



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  
Montana State University  
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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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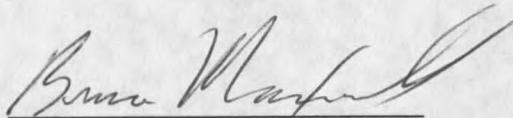
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Of a dissertation submitted by

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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.

Bruce Maxwell, Ph.D.

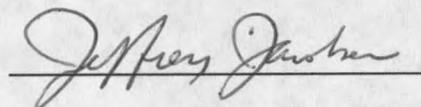


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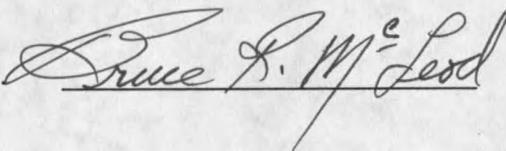


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## ABSTRACT

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.

## 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 "learning 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 GPSSummary

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 ( $0.2 \text{ T ha}^{-1}$ ). 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.

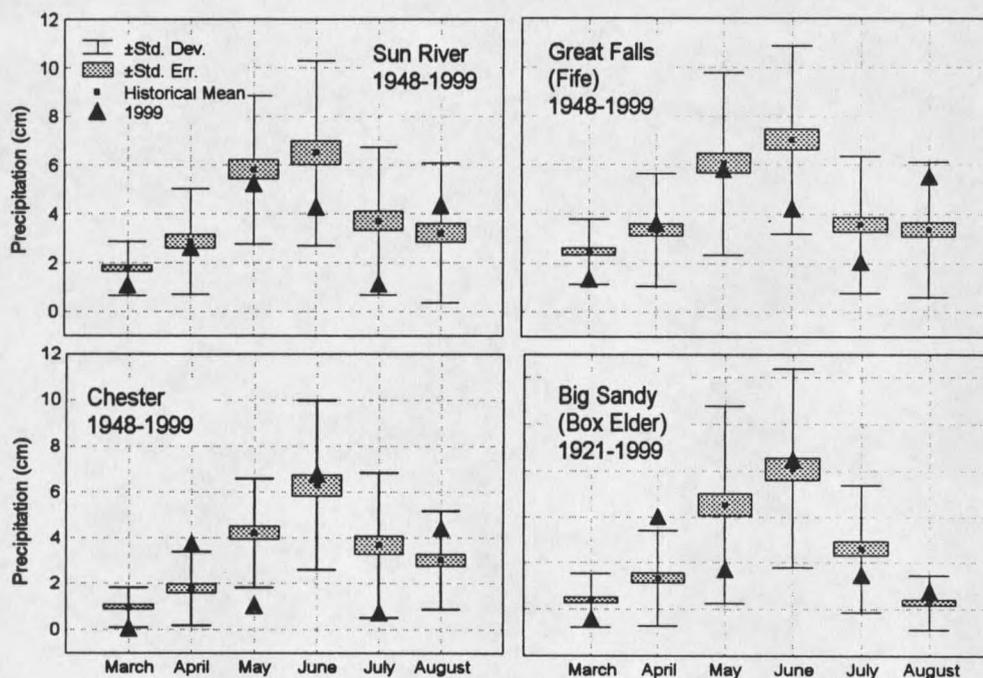


Figure 2.1. Historical and 1999 precipitation for study sites.

### 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 <sup>a</sup> |      |      | 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      |

<sup>a</sup>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<sup>1</sup> 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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<sup>1</sup> Ashtech Ag Navigator, Model RDAC, Magellan Corp., 469 El Camino Real, Santa Clara, CA. 95050.































































































































































































