameter point estimates were substantially different than the quadrat scale estimates. Figures 3.1, 3.2 and 3.3 show the weed density versus yield for the different analysis methods on field F-98. Analysis using the quadrat scale resulted in slope parameter estimates for the sprayed and unsprayed areas that differed by 34% (Figure 3.1) and 26% (Figure 3.2) respectively, whereas the slope estimates for sprayed and unsprayed areas using the CCM procedure (Figure 3.3) differed by 60%.

The per unit effect of weed on yield (slope parameter) for the 16 m scale analysis was greater than 250% of the estimate in the quadrat scale analysis (Table 3.1). This difference was probably due to the fact that yield was determined (at a minimum) on the 10 m scale and individual samples of weed density were poor estimators of the mean on that scale. Use of the CCM procedure resulted in per unit weed impacts that were remarkably consistent (between fields and years). The estimates were also similar in magnitude to estimates of small plot interference experiments (Luschei, unpublished analysis) indicating the CCM decision scale analysis should be considered the preferred method of estimating wild oat density impact for this particular phenomenological model.

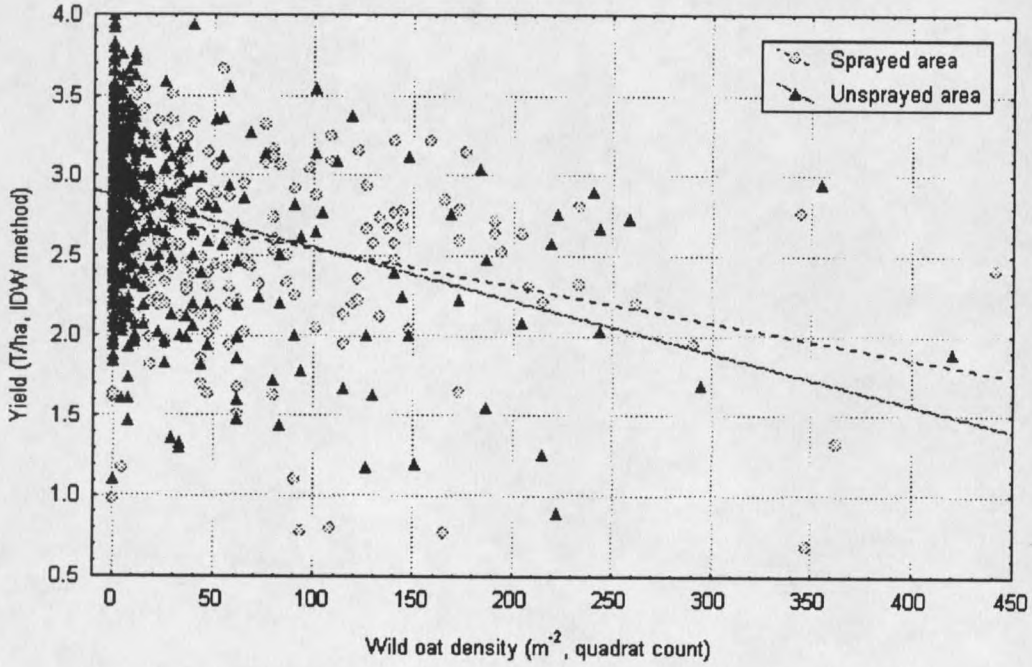


Figure 3.1. Data and response model for the quadrat scale analysis of field F-98 where yield values were determined using IDW.

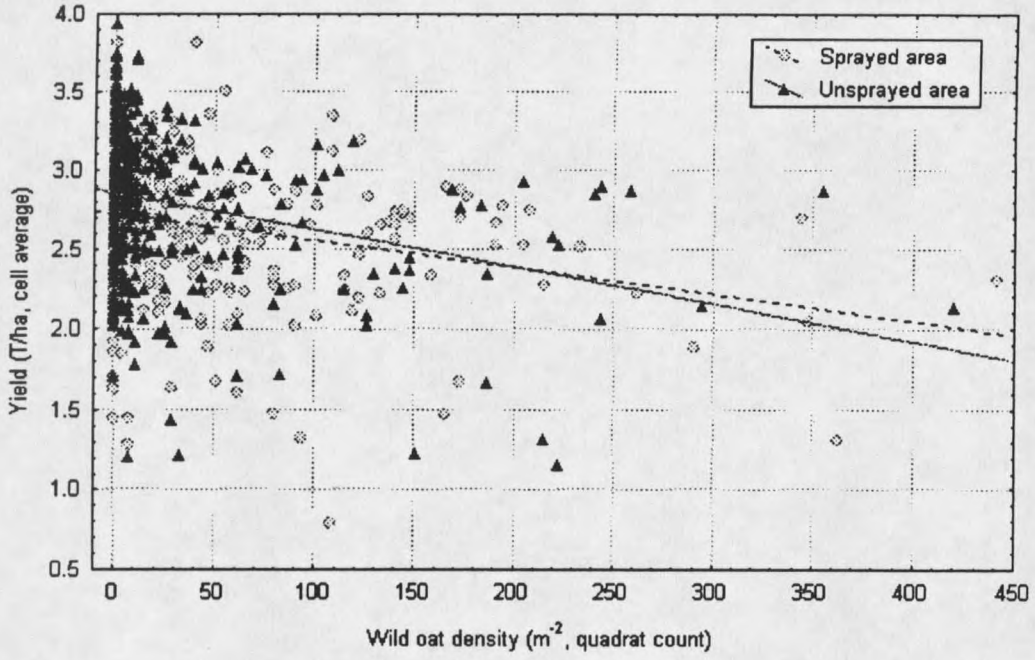


Figure 3.2. Data and response model for the quadrat scale analysis of field F-98 where yield values were determined by spatial average.

Different analysis methods produced relatively consistent estimates of expected weed-free yield (Table 3.1). The large value (3.13 T ha^{-1}) of the intercept for the unsprayed SR-99 field was caused by the extremely small number of cells that were unsprayed on that field and the relatively small difference between the means of the quadrat counts between areas marked in and out of patch by the consultant. This created a situation where measurement error in weed or crop had a large influence on the intercept.

The parameters estimated in Table 3.1 were used to estimate yield under the various strategies (H+, H-, SS). This estimate was used in Equation 3.1 to calculate single year net return under the strategy (Table 3.2).

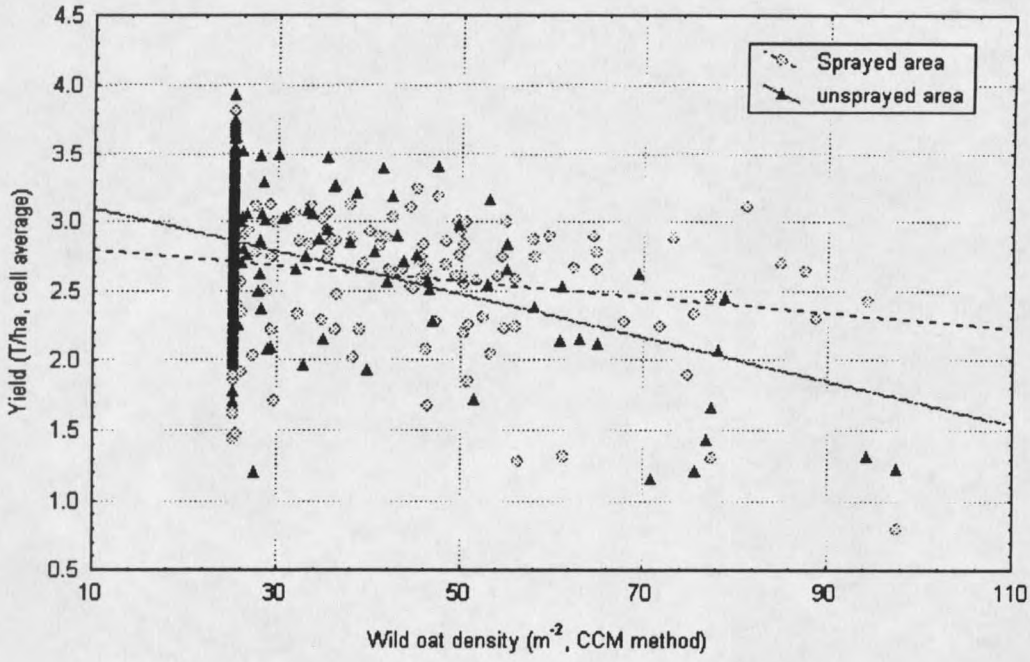


Figure 3.3. Data and response model for the decision scale analysis of field F-98 where yield values were determined by spatial average and weed densities were determine with the CCM method.

The only field where use of precision techniques did not result in a predicted advantage of site-specific over broadcast herbicide treatment was SR-99. SR-99 was estimated to be 93% infested by the consultant mapping procedure. In every case, net returns were highest when no herbicide was applied to control wild oats. However, this single year economic assessment does not take into account the future weed populations that could arise from lack of treatment.

Table 3.1. Site specifically parameterized functions for a linear yield response model parameterized on two different spatial scales with two different yield interpolation methods.[a]

Field	Parameter estimate					
	Decision scale		Quadrat scale 1		Quadrat scale 2	
	H+	H-	H+	H-	H+	H-
	Slope					
	$T\ ha^{-1}\ m^{-2} \times 10^{-2}$					
F-98	-0.70	-1.71	-0.21	-0.23	-0.17	-0.32
F-99	-0.80	-1.77	-0.21	-0.23	-0.22	-0.60
C-99	0.27	-1.42	0.26	-0.25	0.11	-0.39
BE-99	-0.02	-1.40	-0.22	-0.35	-0.24	-0.07
SR-99	0.06	-2.88	-0.22	-0.03	-0.21	-0.05
	Intercept					
	$T\ ha^{-1}$					
F-98	2.87	3.28	2.72	2.86	2.75	2.87
F-99	2.55	2.59	2.44	2.33	2.48	2.38
C-99	0.70	0.61	0.65	0.64	0.64	0.67
BE-99	1.17	1.27	1.22	1.29	1.22	1.30
SR-99	0.41	3.13	0.68	0.25	0.67	0.28

[a] H+ corresponds to herbicide treated areas, H- corresponds to untreated areas.

The economic results are consistent with the notion that the advantage of using site-specific herbicide application depends mainly on the proportion of the field to be targeted with herbicide (Luschei et al. 2001). The shift in the yield expected under a control measure can be estimated (a posteriori) from site-specific data. The extent that different sources of variation impact the parameter estimates in the relationship between yield and weeds has yet to be determined.

Table 3.2. Estimated per area net return under different weed control strategies using yield response functions locally parameterized with a decision scale analysis.[a]

Field	Net Return		
	H+	H-	SS
		$/ha	
F-98	134.22	190.38	174.92
F-99	103.93	131.65	103.96
C-99	-87.70	-66.16	-79.86
BE-99	-34.88	13.74	-15.71
SR-99	-110.47	-90.23	-119.55

[a] H+, H- and SS correspond to broadcast spray, no spray and site specific spray strategies respectively.

Possible sources of variation include spatial and temporal fluctuations in the process of interference itself (complexities of the biological interaction such as relative emergence time of the crop and weed, resource levels, etc.) or measurement error (including interpolation of different scale measurement onto the same scale). As individual producers collect parameter estimates for a given field over time, empirical frequency distributions can be developed to assess the probabilities of the yield impact induced by weeds. Empirical Bayesian methods provide the recipe for creating and updating these distributions over time and using them in prediction of future yield impacts by weeds.

The usual way to assess the relative ability of different interpolation methods is by subsampling data (e.g. Rew et al. 1997, Marshall 1988, Clay et al. 1999). While this procedure is effective for evaluating the prediction accuracy on the scale of the sampling unit, a decision made on a scale much larger than this unit must take into account error involved in the estimation of the decision scale property. The maximum resolution of the yield map is given by the size of the combine header. To ascribe values of yield determined by the combining operation to a quadrat-sized area introduces a potentially

large error. To then use the quadrat scale yield estimate in conjunction with a weed map that relies on interpolation to estimate unmeasured weed densities compounds measurement error. Developing relationships on the decision scale avoids the error in estimating yield on the quadrat scale. As a result, smaller values of slope parameter were consistently observed when using the quadrat-scale analysis compared to decision scale analysis.

We recognize that there are many issues related to model selection that may improve the "realism" of the interference model or account for a larger amount of the variation. However, such finesse may be unwarranted until issues surrounding the magnitude of error induced by the measurement and interpolation processes are better understood. The difference between the yield response of a linear and "saturation" type model would be much smaller than the difference due to measurement and data aggregation methodology.

Conclusions

Certainly there are many factors that can have a more dramatic effect on crop yield than the presence of weeds. However, the producer who is dealing with a weed problem may not be overly concerned with an explanation of the sources of variation. If the primary concern is expected present year yield impact if treatment is forgone, then this paper has outlined a methodology by which data may be utilized to estimate impact for the simplest of phenomenological models. The estimates may be obtained from yield maps in conjunction with consultant scouting maps, provided some quadrat samples are

taken to calibrate the meaning of the consultant ratings. As quadrat sampling can be tedious and expensive, an optimization of sampling is necessary. Future work will involve resampling the empirical wild oat quadrat count distributions to determine the consequences of minimizing the numbers of samples for calibration.

The ultimate usefulness of site-specific parameterization of weed damage functions depends on the capacity of the methodology to render accurate parameter probability distributions. When such distributions can be assessed, Monte-Carlo techniques can be used to evaluate risk within the context of the decision system. Bayesian methodology provides a framework within which individual producers can improve their ability to assess that risk over time. Our ability to determine the accuracy of parameter probability distributions is currently limited by our understanding of the error processes involved with measurement of yield and weed densities. As our understanding of error improves, so will the models and the promise of the technique.

CHAPTER 4

PREDICTING WILD OAT (*Avena fatua* L.) DENSITY THRESHOLDS IN WHEAT USING SMALL-SCALE COMPETITION DATA

Summary

A simulation study was conducted to investigate the effect of inclusion of soil moisture on the prediction of the economic threshold for a wild oat (*Avena fatua* L.) – spring wheat (*Triticum aestivum* L.) system in north-central Montana. Specifically, we consider whether inclusion of precipitation data are likely to improve predictability in light of the variation that is encountered in small-plot competition experiments (SPCE). The effect of model uncertainty, variation in precipitation, and lack of full knowledge of precipitation are investigated using a simulation model. The simulation model was used to generate data sets reflecting several different hypotheses about the interrelationship between moisture and wild oat competitive effect. Different candidate predictive models were parameterized with the simulated data in order to determine how prediction accuracy relates to models of varying complexity.

We investigated the impact of the following factors on prediction accuracy: (1) model complexity, (2) partial knowledge of the current year's rainfall and, (3) the presence of temporally constant yield-influencing factors. Our results indicate that inclusion of precipitation data with SPCE is likely to improve prediction, but that improvements may be relatively minor. We argue that on-farm or on-site experimentation may be able to overcome extrapolation problems that are inherent in SPCE and thereby improve production practices.

Introduction

On-farm weed control decision-making is often focused on consistent suppression of problem weeds. While this is desirable from a weed management standpoint, weed control decisions are but one element of the farming operation. Overall profit consideration underlie the justification of weed management input costs. Control costs can be lowered by decreasing herbicide rates or by temporally or spatially forgoing control, yet each of these tactics may cause an increase in the variability of profits. Input decision-making could be improved, in the presence of potential uncertainty in profits, if the response of the weed and crop to lowered input tactics were more predictable.

Most attempts to improve prediction have focused on the use of deterministic models and hypothesis-testing methodologies that have unequivocally demonstrated that few-parameter models do not have consistent parameter estimates across space or time (e.g. Lindquist et al. 1996, Jasieniuk et al. 1999, Lindquist et al. 1999). In an attempt to improve prediction, many researchers have investigated the effects of additional factors. The list of influences on weed-crop impact is long: relative time of emergence of the crop and weed (O'Donovan et al. 1985, Cousens et al. 1987, Blackshaw 1993, Dieleman 1996), available moisture (Mortensen and Coble 1989), pH (Weaver and Hamill 1985), soil type (Firbank et al. 1990), not to mention cropping system related attributes: crop planting date, variety, density, residue, tillage, row spacing, rotation and fertilizer placement.

Threshold-based post-emergence weed control decisions depend on comparing a predicted value of yield in response to a treatment against the cost of the treatment (Coble and Mortensen 1992). A brief overview of the threshold concept in weed science was given by Norris (1999) and earlier by Cousens (1987). The single-season or economic threshold (ET) was researched for many crop-weed combinations and have been cited elsewhere (e.g. Swanton et al. 1999, Lindquist and Knezevic 2001). There is frequent suggestion that we should improve impact prediction accuracy by including factors to account for variation in weed-crop impact prediction models (e.g. relative time of emergence of the crop and weed), yet it is rare to find studies that address potential overfitting or the generality of results that may come with increasing the number of model parameters.

Given that there are a multitude of potential influences on weed-crop competition, how should we go about trying to estimate impact and thereby predict the value of management effort? The answer has three components: model selection, parameter estimation and defining the "domain of inference" for the data used in selection and estimation. Modeling for prediction involves considering the first two components *in light of the data.* As Box (1976) states, "all models are wrong but some are useful." There is only a best choice according to some measure of model performance with respect to the data. The generality of the results directly reflects the degree to which the sample data reflected the "population" about which we want to make an inference (Firbank 1993a).

When a model is too simple, it cannot "track the signal" and can consistently under or over predict (i.e. it is biased). When a model is too complex it may "track noise" as if it were signal, and produce a large variance between predicted and actual results. Model selection procedures seek to balance such under and overfitting errors.

There are several theoretically well-investigated methods for identifying optimal model complexity. These approaches include resampling (e.g. jackknife cross-validation) and information theory (e.g. Akaike information criteria) based methods. Explanation of the methods can be found in many texts (e.g. Linhart and Zucchini 1986, Efron and Tibshirani 1993, Burnham and Anderson 1998).

An alternative way to examine model selection and generality involves making assumptions about the process (in our case the factors involved in determining weed impact on crop yield) and simulating the data gathering, parameter estimation and prediction processes. In fisheries, Ludwig and Walters (1985) used an analogous methodology to demonstrate that simple (non-age structured) models could sometimes improve decision-making, even when age-structure was determining the dynamics of the fish populations.

Dryland spring wheat production in north-central Montana is heavily influenced by plant available water. The majority of available water comes from growing season precipitation, particularly for areas in which crops are continuously grown. Thus, the value of production is dependent on the unpredictable weather. However, there are many other factors that can potentially influence yield. These non-moisture factors can also vary temporally and/or spatially. The spatial variation may furthermore manifest itself

over a smaller or larger scale than the data used to parameterize the predictive model. If we are predicting on a different spatial scale than we are gathering data, then we may exclude or include spurious sources of variation.

In this simulation based study we investigate the effect of including a measure of precipitation on single-year threshold prediction for spring wheat and wild oat systems of north-central Montana. The specific objectives were: (1) to investigate the accuracy of a hierarchy of increasingly complex models in determination of the economic threshold, (2) to determine the effect of our lack of knowledge of post-decision precipitation on threshold prediction accuracy and, (3) to determine the impact of a temporally constant yield-influencing factor on threshold prediction accuracy.

Materials and Methods

Evaluation of prediction accuracy

Having chosen and parameterized a model we have several methods by which to assess its predictive power. Conceptually, the most straightforward method is: use the model to predict and calculate a distribution of prediction errors (validation) from real observations. Provided the predictions are made for spatial scales similar to those we want to make future predictions for, and provided the sampling includes all of the variation we are likely to encounter in the future, this method will approximate the correct "domain of inference" but, it is potentially very expensive. In practice it is almost never done.

Given one or several data sets, we could use model selection methodologies to find the best predictive model. However, if the data do not include locations or spatial scales for which we want to predict, then we are left without any true measure of prediction accuracy and no way to assess the generality of results.

As an alternative, we examined a model that we assumed represented the process (that we will henceforth call the process model) and "simulated experiments" using the process model. We then analyzed the "experiments" and attempted to predict an independent trial (validation). The procedure was a "what if" scenario concerning the potential results of a validation. The details of the approach are described in greater detail below.

Clearly the significance of such validation results is dependent on the choice of process model and set of predictive models considered. However, we suggest that as parameter values and relationships are all consistent with the data from a large set of wild oat-cereal competition studies (Luschei, unpublished analysis) and corresponding environmental data, this methodology was a cost effective way to explore what kind of data should be collected in order to improve threshold-based decisions.

Simulated validation procedure

The simulated validation procedure began with a process model and process error. This model was used to simulate data from 8 independent SPCE between a weed and crop. A level of growing season precipitation was assigned to each SPCE based on a random draw from a distribution of precipitation records assembled for 985 (post-editing)

site-years of data from 27 sites within the "golden-triangle" wheat producing area of north-central Montana.

Non-linear least squares was used to fit the set of SPCE data with each of the models that range in complexity from 3- to 6-parameters (Table 4.1). The 6-parameter model was identical in form to the process model that generated the pseudo-data. We then performed 100 trials where we drew a random sample from the weather station records and calculated the predicted economic threshold from the predictive model to compare to the "actual" economic threshold that was computed from the process model. We also calculated the mean and standard deviation of the prediction error of the value of control at the threshold (the actual value was equal to the herbicide cost by definition). In order to examine the accuracy of using our set of SPCE to predict the value of weed control, we repeated the whole process 100 times and reported an average mean and an average standard deviation of the prediction accuracy.

Process model

For the process model, we used the functional form given in Table 4.1, where the parameters were established from experiment station data or biologically reasonable estimates. The process model form was selected based on the commonly used saturation function of chemical kinetics promoted by Cousens (1985):

$$y(x) = y_0 \cdot \left(1 - \frac{i \cdot x}{1 + i \cdot x / a}\right) \qquad (4.1)$$

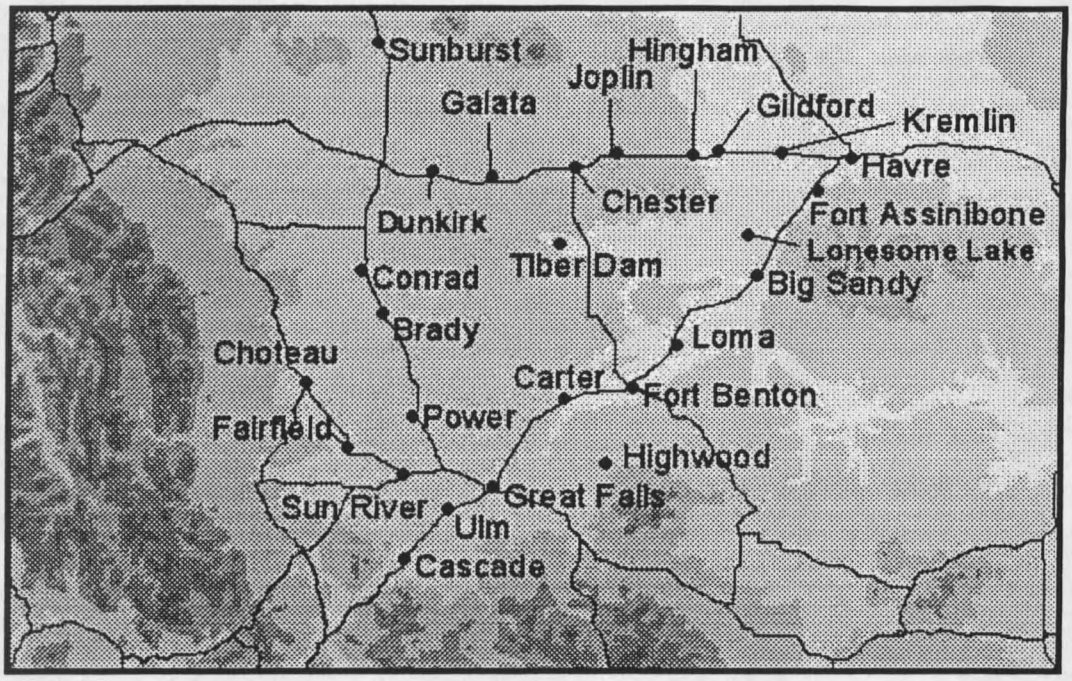


Figure 4.1. North-central Montana cities used for precipitation data records.

The variable x represented weed density, parameter y_0 represents the weed-free yield, and 'i' represents the per-weed yield impact for small weed densities, and 'a' represents the maximum proportional yield-loss. The process model included resource dependency (growing season precipitation or 'z') by expanding y_0 as a second order polynomial in 'z' and fitting the relationship to experiment station data (Engel, unpublished 3-year study, assuming 100 lbs a^{-1} nitrogen fertilization).

$$y(x,z) = (c_0 + c_1 z + c_2 z^2) \cdot \left(1 - \frac{(b_0 + b_1 z)x}{1 + (b_0 + b_1 z)x/a} \right) \qquad (4.2)$$

As it was unclear whether 'i' might also be a function of moisture (Mortensen and Coble 1989), we examined three separate cases, 'i' constant ($b_1 = 0$), 'i' a negatively

sloped linear function of growing season precipitation ($b_1 < 0$) and 'i' a positively sloped linear function ($b_1>0$).

The parameter 'a' in Equation 4.1 was assumed constant and equal to a value of 0.8 in order to simplify the interpretation of results. Variation in 'a' would have an effect on results, however, as the economic threshold was frequently found to be much higher than the density of 8 to12 plants m^{-2} widely reported as the economic threshold for wild oat (Cousens 1986). The parameters of the process model were:

$$\begin{aligned} c_0 &= -1.0557 \\ c_1 &= 0.4415 \\ c_2 &= -0.0070 \\ b_0 &= \{0.010, +0.0150, -0.0050\} \\ b_1 &= \{0.000, -0.0005, +0.0015\} \\ a &= 0.8 \end{aligned} \tag{4.3}$$

Where the three values listed for the b's correspond to cases where the 'i' parameter is a constant, negative and positive linear function of growing season precipitation.

Simulated small-plot data

The predictions were accomplished by simulating the results of an additive design experiment for sets of 8 SPCE. The weed densities used were {0, 10, 25, 50, 100, 200 plants m^{-2}} replicated four times. Process noise (Hilborn and Mangel 1997) was added to data, with $\varepsilon \sim N(1,0.2)$:

$$y_i(x,z) = y(x,z) \cdot \varepsilon_i \tag{4.4}$$

The noise was added in such a way as to produce a constant proportional variation rather than the constant absolute (additive) variation. This was in direct contrast to the assumptions of the regression model used to fit this data. If the factors responsible for process noise were connected with plant growth factors, then this assumption was reasonable.

The standard deviation of the proportion represented by the noise was 0.2 (or 20%). This value was a reasonable and conservative estimate of the level of process noise found in most wild oat small-plot competition experiments (Luschei, unpublished analysis).

Fixed site-factor

In order to determine the loss of predictive accuracy that might accompany the variation of a site-factor that differs from location-to-location but not year-to-year, each SPCE yield potential was multiplied by $\gamma \sim N(1,0.2)$:

$$y_0(z;\gamma) = (c_0 + c_1 z + c_2 z^2) \cdot \gamma \qquad (4.5)$$

All of the data from any SPCE (i.e. all of the plots in an additive design experiment) were multiplied by the same factor. This factor was called a "fixed site-factor" because it was designed to represent a temporally constant local influence on the yield (e.g. depth to hardpan). When extrapolating results, a different draw influenced the yield for the site where prediction was taking place, unless prediction was occurring in the same location.

Table 4.1. Process model and candidate prediction model structures. Parameters with "hats" are estimated from the SPCE data generated by the process model.

Parameters	*Model Structure*
Process model	$y(x,z)=(c_0+c_1z+c_2z^2)\cdot\left(1-\frac{(b_0+b_1z)x}{1+(b_0+b_1z)x/a}\right)$
3	$y(x)=\hat{c}_0\cdot\left(1-\frac{\hat{b}_0x}{1+\hat{b}_0x/\hat{a}}\right)$
4	$y(x,z)=(\hat{c}_0+\hat{c}_1z)\cdot\left(1-\frac{\hat{b}_0x}{1+\hat{b}_0x/\hat{a}}\right)$
5	$y(x,z)=(\hat{c}_0+\hat{c}_1z+\hat{c}_2z^2)\cdot\left(1-\frac{\hat{b}_0x}{1+\hat{b}_0x/\hat{a}}\right)$
6	$y(x,z)=(\hat{c}_0+\hat{c}_1z+\hat{c}_2z^2)\cdot\left(1-\frac{(\hat{b}_0+\hat{b}_1z)x}{1+(\hat{b}_0+\hat{b}_1z)x/\hat{a}}\right)$

Distribution of growing season precipitation

The March through May precipitation (pre-decision precipitation) and the March through August precipitation (total growing season precipitation) were calculated from north-central Montana weather station records. Data were edited to remove any years with incomplete records. The pairs of pre-decision and total growing season precipitation (GSP) are shown in Figure 4.3. Pairs were randomly sampled in the simulations. The prediction based on the March through May precipitation was made by regressing total

growing season precipitation on pre-decision precipitation, resulting in the equation ($r^2 = 0.51$):

$$P_{GSP} = 11.426 + 1.188 \cdot P_{March-May} \quad (4.6)$$

The within-site (across years) and within-year (across sites) variation are shown in Figure 4.4. Some of the weather records began in 1893, so the portion shown in the graph is a subset of all the data collected. The average within-year variation (for those years with more than 4 sites) was approximately 3 times smaller than the within-site variation. This indicates that there was both a temporal and a spatial component to precipitation variability and the temporal component is largest. For the purposes of this study, it was assumed that there was no correlation between samples from the weather records.

Prediction model and validation

Candidate prediction models were considered that ranged from 3 to 6 parameters (Table 4.1). They form a hierarchy (more complex models reduced to simpler ones if some parameters were set to zero). For the case where 'i' is a function of precipitation, the 6-parameter model was identical to the process model. When 'i' is constant, the 5-parameter model was identical in form to the process model.

For each SPCE, a random draw from the weather records determined the level of growing season precipitation at the site. The simulated SPCE data and the associated total growing season precipitation were grouped together into sets of 8 SPCE. The data set was then fit with each candidate model (Table 4.1) using nonlinear least squares.

Each parameterized candidate model was then allowed to make 100 independent predictions of the economic threshold and the value of weed control at the "actual threshold" (which could be calculated because we were in possession of the process model). Each prediction was the result of an independent trial (draw from the weather data). The difference between the predicted and the "actual" value of weed control (90% of the weeds killed by the herbicide at the actual threshold) was recorded.

$$\varepsilon_{i,j} = \left(\Delta\hat{y}_i(x^*, z_j) - \Delta y(x^*, z_j)\right) \cdot p \qquad (4.7)$$

Where the subscripts 'i' and 'j' refer to a particular set of 8 SPCE and to a particular draw from the precipitation distribution respectively. The quantities $\Delta\hat{y}$ and Δy are the predicted and actual difference in yield that occurred when using the control treatment. The difference was defined to be:

$$\Delta y(x^*, z) = y(0.1 \cdot x^*, z) - y(x^*, z) \qquad (4.8)$$

The weed density x* is the economic threshold, or the density for which the value of yield recouped by application was equal to the herbicide treatment cost. It was found by solving Equation 4.8 for x*:

$$\Delta y(x^*, z) \cdot p = c_{herb} \qquad (4.9)$$

The crop price used was \$114 ha^{-1}. The herbicide cost was \$44.48 ha^{-1}. As the threshold depends on the value of the yield lost, it also depends on all factors that modify the yield, as well as the crop price and the herbicide cost as discussed by O'Donovan (1996). For each set of 8 SPCE results we performed n = 100 validation trials and reported the mean error and the standard deviation of the error:

$$\varepsilon_i = \frac{1}{n}\sum_{j=1}^{n}\varepsilon_{i,j}$$
$$\sigma_{\varepsilon_i} = \left(\frac{1}{n}\sum_{j=1}^{n}\left(\varepsilon_{i,j} - \varepsilon_i\right)^2\right)^{\frac{1}{2}} \qquad (4.10)$$

The subscripts 'i' and 'j' index the sets of 8 SPCE and validation trials respectively. In order to know, on average, how accurate the predictions were, we iterated the whole procedure m=100 times and reported the mean bias and the mean standard deviation. All calculations were performeded in Mathematica (1999).

$$\bar{\varepsilon} = \frac{1}{m}\sum_{i=1}^{m}\varepsilon_i$$
$$\bar{\sigma}_{\bar{\varepsilon}} = \frac{1}{m}\sum_{i=1}^{m}\sigma_{\varepsilon_i} \qquad (4.11)$$

Figure 4.2. Precipitation (March + April + May) versus total growing season precipitation for 985 site-years of weather station data in north-central Montana.

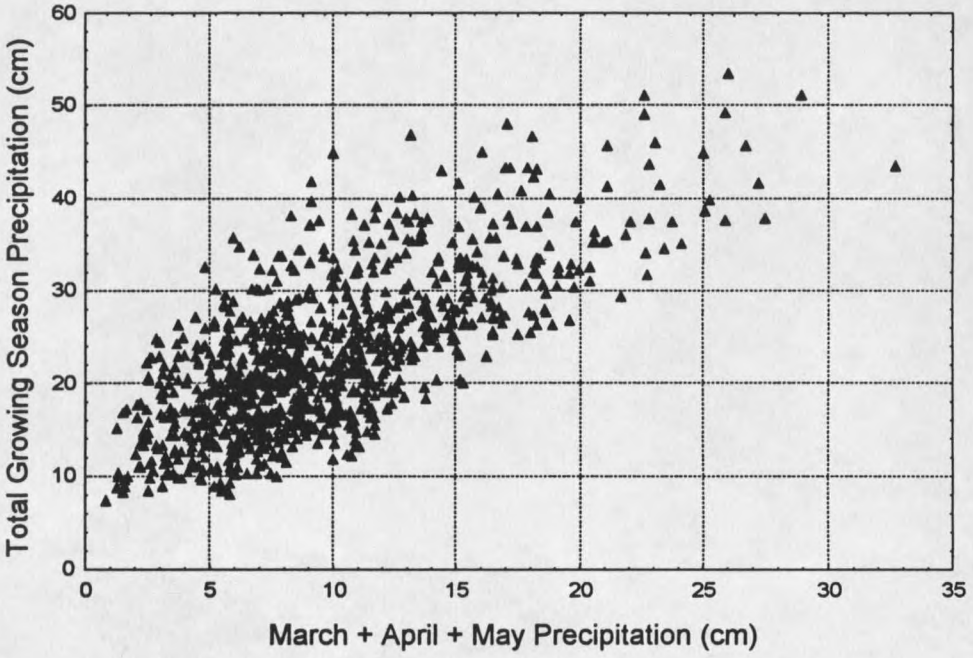
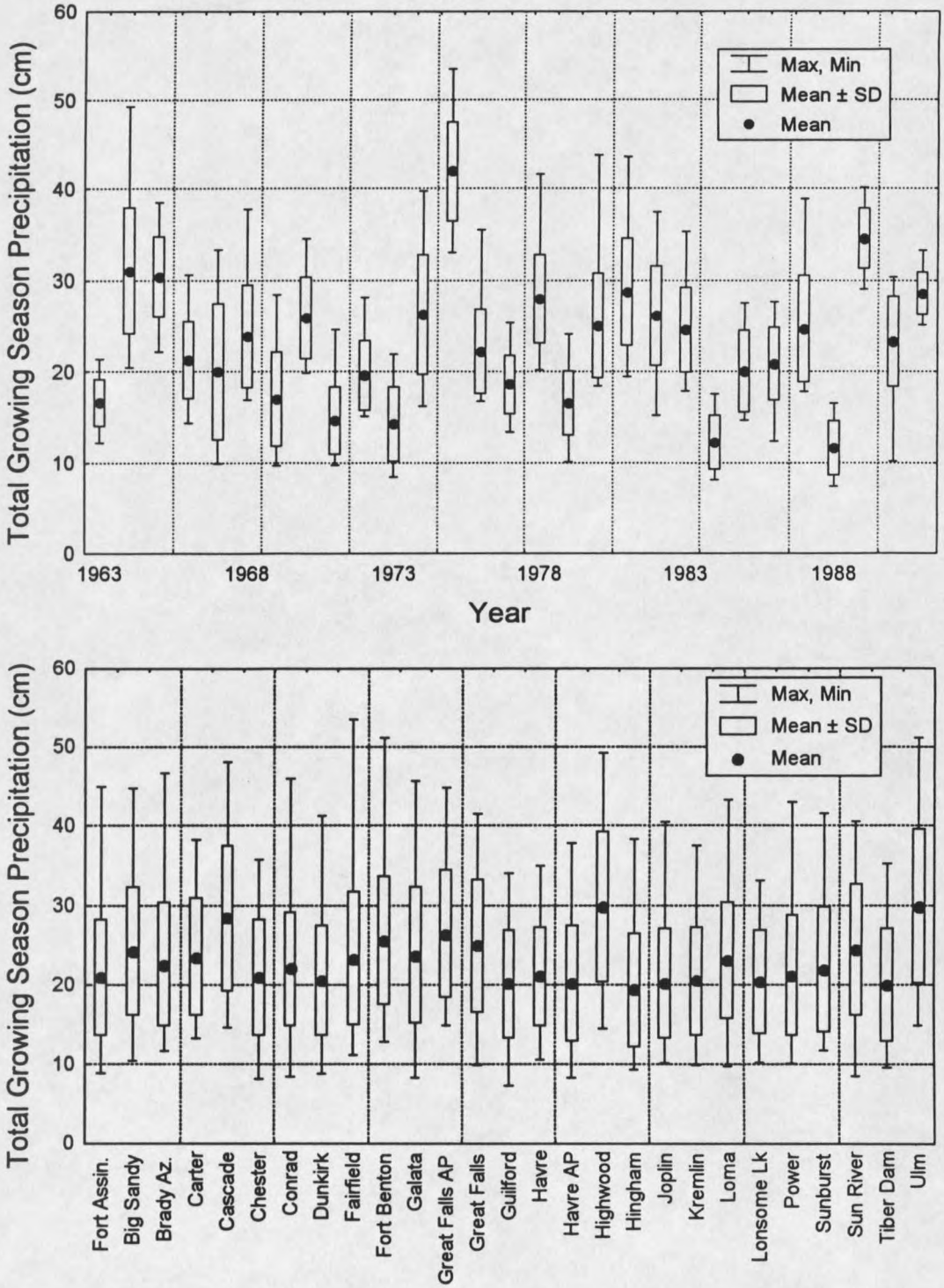


Figure 4.3. Mean, standard deviation, maximum and minimum growing season precipitation for spring-wheat growing areas in north-central Montana.



Results

In order to determine the value of increasing model complexity by adding parameters to the weed-crop yield function, model accuracy was assessed for the prediction of two different quantities: (1) the value of control at the threshold corresponding to Equation (4.7), using the statistics defined in Equation (4.11) and, (2) the value of the threshold itself, defined by Equation (4.9). The predicted versus actual thresholds are displayed as scatterplots (Figures 4.6 - 4.10).

Prediction accuracy of the value of control at the threshold

The mean bias and standard deviation of prediction error declined when precipitation was included in the model structure (i.e. moving from 3 to a larger number of parameters) for the case where competitive impact is independent or a negative linear function of precipitation ($b_1 \leq 0$). Mean bias and standard deviation increase when competitive impact is a positive linear function of precipitation ($b_1 > 0$) (Figure 4.4). Using only March-May precipitation to predict, a similar result was achieved, where the behavior of the bias and standard deviation favor the models (4-6 parameter) that included a measure of moisture (Figure 4.5). The values of the mean standard deviation in Figure 4.5 were inflated relative to the case where we knew the value of the total growing season precipitation (GSP) (Figure 4.4). In the case where the bias was low (4-6 parameter model for $b_1 \leq 0$), the corresponding standard deviation was 10-15 \$ ha^{-1}, which represents 20-30% of the value of the herbicide cost.

Figure 4.4. Mean bias and standard deviation of prediction error for models with 3-6 parameters under 3 different competitive scenarios with full GSP information.

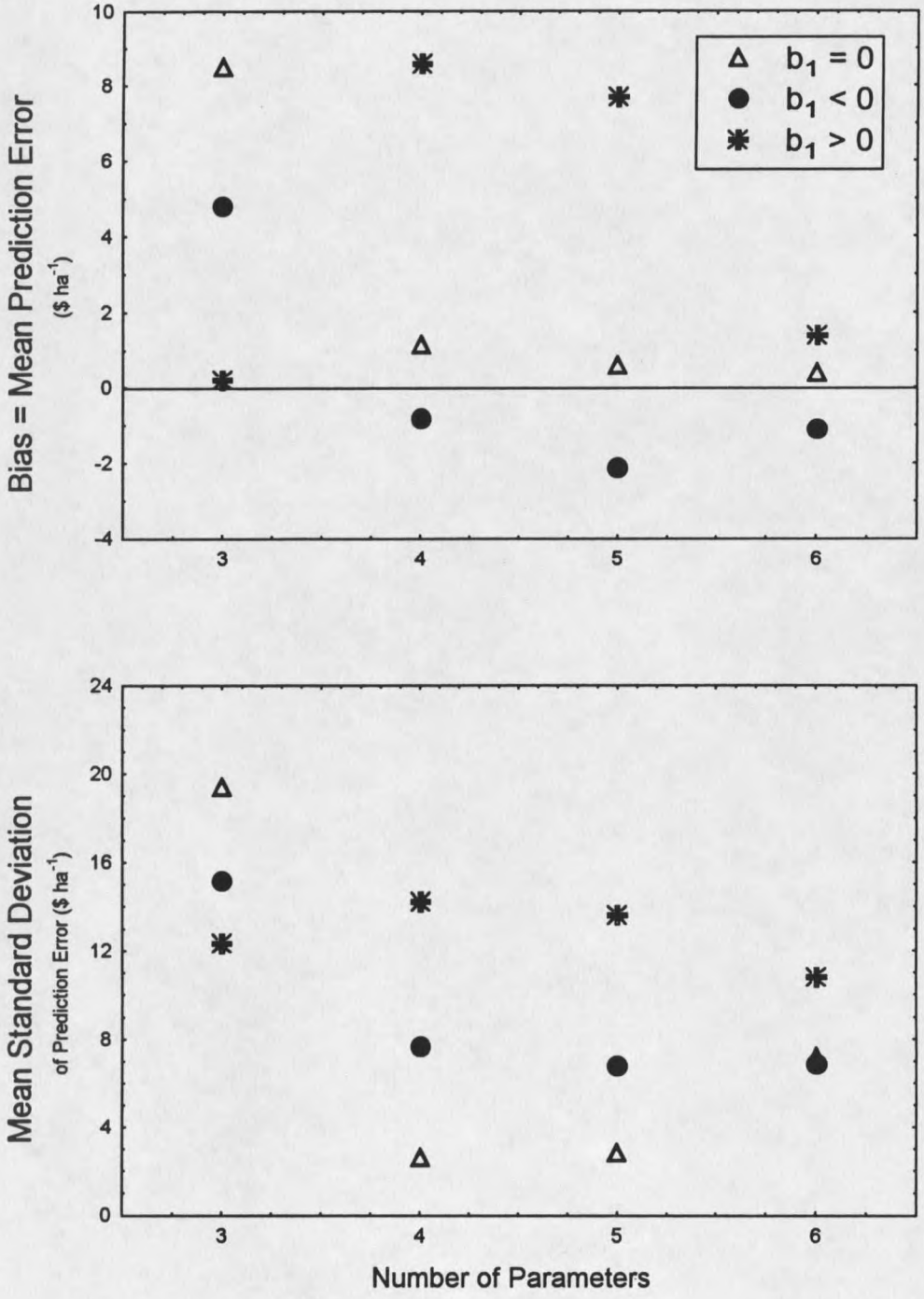
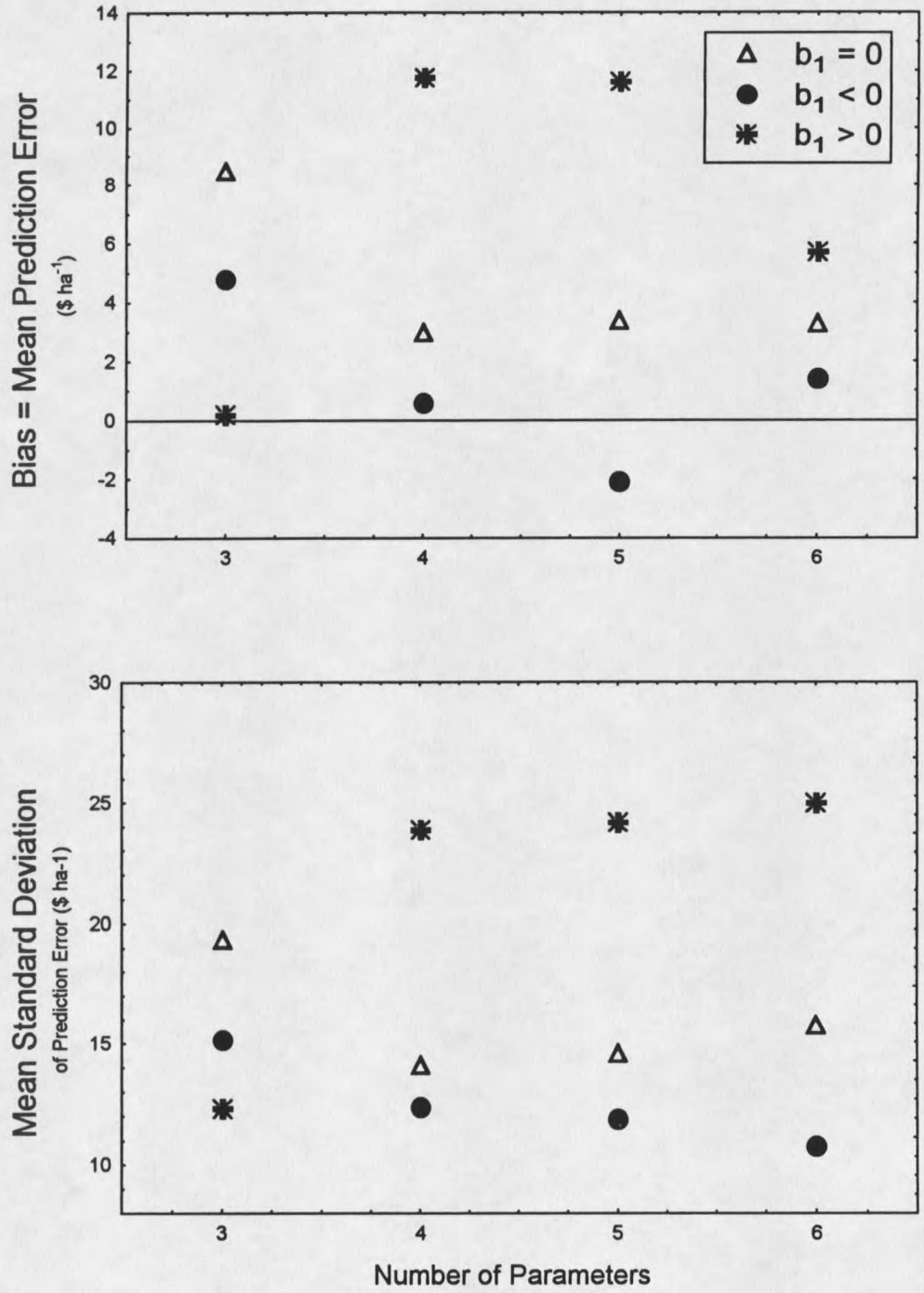


Figure 4.5. Mean bias and standard deviation of prediction error for models with 3-6 parameters under 3 different competitive scenarios with pre-decision precipitation information.



Prediction accuracy of the economic threshold

The scatterplots in Figures 4.6 - 4.9 show the predicted economic threshold (x-axis) versus the "actual" economic threshold (y-axis). A relationship that could predict without error would thus produce points on the line with slope 1 that passes through the origin. Each point within the plots represents a single validation trial for a relationship parameterized from a set of 8 SPCE. As there were 100 iterations of 100 predictions, there are 10^4 points on each plot. If the points accumulated above the 1:1 line, it indicates a systematic underprediction of the threshold and if they accumulate below the line, it indicates overprediction.

In all of the scatterplots, the predicted and actual thresholds were higher than the 8-10 plants m^{-2} reported in the literature. This was a direct reflection of the low value (both price and yield) of the wheat crop. Furthermore, the 3-parameter model (Figure 4.6) was incapable of predicting the threshold for any of the scenarios. This was not surprising because moisture was included in the process model as a primary determinant of yield and the 3-parameter model does not include moisture. If we make threshold decisions using such a model, we will apply herbicides in many cases where it is not justified on 1-year economic grounds. This reflects the large bias present for both $b_1 \leq 0$ cases (competitive impact a constant or negative function of growing season precipitation).

Prediction of the economic threshold improved when the number of parameters increased from 4 to 5 when competitive impact was resource independent ($b_1 = 0$) (Figure 4.7) but decreased with the 6-parameter model (Figure 4.7, bottom left panel).

This overfitting might have been expected, as the process model form was 5-parameter when $b_1 = 0$. With only March-May precipitation known, the benefit of adding more than one parameter describing moisture effects was small (right panels of Figure 4.7).

When competitive impact was a negatively sloped function of precipitation ($b_1 < 0$), the results were similar to $b_1 = 0$ (Figure 4.8). This was a direct reflection of the weed impact being greatest when the yield is the lowest. As the loss caused by the weed was proportional to yield, the value of that loss is diminished in the low-moisture conditions, even though the per-unit weed impact was greater. This explains why the performance of the predicted value of control appeared better for $b_1 < 0$ than for $b_1 = 0$ (Figures 4.4 and 4.5).

The case where competitive impact is a positive linear function of precipitation ($b_1 > 0$) is entirely different. In this case, adding any measure of moisture into the predictive equations increased both the mean bias and standard deviation of the prediction error (Figure 4.9). The weed impact was overpredicted unless the effect was explicitly included in the model (6-parameter model, Figure 4.9, bottom left panel). Both the mean bias and standard deviation were degraded by uncertainty in the total growing season precipitation. Clearly if weed impact was correlated to growing season precipitation, then the bias caused by the correlation would cause one to make frequent incorrect decisions.

The inclusion of the fixed site-factor (e.g. depth to hardpan) described in Equation 4.5 was tested (Figure 4.10). Predictions were markedly degraded when compared to the case where there are not site-factors present (Figure 4.10 compared to Figure 4.7). After

adding the site-factor, the standard deviation of the predicted value of control increased from \$3 to \$15 ha^{-1} ($b_1 = 0$ in the 4-parameter model). When the threshold was predicted based on March-May precipitation, the standard deviation increased from \$15 to \$21 ha^{-1} for the same case as above ($b_1 = 0$ in the 4-parameter model).

Discussion

One of the advantages of exploring prediction accuracy using simulation was that we could determine what effects different types of error had on prediction. The primary source of error was process noise in the SPCE plot data. The secondary source of error arose from real-world variation in precipitation. In combination, these two sources of error alone were sufficient to produce a prediction error in the weed density threshold for management corresponding to approximately 25% of the value of control (\$10 ha^{-1}) for the case where we only knew 3 months precipitation. The magnitude of the SPCE process error (20% variation) was a very conservative estimate of what occurs in practice and there were *many* potential sources of variation that were not included. Thus, 25% error in the value of weed control may serve as a bound on the potential of precipitation inclusion in the model to improve accuracy for the wild oat-wheat system in north-central Montana. That is, if one had 8 experiment station small-plot experiments and precipitation data and undertook to improve prediction by adding moisture to the model, then it is *very* unlikely the prediction error could be reduced below 25% of the value of control.

Adding more SPCE can greatly decrease both the bias and the standard deviation when there is full knowledge of the GSP (e.g. for $b_1 = 0$, using 32 SPCE stations and the 5 parameter model decreases the mean bias to 0.08 and the mean standard deviation to 1.05), but does little to improve the accuracy of the prediction when pre-decision moisture is used in the model.

It is easy to add SPCE in a simulation, but competition study data is very expensive to collect. One value of this study lies in demonstrating the potential importance of adding additional studies. As there is a correlation within years for weather data (Figure 4.3), within year replication across space does not provide as much independent information as replication across time.

A general benefit of simulation studies is that they force the explicit quantitative description of hypotheses about relationships. While the notion of "simulating experiments" seems biased and in some sense absurd, conducting these "experiments" forces us to consider hypotheses about complicated phenomenon, including "error processes". For instance, is the variation between plots in SCPEs caused by variations in fertility or weed plant density? If either is responsible, as we assumed, then "error" is probably related to plant growth factors (directly or indirectly). Thus we chose to model the error as multiplicative rather than additive as standard regression techniques assume.

Figure 4.6. Predicted vs. actual threshold for the 3-parameter model. Predicted threshold is on shown on the x-axis of each plot, and the actual threshold is on the y-axis.

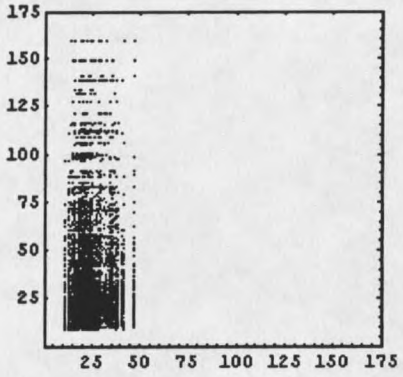
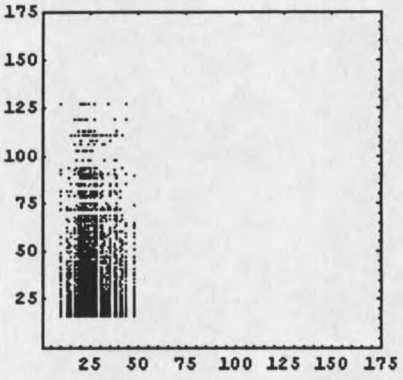
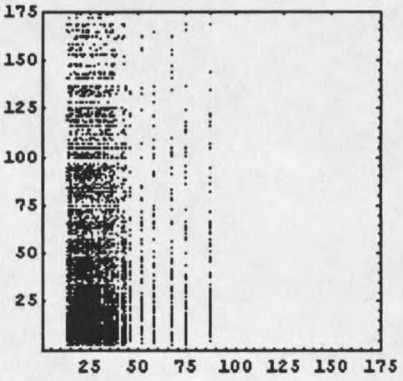
Case	Predicted vs. Actual Threshold (3 parameter model)
$b_1 = 0$	
$b_1 < 0$	
$b_1 > 0$	

Figure 4.7. Predicted vs. actual threshold for case $b_1 = 0$. Predicted threshold is on shown on the x-axis of each plot, and the actual threshold is on the y-axis.

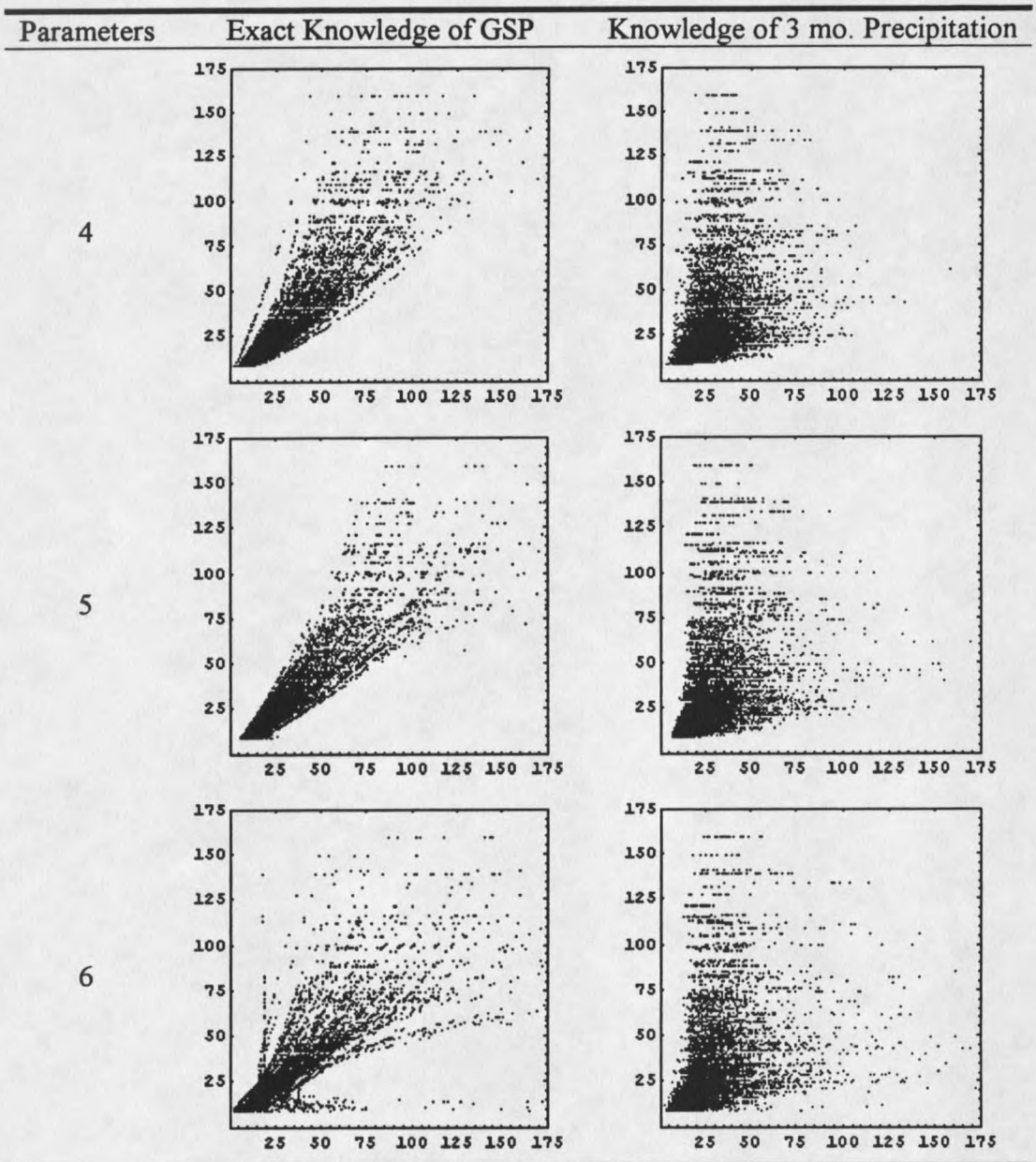


Figure 4.8. Predicted vs. actual threshold for case $b_1 < 0$. Predicted threshold is on shown on the x-axis of each plot, and the actual threshold is on the y-axis.

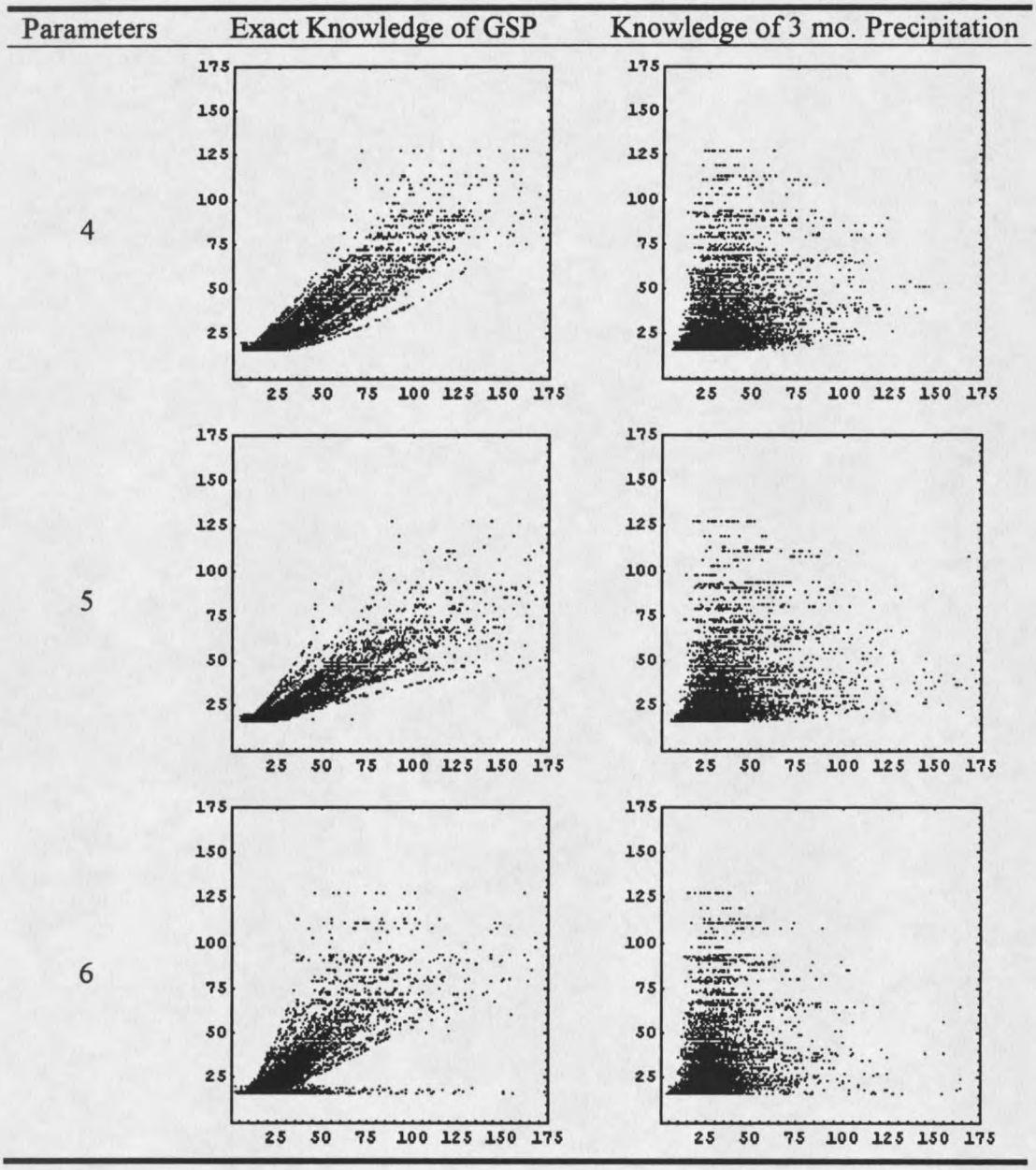


Figure 4.9. Predicted vs. actual threshold for case $b_1 > 0$. Predicted threshold is on shown on the x-axis of each plot, and the actual threshold is on the y-axis.

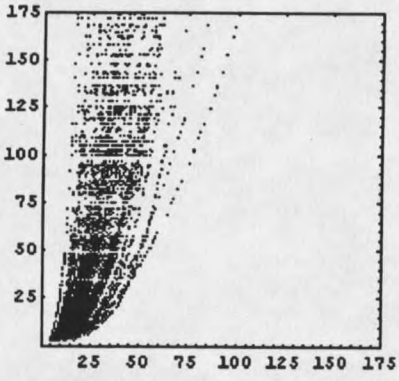
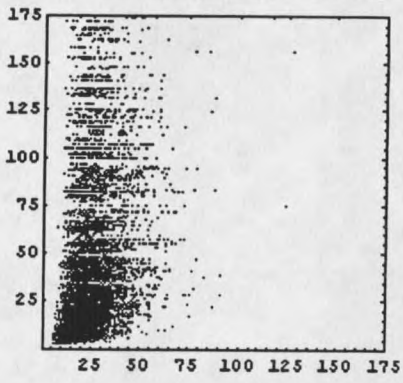
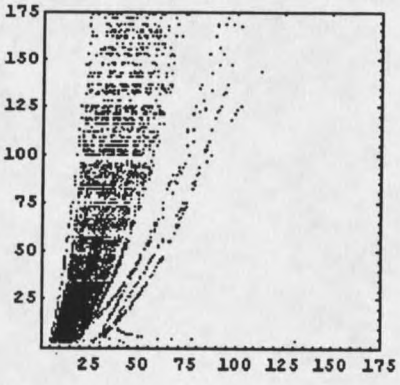
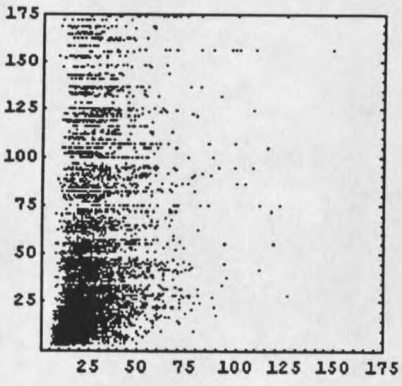
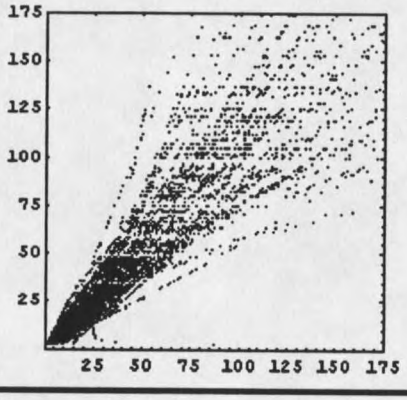
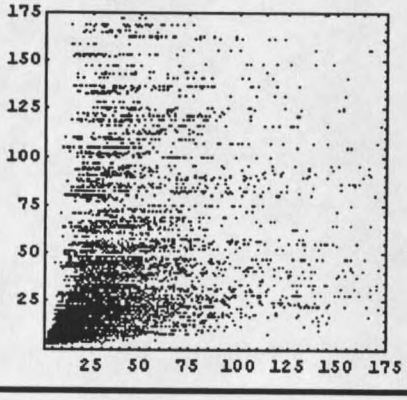
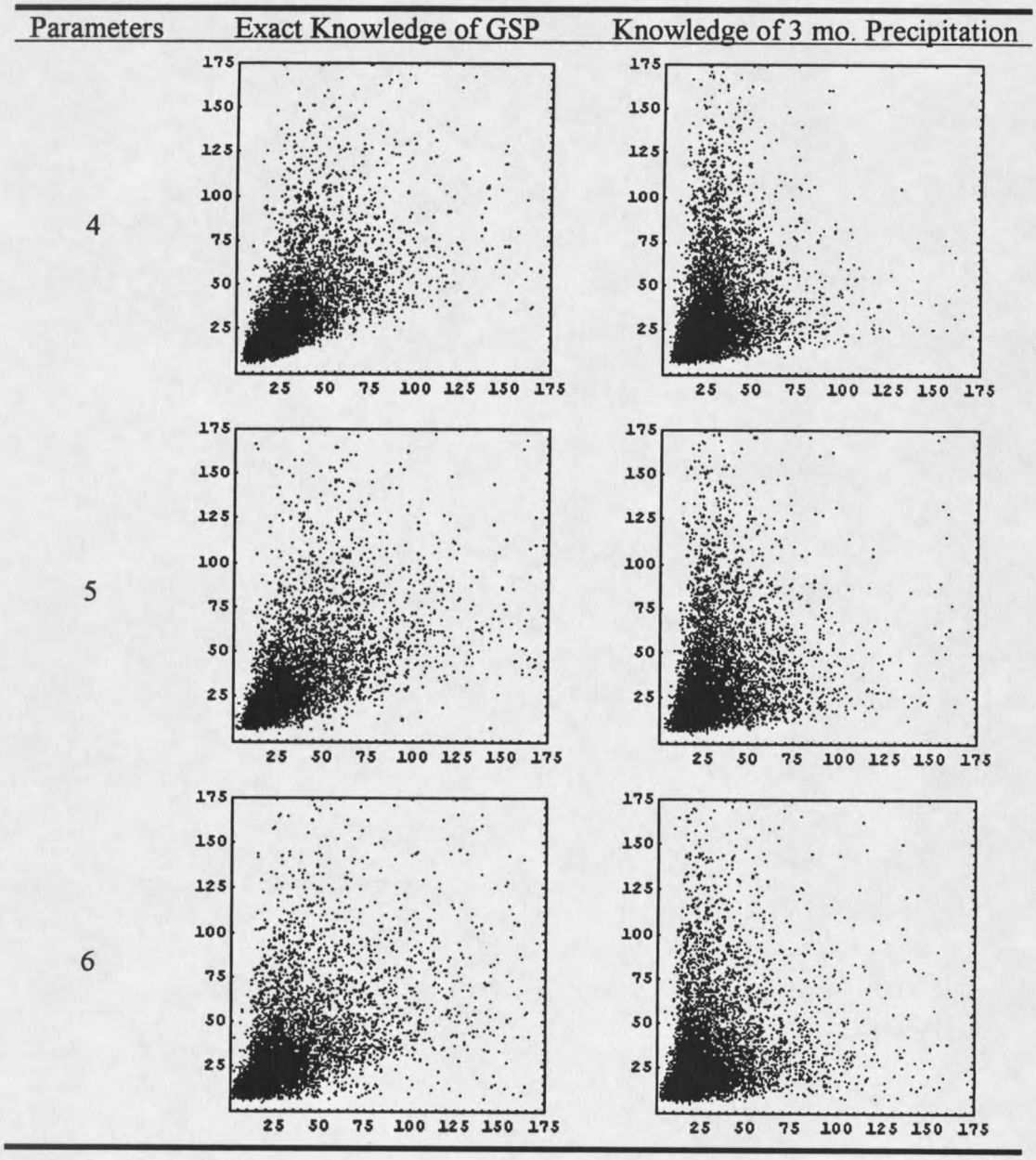
Parameters	Exact Knowledge of GSP	Knowledge of 3 mo. Precipitation
4		
5		
6		

Figure 4.10. Predicted vs. actual threshold for case $b_1 = 0$ and a site-factor. Predicted threshold is on the x-axis, and the actual threshold is on the y-axis.



The second objective of this study was to compare model performance as we increased the number of parameters. Underfitting was clearly observed in the case of the 3-parameter model (there was a large prediction bias) and overfitting was only observed when the candidate model was not correct, for example, fitting the 6-parameter model with the resource independent competitive impact $b_1 = 0$ (for which the 5-parameter model is the form of the process model). In general we are not privy to the 'true form' of the process model, and therefore these results should serve as a general caution.

The number of independent replicates available for an analysis will be vastly increased if site-specific on-farm experimentation ever reaches the point where producers can conduct it with ease (i.e. weed abundance is easily and site-specifically estimated and corresponds to yield monitor information). Even the public availability of site-specific data itself could potentially provide enough information so that more complex, accurate and general models could be constructed.

The addition of an unknown "site-factor" was seen to significantly degrade prediction, both with and without full knowledge of the GSP. There are certainly yield influencing properties of locations that are relatively constant on the field scale but vary over a larger geographic region, depth to hardpan being an important one. In this study we assumed the standard deviation of such an effect was 20%. Provided that this magnitude is reasonable, there would seem to be significant improvements in prediction accuracy to be made by gaining knowledge of such factors. On-farm experimentation would be one method that could improve our knowledge of driving factors and subsequent yield prediction.

There are clearly major barriers preventing precise predictions of impact of weeds, but as the value of production decreases and the costs of inputs such as herbicides become a large fraction of gross returns, economizing by lowering rates or occasionally forgoing the use of weed control may become more of an economic necessity than an option. Thus, studies like this one that seek to improve our ability to broadly predict management thresholds from experimentation are essential.

CHAPTER 5

THE INFLUENCE OF WEED POPULATION GROWTH RATE ON THE LONG-TERM MANAGEMENT THRESHOLD

Summary

Weed threshold management strategies may be an important way to increase farmer profits and decrease off-target pollution effects of inputs. However, the potential for reducing costs associated with weed control must be considered in the context of weed population management. In general, our understanding of population dynamics and the effect of control efforts on weed demography are not precise enough to accurately determine the benefits of reducing weed management costs. Uncertainty surrounding both the short-term predicted benefit of control and the long-term costs associated with uncontrolled weeds has produced skepticism about the use of management thresholds, yet they address an important means to curb the erosion of farmer profit margins. We argue that, in spite of uncertainty in prediction, we must attempt to classify the conditions under which threshold decision making may be a useful way to increase overall farm profits under the condition where uncertainty in prediction is considered. As a case study, we analyze the potential benefit of threshold use on the extremely high growth rate weed, barnyardgrass (*Echinochloa crus-galli* L.), in high value crop, processing tomato (*Lycopersicon esculentum* L.). We utilize published data on barnyardgrass demography and tomato yield impact to examine the relative benefit of control in the short and long term. Our results confirm that simplistic threshold strategies do not make sense for

extremely high growth rate weeds, particularly when control costs are proportional to the intensity of infestation. We highlight the importance of estimating the distribution of possible growth rates realized in particular cropping systems and provide an analytical solution for the deterministic long-term threshold.

Introduction

Perhaps the most critical decision a weed manager must make is whether control is warranted. In order to create some systematic means of identifying situations where control should be used, weed science has borrowed the concept of "pest threshold" from entomology, wherein the value of benefit ensuing from the control measure is weighed against cost (Coble and Mortensen 1992). Economic injury level (EIL) was used by entomologists to describe the same concept and may be preferable to decrease confusion (Stern et al. 1959, Maxwell 1992).

As the EIL relies on a comparison of the relative economic value of two decisions, control and no-control, and the economic consequences of these decisions invariably depends on many factors, there is some question about the practical application of the threshold concept. Some researchers have argued that one-year economic returns cannot be used because they ignore the population consequences of the management action (Norris 1992a, Sattin et al. 1992, Norris 1999). These criticisms call attention to the fact that short-term economic considerations cannot be divorced from the broader objective of containing or eliminating weed populations over the long-term. The

natural means to integrate the twin objectives of profit and control is to model the weed demographic consequences of control decisions.

Cousens (1987) coined the term the economic optimum threshold (EOT) to represent the weed density that includes the future costs associated with the demographic consequences of a control action. The most straightforward way to assess the EOT is to integrate weed demographic and impact models (Cousens 1986, Jordan 1992, Maxwell 1992). The inherent variability that accompanies the complexity of agroecosystems has resulted in economic assessments that, likewise, are variable. O'Donovan (1996) suggests that attempting to model the complexity in order to improve the accuracy of long-term economic assessment is tantamount to a pipe dream. Firbank (1993a) advocates reclassifying deterministic population/economic models as "guides" rather than "predictors".

An alternative approach considers the system as stochastic rather than deterministic. Stochastic models are relationships in which parameters are not necessarily fixed, but are sampled from distributions (e.g. Pandey and Medd 1991, Jordan 1992, Firbank 1993a, 1993b). Once parameter distributions are estimated, a model can be used to assess risk or the potential variability in a response variable by randomly drawing from the parameter distributions (the Monte-Carlo method). Monte-Carlo simulation can be used in conjunction with life-cycle models (Cousens and Mortimer 1995) to assess optimal levels of control that include consideration of demography (Maxwell and Colliver 1995, Bussan and Boerboom 2001a, 2001b). Firbank (1993a) notes that the general methodology has been established in conservation biology for

threatened and endangered species for some time, but that necessary data on parameter variability simply does not exist for weeds.

While stochastic models are a flexible way to describe processes that are by their very nature variable, the use of such models poses some trouble. The most difficult obstacle is inferring the parameter distributions from data. First, the data is often incomplete or lacking. Second, in order to make the claim that Monte-Carlo simulation renders probability distributions for response variables, we need to know the joint probability distribution of the parameters, the marginal parameter distributions alone are insufficient. Classical statistical inference cannot achieve this goal.

Weed demography has received increasing theoretical and applied attention in the past decade. Cousens and Mortimer (1995) have written a comprehensive text on the subject. Yet, despite this attention, actual attempts at prediction are rare (Maxwell et al. 1993, Cousens 1995) and those that do exist have concluded predictability is poor (e.g. Firbank et al. 1985). This comes as no surprise as many demographic processes are clearly stochastic -- who could predict the arrival of a flock of seed eating birds on a plot five years in the future?

Freckleton and Watkinson (1998a) point out that the data simply do not exist to parameterize population dynamic models of weeds, because of gaps in time series and lack of spatial replication. They also observe that a lack of temporal replication can severely bias results (Freckleton and Watkinson 1998b). This work highlights an important consequence of demographic variability of weeds; variability itself can affect the maintenance of weed populations (Reader 1985, Gonzalez-Andujar and Perry 1995).

There have been theoretical investigations that have questioned the motivation of threshold-based decisions. Wallinga and van Oijen (1997) elegantly demonstrated with a simple non-stage structure model that the long-term frequency of herbicide use does not depend specifically on the threshold, but rather on the growth rate of the weed with and without control. They also show, in the context of their assumptions, that threshold-based decisions can lead to chaotic weed dynamics, and therefore enhance unpredictability. Wallinga (1998) demonstrates that when decisions include variable dose-rates, long-term herbicide use is primarily determined by factors influencing the growth rate of the weed rather than short-term economic considerations.

Despite Wallinga's findings, many studies focus on short-term economics without regard to a central objective of weed population management: adequate long-term suppression of weed populations. Conversely, focusing on the suppression of weed populations without regard to the economics of control is a luxury that an increasing number of producers cannot consider.

Understanding the relationships between a control measure and its contribution to containing or eradicating a weed problem requires knowledge about the demography of weed populations. Certain parts of the weed life cycle have been studied more thoroughly than others, primarily seed production. While seed production sets the maximum growth rate, the realized growth rate depends on a host of ecological processes, including the pre- and post-dispersal predation, seedbank decay, germination and establishment (Harper 1977).

There is very little quantitative information about mortality factors, perhaps because they depend on the variable distribution of animals, fungi, bacteria and environmental conditions that can inflict mortality. Exceptions do exist for certain species. For example, Burton (2000) studied a suite of factors influencing wild sunflower (*Helianthus annuus* L.) demography in a ridge-tilled Nebraska corn system and found that soil organic carbon and topography could influence seedling recruitment. Lindquist and Knezevic (2001) reviewed what little is known about the relationship between cropping systems and seed mortality factors and concluded that further research is needed.

The poster child for weeds with high growth potential is arguably barnyardgrass, listed as the third worst weed in the world by Holm et al. (1977). Norris (1992b) has observed that a barnyardgrass plant can produce over 1 million seeds when grown in isolation and between 30,000 and 200,000 seeds per individual in a sugarbeet crop. Recent studies of barnyardgrass demography in a processing tomato crop provide data on density dependent seed production and yield impact at a range of tomato plant densities (Norris et al. 2001a, 2001b). Considering the exceptionally high potential growth rate of barnyardgrass, Norris (1992a) has raised the question of whether it can ever be economically rational to forgo control.

Given the uncertainty surrounding demographic processes, we wanted to examine the logic of the claim that barnyardgrass should not be allowed to set seed in tomato and explore how to combine considerations of population growth rate, demographic uncertainty and economics. The specific objectives of this study were: (1) to determine if

an EOT exists for barnyardgrass, (2) derive an analytical approximation for the EOT that clarifies the importance of demography, (3) investigate the potential influence of stochasticity on our analysis and (4) speculate as to situations where threshold decision-making may be useful.

Materials and Methods

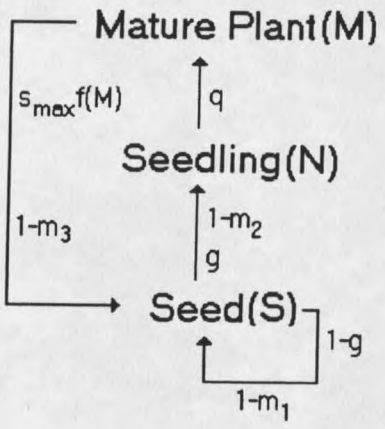
Analytical model

We used a life-cycle model of an annual weed wherein a census of the seedbank was taken each winter. The series of stages and life-cycle transitions are shown in Figure 5.1. The transitions between stages determined the number of seeds present in the following year:

$$S_{t+1} = \left[g(1-m_2)qs_{\max} f(g(1-m_2)qS_t)(1-m_3)\right]S_t + \left[(1-m_1)(1-g)\right]S_t \qquad (5.1)$$

The function f is the density dependent seed production per plant and $s_{\max}$ is the maximum seed produced per plant. The parameter q represents the proportion of plants surviving control, g is the probability that a seed germinated and survived to become a seedling. The mortality events m_1, m_2 and m_3 describe the probability of seed decay, germination/establishment mortality and pre/post dispersal predation/decay respectively.

Figure 5.1. Weed life-cycle model depicting the stages traversed during the life of an annual weed.



The seed production function f, has the following form:

$$f(M) = [1 + cM]^{-k} \tag{5.2}$$

Where M is the mature plant density, the parameter c describes the interspecific competition between weed plants and k scales the allometric relationship between seed production and plant weight (Freckleton and Watkinson 1998a). Following Freckleton and Watkinson, we drew on data presented by Norris et al. (2001b) and estimated the parameter c as the inverse of the density at which the per-plant barnyardgrass biomass declines by one-half. The parameter k was estimated from the regression of log(n) on log(w):

$$\log(n_i) = \log(d) + k\log(w_i) \tag{5.3}$$

Where n_i is the number of seed produced for a plant with biomass w_i and the parameter d is a coefficient in the allometric relationship not utilized in further analysis. The estimates and an approximate range are given in Table 5.1.

Weed economic impact

The presence of mature weed plants was assumed to impact yield in a saturating manner as encouraged by Cousens (1985):

$$y(M) = y_0 \cdot \left(1 - \frac{i \cdot M}{1 + i \cdot M / a}\right) \tag{5.4}$$

Equation 5.4 describes yield, y, as a function of mature plant density; y_0 is the weed-free yield and M is the mature plant density.

The net return of the operation (π) is shown below in Equation 5.5, where p is crop price, q is the seedling survivorship, N is the seedling density and c_1 is the cost of control, which for barnyardgrass we take to be a function of seedling density. The parameter c_0 represents all other costs.

$$\pi(q, N) = y(qN) \cdot p - c_1(N) - c_0 \tag{5.5}$$

Norris (1999) estimated the density dependent costs associated with handweeding. The average worker walks at 5 km/hr and earns about \$7.50 hr^{-1}. On the basis of Norris' estimates of cost associated with handweeding particular densities and the assumption that it would take an hour to walk a weed-free hectare, we estimated a cost function, where N is the seedling density:

$$c_1(N) = 7.5 + 500.0N \tag{5.6}$$

Table 5.1. Barnyardgrass demographic parameter values, distributions and references for the relationships used in modeling the life-cycle.

Parameter	Value (range)	Distribution[a]	Reference
		Demographic parameters	
g	0.60	B(12,8)	Rahn et al. 1968 Barrett & Wilson 1983
m_1	0.20	B(4,16)	Estimate
m_2	0.50	B(10,10)	Estimate
m_3	0.60	B(12,8)	Estimate
s_{max}	10^5	LN(μ,σ)	Norris et al. 2001a
c	1.5 (1.0-2.0)	1.0+B(2,2)	Norris et al. 2001a
k	1.2 (1.0-1.2)	1.0+0.2*B(5,5)	Norris et al. 2001a
μ	11.5129		Norris et al. 2001a
σ	0.35		Norris et al. 2001a
		Economic parameters	
Y_0	90 T ha^{-1}	Weed-free yield	Norris et al. 2001b
i	0.60	Impact parameter	Norris et al. 2001b
a	0.66	Impact parameter	Norris et al. 2001b
P	\$55 T^{-1}	Price per ton	Estimate
δ	0.05	Discount rate	-

[a] B(a,b) represents a beta-distribution with parameters 'a' and 'b'. LN(μ,σ) represents a lognormal distribution with mean, μ, and standard deviation, σ, of the underlying normal distribution.

The finite rate of increase

The finite rate of increase, λ_q, is defined as the proportional increase of the population from one year to the next. Algebraically:

$$\lambda_q = \frac{S_{t+1}}{S_t} = [g(1-m_2)qs_{\max} f(g(1-m_2)qS_t)(1-m_3)] + [(1-m_1)(1-g)] \qquad (5.7)$$

Equation 5.7 can be rewritten as:

$$\lambda_q = \lambda_r \cdot [1 + c(g(1-m_2)qS_t)]^{-k} + \lambda_{SB} \qquad (5.8)$$

The total growth-rate is indexed by the survivorship because it depends on the amount of control used and the control acts by decreasing the survivorship of seedlings. λ_q cannot be smaller than λ_{SB} or larger than $\lambda_r + \lambda_{SB}$. The component of the growth rate λ_r represents the maximal growth rate of replenishment and λ_{SB} sets the rate at which the seedbank population declines in the absence of replenishment (q=0).

$$\lambda_r = g(1-m_2)(1-m_3)qs_{\max} \qquad (5.9)$$

$$\lambda_{SB} = (1-m_1)(1-g) \qquad (5.10)$$

We determined the efficacy required for containment by setting $\lambda_q = 1$ in Equation (5.8) and solving for q. We found that $q = q^* = 5.67 x 10^{-5}$ corresponding to greater than 99.99% efficacy. The relationship between the growth rate and seedling survivorship is shown in Figure 5.2.

Analysis and Discussion

Threshold calculation

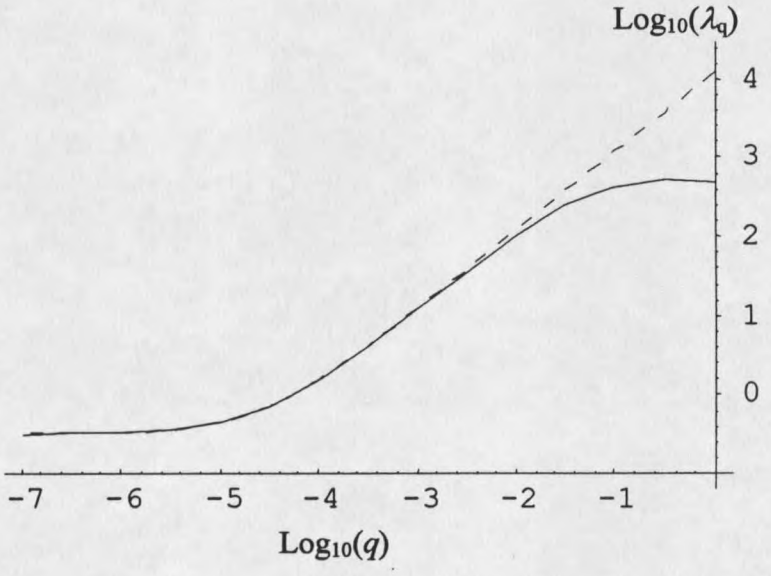
We calculated the single season economic threshold (EIL) by setting the net return with weed control equal to the net return without control. It was assumed that the

act of handweeding resulted in achieving the critical survivorship (q^*). We solved the Equation (5.11) for the EIL seedling density N*:

$$y(q^*N^*)p - c_1(N^*) - c_0 = y(N^*)p - c_0 \qquad (5.11)$$

The EIL was smaller than 2.5×10^{-5} plants m^{-2}, or about 1 plant every 4 ha. If the weeds are present at very low densities (when we would be likely to consider such a plan), the corresponding growth rate would be approximately $\lambda_1 = 1.2x10^4$. If we use the containment efficacy (q^*) after forgoing control the first year, then with future use of this

Figure 5.2. The relationship between seedling survivorship and the growth rate of the weed. [a]



[a] The dashed line corresponds to the case where there is no density dependence and the solid line represent the case where there are 30 barnyardgrass seeds m^{-2}. If the survivorship is q=0, then the growth rate is λ_0, if the survivorship is q=1, then λ_1.

level of control, the population will not increase after the first year. The relative 1-year loss in profit due to weeds will be realized every year if $\lambda = 1$.

The amount of time, on average, that would be required to return the population to its original level after one year of non-control and 100% control thereafter is:

$$t = -\frac{\log(\lambda_1)}{\log(\lambda_0)} = 8.24\,yr \tag{5.12}$$

Which reconstitutes the old adage that "one year seeding means seven years weeding" with acceptable accuracy. If we do not use management when we are slightly below the threshold level and it takes 8 years for the population to return to the initial density, then we only save the control cost 11% of the time (including the non-control year the whole cycle takes $\tau = t + 1$ years). All the meanwhile we would incur additional losses. Wallinga and van Oijen (1997) calculated the long-term frequency of control that would result from using a threshold strategy. Their derivation gave an estimated control frequency for barnyardgrass in tomato, if 100% efficacy could be achieved, of:

$$\nu = \frac{\ln(\lambda_1)}{\ln(\lambda_1) - \ln(\lambda_0)} = 89\% \tag{5.13}$$

Equation (5.13) takes into account the fact that the return time is not necessarily an integer, and this leads to cycles of long (or infinite) period and can be shown to be equivalent to Equation 5.12. If handweeding barnyardgrass at very low densities costs \$10 ha^{-1}, then total savings on weed control costs, averaged over the frequency of control is only slightly more than \$1.10 ha^{-1}. The additional losses incurred will certainly be larger than that value.

Analytical approximation for the long-term threshold

We next considered the case where the control cost is not a function of density, but is related to efficacy (this representing a more common situation than handweeding barnyardgrass). If we adopted a threshold strategy, the benefit received from not controlling weeds was realized only when weeds were below the threshold. Weed populations increased by λ_1 when no control was applied, then subsequently decreased to their original level in an amount of time governed by λ_q. The total cycle period, τ, was calculated from Equation 5.12 (using λ_q in place of λ_0). The economic cost of future populations was the difference in the yield impact between the continuous and threshold strategies, discounted over time.

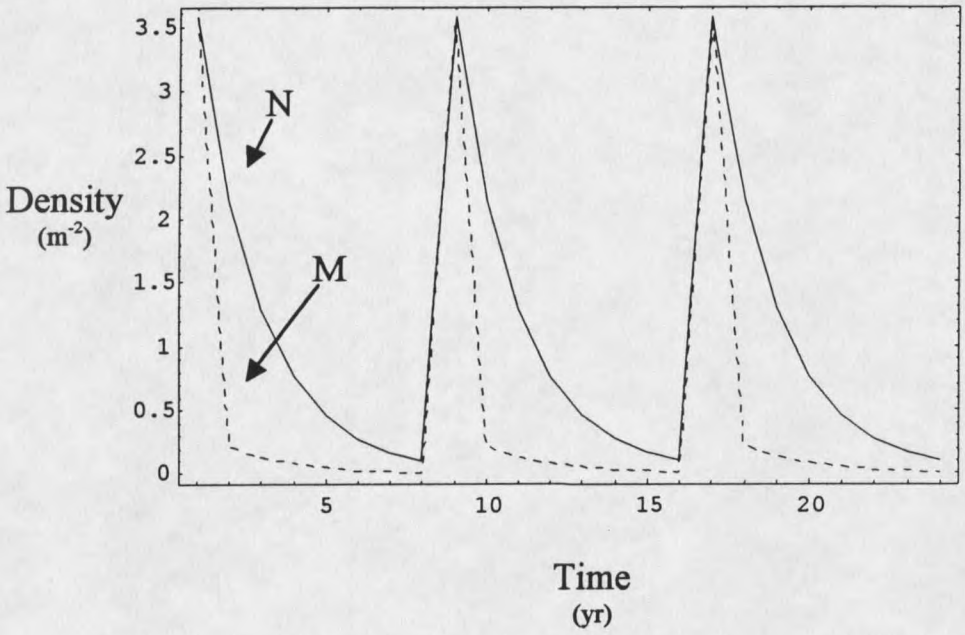
The EOT can be defined as the initial density for which the sum of the discounted treatment cost savings balances the total discounted losses due to future weed problems. We made several assumptions: (1) the mature plant density was small (thereby yield loss was approximately linear and growth rates were approximately density independent) and, (2) the return-time (Equation (5.12)) was an integer, we could then write an algebraic expression for the EOT. We began by approximating Equation (5.4):

$$y_0\left(1-\frac{iM}{1+iM/a}\right)\approx y_0(1-iM) \tag{5.14}$$

In a given year, t, the threshold strategy caused greater loss in yield and net return than the continuous control strategy due to the higher density of mature plants. The difference in value between the two strategies was:

$$\Delta V_t = y_0(1-iM_t)-y_0(1-iM_t')=y_0 pi(M_t'-M_t) \tag{5.15}$$

Figure 5.3. Population trajectory of seedling (N) and mature plant density (M) under a threshold strategy.



In order to determine the long-term economic threshold, we summed the discounted values over time. Example threshold-strategy population trajectories for both seedling and mature plant densities are shown in Figure 5.3. The continuous control strategy resulted in an exponentially decaying trajectory. The total sum of discounted relative values can be written:

$$\Delta V_{TOT} = \sum_{j=0}^{m-1} \sum_{k=0}^{\tau-1} \frac{\Delta V_{j\tau+k}}{(1+\delta)^{j\tau+k}} \tag{5.16}$$

The two summation signs in Equation (5.16) represent the sum within cycles (k) and over cycles (j). We used the growth rate, in combination with Equation (5.15) and Equation (5.16) to write an expression for the total discounted value. We derived the

appropriate expression by example. We considered a hypothetical situation in which we have a cycle length $\tau = 4$ with a number of cycles $m = 3$:

Table 5.2. Example seedling and mature plant densities under threshold and continuous control treatment strategies.[a]

T	Threshold Strategy			Continuous Control Strategy			C	Difference in Mature plant density
	q	N'	M'	q	N	M		M'-M
0	0	N_0	N_0	q	N_0	qN_0	c_1	$(1-q)N_0$
1	q	$\lambda_1 N_0$	$q\lambda_1 N_0$	q	$\lambda_q N_0$	$q\lambda_q N_0$	0	$q(\lambda_1-\lambda_q)N_0$
2	q	$\lambda_1\lambda_q N_0$	$q\lambda_1\lambda_q N_0$	q	$\lambda_q^2 N_0$	$q\lambda_q^2 N_0$	0	$q(\lambda_1-\lambda_q)\lambda_q N_0$
3	q	$\lambda_1\lambda_q^2 N_0$	$q\lambda_1\lambda_q^2 N_0$	q	$\lambda_q^3 N_0$	$q\lambda_q^3 N_0$	0	$q(\lambda_1-\lambda_q)\lambda_q^2 N_0$
4	0	N_0	N_0	q	$\lambda_q^4 N_0$	$q\lambda_q^4 N_0$	c_1	$(1-q\lambda_q^4)N_0$
5	q	$\lambda_1 N_0$	$q\lambda_1 N_0$	q	$\lambda_q^5 N_0$	$q\lambda_q^5 N_0$	0	$q(\lambda_1-\lambda_q\lambda_q^4)N_0$
6	q	$\lambda_1\lambda_q N_0$	$q\lambda_1\lambda_q N_0$	q	$\lambda_q^6 N_0$	$q\lambda_q^6 N_0$	0	$q(\lambda_1-\lambda_q\lambda_q^4)\lambda_q N_0$
7	q	$\lambda_1\lambda_q^2 N_0$	$q\lambda_1\lambda_q^2 N_0$	q	$\lambda_q^7 N_0$	$q\lambda_q^7 N_0$	0	$q(\lambda_1-\lambda_q\lambda_q^4)\lambda_q^2 N_0$
8	0	N_0	N_0	q	$\lambda_q^8 N_0$	$q\lambda_q^8 N_0$	c_1	$(1-q\lambda_q^8)N_0$
9	q	$\lambda_1 N_0$	$q\lambda_1 N_0$	q	$\lambda_q^9 N_0$	$q\lambda_q^9 N_0$	0	$q(\lambda_1-\lambda_q\lambda_q^8)N_0$
10	q	$\lambda_1\lambda_q N_0$	$q\lambda_1\lambda_q N_0$	q	$\lambda_q^{10} N_0$	$q\lambda_q^{10} N_0$	0	$q(\lambda_1-\lambda_q\lambda_q^8)\lambda_q N_0$
11	q	$\lambda_1\lambda_q^2 N_0$	$q\lambda_1\lambda_q^2 N_0$	q	$\lambda_q^{11} N_0$	$q\lambda_q^{11} N_0$	0	$q(\lambda_1-\lambda_q\lambda_q^8)\lambda_q^2 N_0$

[a] The seedling and mature plant densities under the threshold strategies are N' and M' while under the continuous control strategies they are N and M. C is control cost savings for the time period (T) of the threshold strategy over the continuous control strategy.

Table 5.3. Discounted savings from the control cost and difference in mature plant densities.

Time	Control Cost	Difference in Mature Plant density	
T		M'-M	
0	$\frac{c_1}{(1+\delta)^0}$	$\frac{(1-q)N_0}{(1+\delta)^0}$	
1	0		$\frac{q(\lambda_1-\lambda_q)N_0}{(1+\delta)^1}$
2	0		$\frac{q(\lambda_1-\lambda_q)\lambda_q N_0}{(1+\delta)^2}$
3	0		$\frac{q(\lambda_1-\lambda_q)\lambda_q{}^2 N_0}{(1+\delta)^3}$
4	$\frac{c_1}{(1+\delta)^4}$	$\frac{(1-q\lambda_q{}^4)N_0}{(1+\delta)^4}$	
5	0		$\frac{q(\lambda_1-\lambda_q\lambda_q{}^4)N_0}{(1+\delta)^5}$
6	0		$\frac{q(\lambda_1-\lambda_q\lambda_q{}^4)\lambda_q N_0}{(1+\delta)^6}$
7	0		$\frac{q(\lambda_1-\lambda_q\lambda_q{}^4)\lambda_q{}^2 N_0}{(1+\delta)^7}$
8	$\frac{c_1}{(1+\delta)^8}$	$\frac{(1-q\lambda_q{}^8)N_0}{(1+\delta)^8}$	
9	0		$\frac{q(\lambda_1-\lambda_q\lambda_q{}^8)N_0}{(1+\delta)^9}$
10	0		$\frac{q(\lambda_1-\lambda_q\lambda_q{}^8)\lambda_q N_0}{(1+\delta)^{10}}$
11	0		$\frac{q(\lambda_1-\lambda_q\lambda_q{}^8)\lambda_q{}^2 N_0}{(1+\delta)^{11}}$
SUM	$c_1\sum_{j=0}^{m-1}(1+\delta)^{-j\tau}$	$N_0\sum_{j=0}^{m-1}\frac{(1-q\lambda_q{}^{j\tau})}{(1+\delta)^{j\tau}}+qN_0\sum_{j=0}^{m-1}\sum_{k=1}^{\tau-1}\frac{(\lambda_1\lambda_q{}^{-1}-\lambda_q{}^{j\tau})\lambda^k}{(1+\delta)^{j\tau+k}}$	

Table 5.2 contains the schedule of control cost savings and the schedule of losses realized by difference in mature plant densities with the two strategies. The schedules of discounted control costs and lost yields were summed as shown for the example in Table 5.3.

If we set the sum of the discounted savings equal to the sum of the additional losses because of higher mature plant densities under the threshold strategy then:

$$c_1\sum_{j=0}^{m-1}(1+\delta)^{-j\tau} = y_0 \cdot p \cdot i \cdot N_0\left[\sum_{j=0}^{m-1}\frac{(1-q\lambda_q{}^{j\tau})}{(1+\delta)^{j\tau}} + q\sum_{j=0}^{m-1}\sum_{k=1}^{\tau-1}\frac{(\lambda_1\lambda_q{}^{-1}-\lambda_q{}^{j\tau})\lambda^k}{(1+\delta)^{j\tau+k}}\right] \tag{5.17}$$

Next we define:

$$h_{r,m} \equiv \sum_{k=0}^{m-1} r^k = \frac{1-r^m}{1-r} \tag{5.18}$$

From Equation (5.17) we can then calculate:

$$\begin{aligned} c_1 h_{(1+\delta)^{-\tau},m} = y_0 \cdot p \cdot i \cdot N_0\Big[&\left(h_{(1+\delta)^{-\tau},m} - q h_{\lambda_q{}^{\tau}(1+\delta)^{-\tau},m}\right) \\ &+ q\left(\lambda_1\lambda_q{}^{-1}h_{(1+\delta)^{-\tau},m} - h_{\lambda_q{}^{\tau}(1+\delta)^{-\tau},m}\right)\left(h_{\lambda_q(1+\delta)^{-1},\tau} - 1\right)\Big] \end{aligned} \tag{5.19}$$

The EOT is found by solving Equation (5.19) for N_0:

$$N_0{}^{EOT} = \frac{c_1}{y_0 \cdot p \cdot i}\left[\frac{\alpha}{(\alpha - q\beta) + q\left(\lambda_1\lambda_q{}^{-1}\alpha - \beta\right)(\gamma - 1)}\right] \tag{5.20}$$

With:

$$\begin{aligned} \alpha &= h_{(1+\delta)^{-\tau},m} \\ \beta &= h_{\lambda_q{}^{\tau}(1+\delta)^{-\tau},m} \\ \gamma &= h_{\lambda_q(1+\delta)^{-1},\tau} \end{aligned} \tag{5.21}$$

If we consider the case where:

$$q\beta << \alpha$$
$$\beta << \lambda_1 \lambda_q^{-1} \alpha \tag{5.22}$$

Then Equation (5.20) becomes:

$$N_0^{EOT} = \frac{c_1}{y_0 \cdot p \cdot i}\left(\frac{1}{1+q\lambda_1\lambda_q^{-1}(\gamma-1)}\right) \tag{5.23}$$

As yield loss is a monotonically decreasing function of weed density, and the 'i' parameter is the maximum slope, the assumption of linearity of the yield loss function results in an "actual" EOT that lies above that calculated in Equation (5.20). The assumption of a sufficiently small mature plant weed density is also necessary for the growth rate without control, λ_1, to be approximately constant. As density dependence would depress the growth rate without control, it would also tend to lead to an overuse of control measures. In contrast to other sources of uncertainty present (e.g. uncertainty in the impact or weed-free yield), the error introduced by the "sufficiently small M" assumption is probably of minor importance.

The derivation of Equation (5.20) also required that the period, $\tau = t+1$, with t defined in Equation (5.12), be an integer and that the total planning period, consisting of 'm' cycles, also be an integer. The second requirement is up to the discretion of the decision-marker so it is not a problem, but the first condition would almost never occur in practice. For an analysis that includes future effect by looking at a single cycle, non-integer periods would not pose difficulty. For multiple cycles, the fact that future values are discounted will decrease the importance of the assumption. One could establish an effective range of EOTs by using the formula with both the integer directly below and

above the non-integer value. If 100% efficacy is attained, the EOT collapses to the expression for the ET as calculated by Marra and Carlson (1983). The reason the EOT is not smaller than the ET is that (with 100% efficacy) no mature plants are produced, except in years without control. The future losses are always paired with future savings of the control cost.

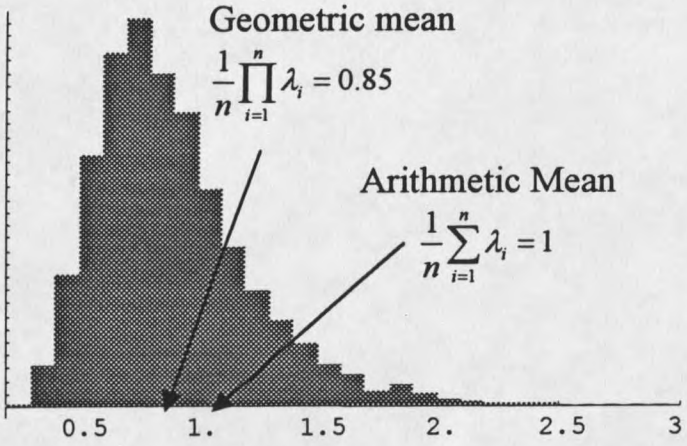
Environmental Stochasticity

Inclusion of variability in the demographic parameters depresses the effective growth rate (Freckleton and Watkinson 1998b). As population growth occurs by multiplying each successive population density by the growth rate, the long-term growth rate of an isolated population is the geometric mean instead of the arithmetic mean of the distribution of growth rates (Cohen 1966). We explored the effect of environmental stochasticity by performing a simulation where independent draws were made from the demographic parameter distributions given in Table 5.1. The geometric mean growth rate was approximately 85% of the arithmetic mean growth rate. The effects can be seen in Figure 5.4. The potential growth rate is so large that the required efficacy is not substantially altered.

Field size, demographic stochasticity and weed information

For a 1 ha field, the weed density cannot be less than 10^{-4} plants m^{-2}, because plants occur as individuals. What's more, mortality either occurs or it doesn't, therefore application of a 90% effective control would reduce the density of 10^{-4} plants m^{-2} to zero 9 times out of 10. The smaller the field size, the more important demographic

Figure 5.4. Distribution of λ with corresponding arithmetic and geometric means.[a]



[a] The simulation involved drawing 10^4 random deviates from the distributions specified in Table 5.1, given q* from the deterministic model Equation 5.8 and q*S << 1. The corresponding geometric and arithmetic distribution means are shown.

stochasticity (the discreteness of mortality or reproductive events) may become for assessing when a strategy is economically favorable. Another scale effect that is important when considering a very high growth rate weed is uncertainty surrounding the estimate of weed seedling density.

For large fields, the accuracies of estimates in relation to sampling (detection) efforts and costs get scant attention (Cousens 1987, Firbank 1993a). The majority of a 1 ha field would need to be surveyed before we could claim reasonable confidence that there was no barnyardgrass present. For low density, high growth rate weeds, extensive monitoring would be essential. If fields were sampled for such low densities, surely it would be most practical for the scout to simply remove the weed when found.

Conclusions

The threshold concept is probably not useful for barnyardgrass in a tomato crop, not because a threshold does not theoretically exist, per se, but because the economic threshold level is so low that the act of monitoring and weeding would become one and the same. We concur with Norris (1992a) that knowledge of the biology and ecology of weeds should form the basis for management. In particular, knowledge of the temporal and spatial variability in λ will be crucial to efficient management.

We have presented a way to estimate the long-term threshold analytically so that demographic considerations can be included in threshold decisions. The advantage of the simplicity of an explicit functional form is that it is readily obvious that the EOT is more or less inversely proportional to the product of the survivorship and the growth rate of a weed. High value crops, for which the ET tends to be very small, with high growth rate weeds (high product of survivorship and growth rate) are obviously not candidates for the threshold management approach.

Weed demography cannot be divorced from cropping systems. The success of weeds depends on resources and mortality factors associated with particular management strategies. A successful weed management program must be able to achieve long-term containment of weed populations if they are shown to have significant negative impact on marketable yield. The profit generated by the operation provides an absolute ceiling on the money that can be allocated toward meeting this objective for the entire spectrum of weeds at a site. If the operation cannot support this cost, then alternatives must be considered.

In systems with relatively low prices for marketable produce (e.g. small grains), many producers find themselves with fewer resources available to meet containment goals. It would be outright negligent not to consider thresholds if it could help them meet their economic management objectives. The lessons learned from the barnyardgrass case are valuable. That is, we need to understand weed demography as it relates to cropping systems. Application of management thresholds may not be important for high value crops where farm inputs compose a relatively minor portion of the net returns (e.g. tomatoes), but those situations are rapidly disappearing particularly for large acreage crops (e.g. wheat). If phenomena other than outright population growth are maintaining weed populations in fields (e.g. dispersal or patch structure), then there is great potential for economic and environmental savings in preventative practices like insuring weed-free seed when sowing.

EPILOGUE

General Summary

I have investigated and assessed the use of on-farm experimentation for determining a treatment effect (the potential advantage of the patch spraying of weeds) and the prediction of weed impact from data gathered in an on-farm experiment. I have explored some of the potential difficulties arising from the collective analysis of small-plot competition data for computing single-year thresholds, and for establishing threshold densities in the presence of future demographic effects. The singular theme being that all facets address the question: "how should we go about making management decisions in the face of the variability we encounter when we try to manage site-specifically or with reduced inputs?"

As weed control decisions cannot be avoided, the question is on one hand a practical one: how can we best utilize site-specific technology to improve weed management? On the other hand, the question is philosophical: do we know enough to recommend low input approaches as being financially beneficial to the farmer? If not, what methods would be most prudent to remedy the situation?

With this work I have suggested some answers: (1) work with producers to facilitate and potentially automate the on-farm research process, (2) use stochastic models to integrate data with decision making, (3) extrapolate small-scale plot data with caution and (4) work toward understanding management decisions in the context of weed demography and the necessity of control.

Future Research

There is much background work that needs to take place before site-specific on-farm research provides the "feedback" into the management process that is its potential. In particular, a rigorous understanding of measurement error in site-specific data is required. Until we can reduce or at least estimate measurement error, we will be unable to differentiate variation stemming from biological or chemical processes from that arising from the measurement process itself. Currently the major benefit of site-specific technology is to provide farmers with qualitative feedback on management efforts. While this may very well help farmers improve their decision-making, the quantitative use of on-farm data may be able to extend this benefit.

After a suitable period of time, data sets should be made publicly available so that they are not forever lost. Particularly data sets arising from publicly funded research, which should be "warehoused" after researchers have published results. There should be standards in place for describing experimental details and methodologies. If we are to predict with data that is gathered over a limited spatial extent, we need to combine it with other studies, at other locations and times, in order to have confidence in our predictions. Warehousing data would also help facilitate the progress of science by encouraging common protocols.

After composing the preceding paragraph, I received the current issue of the Bulletin of the Ecological Society of America (82(2):138-141) wherein there is a three page article describing the "Best practices for preparing ecological data sets to share and archive." I am thinking, how long before weed science follows suit? How long before

we can distill generalities that transcend the particulars of a cropping system or chemistry? How long before we capitalize on what we have already purchased?

I believe not enough is known about weed demography. We need to understand what processes are specifically responsible for the success of some weeds, and what processes regulate populations when they are suppressed. Our landscape is covered with different cropping systems, all providing potential experiments as to which factors influence the success of weeds. We should take advantage of these "natural" long-term experiments.

As Popper stated in the opening quote of the prologue "...in our infinite ignorance we are all equal..." yet we must do our utmost to manage our land well with "...the various little bits we know." I hope this thesis adds something to that endeavor.

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