

WHEAT YIELD PREDICTION MODELING FOR LOCALIZED OPTIMIZATION
OF FERTILIZER AND HERBICIDE APPLICATION

by

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ABSTRACT

The specific goal of this thesis was the development of a five-variable dryland wheat yield prediction model for the optimal localized variable-rate management of fertilizer and herbicide considering varying levels of available water and weed infestation. The motivation for this work was to increase on-farm net return and reduce off-target chemical effects. The five most influential predictor variables of wheat yield were investigated: wheat density, wild oat density, nitrogen fertilizer rate, herbicide rate, and water level

Previously collected field data sets that included dryland wheat yield as the dependent variable and at least one of the predictors were investigated for linear and nonlinear trends. The best-fit nonlinear yield model to the combined field data set included crop and wild oat density, and growing season precipitation; nitrogen and herbicide rates were not significant factors in this model. These results illustrated the large amount of unexplored variation in wheat yield, and the lack of ecological first principles upon which farmers base input management decisions, especially when weed infestation causes competition for limited nitrogen and water.

To take an initial step towards elucidating the biological mechanisms of wheat-wild oat competition with varying combinatorial levels of resources, a five-variable greenhouse experiment was conducted. The best-fitting yield model to the greenhouse data set was a nonlinear equation including all five variables. This predictive model was used to demonstrate how such an equation would help farmers make localized variable rate input decisions within a decision support framework. Monte Carlo simulation was used to produce net return prediction probabilities for site-specific variable-rate management, low level input management, and high level input management of nitrogen and herbicide based on the two sources of parameter estimates—field data and greenhouse data. The variable rate scenario resulted in larger net returns over the broadcast management scenarios in at least 48%, and at most 66%, of the simulations. This initial exploration provided considerable support for future on-farm experiments and yield prediction modeling. In addition, it established a first principle model to be parameterized for use in different dryland spring wheat growing regions.

PROLOGUE: THE VALUE OF RISK, THE STATE OF AGRICULTURE, AND THE ROLE OF EMPIRICAL MODELING

It is the tension between creativity and skepticism that has produced the stunning and unexpected findings of science. –Carl Sagan

I am always doing that which I cannot do, in order that I may learn how to do it. –Pablo Picasso

The PhD process has taught me the value of risk and attempting to do what one does not know how to do in ecological research which has produced, as detailed in this thesis, the empirical ecological model that was embarked upon nearly four years ago. Attempting to quantify truth in ecology through models is a challenging goal because ecological systems are infinitely complex and models will always be wrong. Nonetheless developing creative and the best approximating models is necessary to achieve insight into truth through approximation leading to new ideas, deeper knowledge, testable hypotheses, and more sustainable management decisions. Furthermore, approximating truth is a profound goal such that every quantitative step made closer to full reality lays the foundation for the next set of hypotheses.

The goal of my Ph.D thesis research—to mathematically quantify a wheat agroecosystem for the optimization of input use—has been a risky one with unsettling periods of skepticism and stress over the difficulty of publication and funding as well as simply achieving our goal. Yet, it was not until I fully accepted this risk and the possibility of failure (i.e. not developing the proposed first-principle model) that I began to understand our obligation as ecologists, and the inherent risk and failures that must be endured when data is lacking and difficult to collect, variation is dauntingly large, and the

system is uncomprehendingly complex. In accepting this risk, this thesis represents for me a closer step toward truth in the deeper knowledge of and respect for a profoundly complex ecological system through the best-known approximation of this system.

The ecological system I have addressed and attempted to predict is dryland wheat production, specifically predicting the outcome of crop and weed competition in the presence of controllable farmer-added inputs and uncontrollable environmental variables, such that increased efficiency in agriculture can be attained if fields are managed in a spatially localized manner. Agricultural inputs of fertilizer and herbicide have been historically managed according to mean field conditions (Luschei 2001). Typically, a qualitative early season assessment of the number and density of weed patches, influences the rate at which herbicide is prophylactically applied. Last year's yield, illustrating the success of previous management strategies, typically influences the current season's fertilizer rate decision. Information from spring soil samples may augment the information used to determine how much fertilizer needs to be added to the system, however, the results of a few soil sample tests likely determine the fertilizer rate for the entire field (Luschei 2001). While single-rate broadcast input applications are the norm, farmers and agronomists have reported the variability inherent in fields since at least the 1920's (Gotway-Crawford et al. 1997). Addressing agricultural field variability for increased efficiency of wheat production systems is the over-arching goal of this thesis.

The root of inspiration for this research is the current state of agriculture. Specifically, increased expense of herbicide and fertilizer, relatively low crop prices, environmental concerns of off-target chemical effects, and development of weed

resistance to herbicides have led to research aspirations for more efficient use of herbicide and fertilizer (O'Donovan 1996). The scale of these problems is vast considering the percentage of US land in agricultural production: 37% in the Midwest, 31% in the West, and 30% in the South (NASS 2004). Accordingly, farmers as a group manage more land than any other private entity in this country (USDA Ag Census). Thus, a blueprint for optimizing input use to reduce off-target effects and increase the net return of farms would have sweeping consequences.

To more fully undertake the goal of “addressing field variability” means understanding how wheat yield is influenced by crop density, fertilizer, herbicide, water, weed density, as well as many other important ecological variables such as time (e.g. time of emergence, time of fertilizer application, time of herbicide application, time of precipitation), soil characteristics (e.g. pH, texture, percent organic carbon, and percent silt, sand, and clay) and other ecological influences (e.g. pathogens, herbivory, and allelopathy). “Addressing field variability” in the form of an empirical equation, while logical, quickly becomes a very ambitious and challenging goal.

However, there is hope. The philosophical and technological advances in the fields of agronomy, ecology, agricultural engineering, computer science, and statistics have allowed the development of tools with which to address field variability. Agronomy and ecology have experienced advances in philosophy of science and ecological prediction through empirical and mechanistic theoretical and applied models. Agricultural engineers have continually developed and improved machinery that can collect on-farm data, such as yield maps, localized soil electrical conductivity, and plant densities as farm implements cover the landscape every growing season. Agricultural

engineering has also developed machinery that can apply localized variable rates of seeding, fertilizer, and herbicide. Advancements in computer science have developed faster computation, increased graphic capabilities, and software used in the simulations of stochastic ecological scenarios. Statistical techniques and philosophies have produced more robust methods for assessing model accuracy and the approximation of “full reality” leading to ecologically sustainable management decisions. Thus, the goal of increasing efficiency of fertilizer and herbicide inputs on farms integrates several disciplines.

The specific direction we have taken to address field variability is within the sphere of “empirical” modeling. Before further explanation of our modeling methodology, it is important to clarify the terms “empirical” and “mechanistic”. While “mechanistic” is a reasonable adjective describing *process* models, “empirical” is a poor descriptor for models that describe observable *pattern* in data given its definition. Empirical is defined as “relying on or derived from observation or experiment” (Merriam-Webster 2002). This definition describes both empirical and mechanistic models since they both rely on or are derived from observations and experiments. I would prefer to use the phrase “pattern model” rather than “empirical model” because it is a more accurate adjective for the essence of what is referred to in the literature as empirical modeling. Although this becomes an argument of semantics since “pattern” is not a perfect descriptor either, it is nonetheless a more complementary term to “mechanistic”. For purposes of clarity, however, I will continue to use the conventional descriptions throughout this thesis.

An *empirical* modeling approach, incorporating statistical and experiential components, has been employed rather than a mechanistic model for several reasons: 1) farmers need to make decisions at a specific time, e.g. within days of planting their crops, 2) empirical models are more practical than mechanistic models for farmers to parameterize, and 3) mechanistic models have not necessarily shown to be better predictors than empirical models (Barnett et al. 1997).

While mechanistic models are extremely valuable for investigating physiological and phenological processes, they are generally not as suitable for management *in agriculture* because they require more parameters. More parameter values require more data from which to derive them, and the increased number of parameters in a model can add more bias and variability. For example, the well-studied agricultural mechanistic model CERES-wheat (Ritchie and Otter 1985), which includes plant and soil processes to understand wheat yield, includes at least 25 parameters that need to be estimated. INTERCOM, another well-known mechanistic model requires 19 parameters (Lindquist 2000). Some of the parameters included in these models, for example, are leaf area index, straw and chaff weight at maturity, accumulation of thermal units, absorption of photosynthetic photon flux, total solar radiation, number of tillers, crop nitrogen content, stover nitrogen content at maturity, photoperiod, grain filling duration, soil temperature, soil water, soil nitrogen pools with inorganic-N, amount of fresh organic matter, and mass per m² of soil area for leaves, stems, grains and roots, to name a few. How can a farmer, or even a crop consultant, possibly (and *accurately*) estimate all of these parameters? The *sine qua non* is that farmers need to make nitrogen and herbicide decisions—and this happens days after planting, e.g. at time = 1 week. Early season

information, such as crop seedling stand, weed seedling density, soil fertility, and soil water availability is what matters to a farmer needing to make annual decisions about fertilizer and herbicide rate. What happens environmentally across the entire field after the inputs have been applied – a drought or a period of low thermal units, for example—does little to help a farmer make those once-a-year decisions. Unlike more typical conservation biology cases, where mechanistic models simulate management scenarios that are possible at time = 1, 2, 3, etc., management in the form of herbicide and fertilizer application in agriculture generally happens at one time step, e.g. time=1 week after emergence. Typically no more chemical input management occurs until harvest, i.e. the final time step. For predictive purposes we have assumed that chemical input application occurs once at the optimal time for management. While we could incorporate forecasted values such as growing season precipitation, average solar radiation, and expected temperatures into our model, the model would become more empirical, describing overall patterns.

Additionally, agricultural mechanistic models, while valuable for scientific inquiry, have not shown to be accurate predictors of localized wheat yield within fields. Barnett et al. (1997) investigated the performance of the three well-known mechanistic crop models: AFRCWHEAT2, CERES-wheat and SIRIUS. They concluded, “none of the models accurately predicted historical grain yield between 1976 and 1993. Substantial disagreement was found between the models’ predictions”. While these conclusions initially appear quite dire, Barnett et al. (1997) continue to explain the poor performance of these models:

It seems that one of the main reasons [for lack of prediction accuracy] is that...wheat yields tend to relate to agronomic factors rather than physiological ones. The wheat models are designed to be applied under ideal management so they cannot, in their present forms, predict variations in yields under conditions which exist in practice.

Instead of designing an empirical model “to be applied under ideal conditions”, simplifying assumptions have been made in our model to focus on prediction with enough accuracy to be of value to the farmer, but simple enough to parameterize *on* the farm. These assumptions essentially remove time in the form of $t = 0, 1, 2, \dots, n$ from the model. Thus time of emergence for the wheat and wild oat was assumed to occur at the same time, and agronomic practices (e.g. application of fertilizer and herbicide) were executed at the most ideal time to maximize crop growth. These assumptions removed some variability from the system. From a scientific inquiry perspective, these assumptions are arguably the Achilles heel of our model. A valid question, aimed at that Achilles heel, could be: “how would the model perform, specifically in terms of wheat and wild oat competition, if fertilizer was applied late because the farmer was busy tending to another field?” While this is a valid question strategic assumptions need to be made when modeling a complex system to elucidate ecological first principles. Once the basic ecological principles are established, complexity can be added to the model depending on the objectives for model use.

Specifically, this thesis details the empirical model we have developed that relates wheat yield to wheat density, wild oat density, nitrogen rate, herbicide rate, and water. Given the number of ecological influences previously listed, we have narrowed the model to include *only* 5 predictor variables because they are arguably the 5 most influential in

dryland wheat systems, and they arguably characterize the system adequately. “Only” including these 5 variables is a major advance for yield prediction in the field of agronomy. The non-linear empirical model we have developed uses the inputs of localized wheat seedling density, wild oat density, and early season soil water to optimize fertilizer and herbicide rates throughout the field. This empirical model draws upon the nonlinear agronomic processes that have been reported in the literature over the last several decades.

A challenging but common goal within the discipline of ecology is developing a mathematical equation that describes a complex multi-variable system when there are no experiments that include all the variables of interest. While a vast amount of information in the form of data from plot experiments on agricultural experiment stations and on farms exists, none of these experiments have measured all five specified predictor variables independently and in combination. The exception, as inspired by this lack of information, is the experiment we have conducted, as described in this thesis.

Specifically, Chapter 1 describes the state of knowledge of wheat-wild oat systems in the presence of inputs from experiments and developed models. Chapter 2 integrates independently collected field data with which the building of a five-variable model is attempted. Realizing that a large but sometimes limited amount of inference can be made from independently collected data, a five-variable full factorial experiment was conducted in the greenhouse complex at Montana State University. Chapter 3 details this five-variable greenhouse experiment and further model development. Finally, Chapter 4 uses the best-fitting five-variable empirical model to demonstrate how such an equation would be used to make localized variable rate fertilizer and herbicide recommendations

within a Decision Support System for the benefit of farmers, consumers, rural communities, and the environment.

References Cited

- Barnett, V., S. Laundau, J.J. Colls, J. Craigon, R.A.C. Mitchell, and R.W. Payne. 1997. Predicting wheat yields: the search for valid and precise models. In: Precision agriculture: spatial and temporal variability of environmental quality. Wiley, Chichester Ciba Foundation Symposium 210, p. 79-99.
- Gotway-Crawford, C.A., D.G. Bullock, F.J. Pierce, W.W. Stroup, G.W. Hergert, and K.M. Eskridge. 1997. Experimental design issues and statistical evaluation techniques for site-specific management. In: The State of Site-Specific Management for Agriculture. p. 301-335, F. J. Pierce and E. J. Sadler, eds. American Society of Agronomy/Crop Science Society of America/Soil Science Society of America, Madison, WI.
- Lindquist, J.L. 2001. Performance of INTERCOM for predicting corn–velvetleaf interference across north-central United States. Weed Science: 49: 195–201.
- Luschei, E. 2001. An assessment of the use of site-specific weed control for improving prediction-based management decisions and automating on-farm research. Ph.D Thesis, Montana State University.
- Merriam-Webster Medical Dictionary, © 2002 Merriam-Webster, Inc., <http://dictionary.reference.com/>.
- National Agricultural Statistics Service, 2004. Farms and land in farms. <http://usda.mannlib.cornell.edu/reports/nassr/other/zfl-bb/fmno0204.pdf>
- O'Donovan, J.T. 1993. Weed economic thresholds: useful agronomic tool or pipe dream? Phytoprotection 77:13-28
- Ritchie, J. T and S. Otter. 1985. Description and performance of CERES-Wheat: A user-oriented wheat yield model, In ARS Wheat Yield Project. ARS-38. National Technology Information Service, Springfield, VA., p. 159-175.

CHAPTER 1

REVIEW OF EXPERIMENTS AND MODELS

Abstract

Ecological models allow for more sustainable management decisions. Specifically, management of farm inputs as determined by a wheat yield prediction model could increase economic efficiency and decrease the environmental impacts of crop production. This literature review, as an assessment of prior knowledge, represents the first step of model development whereby localized management decisions can be made. Wheat yield prediction has been explored with the following review of wheat experiments and models, specifically investigating how wheat and wild oat in competition are influenced by wheat density, wild oat density, fertilizer rate, herbicide rate, and available water. Other predictor variables are also discussed. Overall conclusions from the assessment of experiments are 1) individual plant densities of wheat and wild oat govern the outcome of their interference, 2) in wild oat infested fields nitrogen fertilizer increased wheat yield to a threshold, 3) with added nitrogen fertilizer lower wild oat densities caused yield reductions that compared to those caused by higher wild oat densities without added nitrogen, 4) both growing season precipitation and soil moisture affect wheat yield, although there was disagreement about which factor has more influence, 5) lack of yield response to nitrogen fertilizer and herbicide has been shown, which was most likely due to environmental and other site-specific factors, 6) herbicide, in many cases, can be decreased without a decrease in the current year's yield, 7) no studies investigated long-term effects of reducing current-year herbicide rates, 8)

soil properties influenced yield and yield-weed interference; however no studies specifically reported the influence of soil properties on spring wheat-wild oat interference, 9) field experiments illustrated the high degree of variability in wheat yield-wild oat competition studies and the subsequent difficulty of prediction, and 10) several independent field experiments indicated spatial and temporal variability in yield response, suggesting potential benefits of variable-rate localized management of fertilizer and herbicide. Conclusions from the review of wheat yield models include: 1) biologically meaningful yield prediction models are essential for management, 2) the dynamics of species in competition can be modeled, but model parameters vary across sites and years, 3) linear and non-linear trends have been observed for wheat yield as a function of the identified predictor variables (e.g. wheat density, wild oat plant density, wild oat biomass, and herbicide rate) and 4) a widely used generalized model of wheat-wild oat interference including the effects of nitrogen, herbicide and water has not been developed.

Introduction

The following literature review has been motivated by the overall goal of my thesis research: to increase economic efficiency and decrease the environmental impacts of crop production by attempting to enhance the understanding of how individual variables and their interactions influence wheat yield. Specifically, this project has been based upon developing methods to assess how the applied and environmental variables—weed density, fertilizer, herbicide, and available soil water—spatially impact spring

wheat (*Triticum aestivum*, L.) yield. Through field experimentation and subsequent computer modeling, the underlying spatial and temporal mechanisms of the five main variables influencing wheat yield can be elucidated, such that site-specific and variable-rate strategies for fertilization and herbicide application can be developed. Spring wheat-weed interactions are narrowed in this review to wild oats (*Avena fatua* L.)¹ because it is a weed species that has received most attention in a wide range of experiments globally.

In spite of attempts to homogenize plant growth conditions, agroecosystems are spatially variable in terms weed and crop density and soil properties. Weed seedlings are spatially aggregated (Van Groenendael 1988, Thornton et al. 1990, Navas et al. 1991, Wiles et al. 1992, Mortensen et al. 1993, Johnson et al. 1995), which makes site-specific application of herbicide logical. Selective wild oat herbicides such as imazamethabenz, dicloflop-methyl, and flamprop-methyl are expensive and negative gross margins can result from ineffective applications coinciding with low yielding conditions (Martin et al. 1987). Spatially variable soil properties result in varying levels of available soil water and nitrogen, making variable-rate localized fertilizer application within farms warranted.

While precision farming technologies for site-specific management are available and ever improving, there is a lack of information regarding the first principles of the spatial and temporal dynamics of weed populations in agricultural fields (Johnson et al. 1995), as well as a lack of basic understanding of wheat and wild oat inference with varying levels of nitrogen, herbicide, and water. The following literature review is broken into two parts for the two main methods for investigating the influences on wheat yield—field experimentation and computer modeling. Part I describes the many

¹ Wild oat refers to *Avena fatua* unless otherwise stated, e.g. *Avena ludoviciana*

experiments that have sought to elucidate the mechanisms with which wild oat density, wheat density, nitrogen, herbicide, and available water influence wheat yield. Part II describes the development of yield prediction and decision models, which have been based upon years of empirical data and have been developed to aid making management decisions on farms.

Part I. Experiments Investigating Factors Influencing Wheat Yield

The following section of this literature review focuses on experiments that have investigated the five variables that have been deemed most influential on wheat yield in spring wheat-wild oat plant communities by the authors: wheat density, wild oat density, available nitrogen, herbicide rate, and available water. *A.fatua* is the one weed investigated because it is the most serious annual weed in the wheat production regions of Montana, Canada (Sharma and Vanden Born 1978) and Australia (McNamara 1972). For comprehensiveness, I have included the major references that investigated the influence of other predictor variables, specifically time of emergence and soil properties, since several authors consider them as important as the five variables that I have listed above. This section begins with the simplest experiments, those investigating wheat and wild oat interference alone, and proceeds to those that have quantified the influence and interactions of added independent variables.

I have included the influences of the five variables on barley yield as well as spring wheat yield, since wild oat affects these two cereal crops similarly. Specifically, Chancellor and Peters (1974) have reported equal yield losses of barley and wheat due to

wild oat competition, even though it is generally accepted that barley is the more competitive crop since it develops seminal and crown roots more quickly than other cereal crops (Pavlychenko and Harrington 1967, Bell and Nalewaja 1968, Chancellor 1970, Dew 1972, O'Donovan et al. 1985, Cousens et al. 1987). Barley also emerges earlier than wheat and has wider leaf blades that are better oriented to reduce light beneath the plants between rows. Two studies, however, concluded that wheat was more competitive than barley (Thurston 1962, Torner et al. 1985).

While my this review focuses on spring wheat, it is nonetheless useful to acknowledge research results on barley and wild oat interference since barley and wheat are similarly affected by wild oats (Chancellor and Peters 1974). Since winter wheat has a different growing season than spring wheat and barley, the dynamics of its competition with wild oats is somewhat different than the spring cereals; therefore, studies investigating winter wheat and wild oat competition are not included in this review. There are, however, a few references included in this review that investigated crop and weed competition other than between wheat and wild oat; they have been conditionally included because of the relevance of the investigation and findings of the authors. Additionally, I have included a few references to *Avena ludoviciana* for like reasons.

Wild Oat Competition with Wheat

Following are key conclusions from years of wheat-wild oat competition experiments. As reported by Zimdahl (1980), competition between wheat and wild oat happens on a few levels. Below the soil surface competition is believed to occur when

roots compete for water and nutrients. Martin and Field (1988) concluded that when wheat and wild oats were sown simultaneously, wild oat was more competitive due to its greater root competitive ability, however, the two species had similar shoot competitive influence on each other. Pavlychenko and Harrington (1935) reported that wild oat eventually grew a root area four times greater than wheat. Furthermore, all cereals in their study had larger root systems when grown without intra- and inter-specific competition. Due to competition, cereals grown in 15-cm rows did not grow crown roots. Intra-specific competition also occurred for both wild oat and wheat (Pavlychenko and Harrington 1935). As cited by Zimdahl (1980), Pavlychenko (1937) found that intra-specific competition reduced the total root system area by 81-99 times in both wheat and wild oat when compared to single plants grown alone in ten square feet.

A second conclusion reported in several studies is that the densities of wheat and wild oats individually influence the outcome of their interference—crop yield. The effectiveness of wheat in controlling wild oats is determined by the crop's density when the wild oats are germinating and not by the crop's final yield (Thurston 1962). By conducting a field experiment varying the densities of wheat and wild oats, Martin et al. (1987) reported that increasing the density of either wheat or wild oats did not generally decrease the density of the other species at harvest; rather, increasing the density of either wheat or wild oat resulted in significant decrease in tiller number per unit area of the other species. At the lowest wheat density (e.g. 11 kg ha⁻¹) and at the highest wild oat density (e.g. 243 kg ha⁻¹) wheat yields were reduced by 78% and 77% respectively in their two experiments. Stepwise multiple regression analysis revealed that the most influential variable on yield to characterize competition from wild oat was the relative

proportion of wild oats in the total plant (i.e. wheat and wild oat) community (Carlson et al. 1982). Wilson et al. (1990) concluded that competitive effects of wild oat were greatest at low wheat densities. At low wild oat densities, crop yield decreases 1% for each additional wild oat plant per square meter (Wilson et al. 1990). Peterson et al. (1996) added that at very high densities of wild oats intra-specific competition is also likely to have a significant effect. Contrary to Bowden and Friesen (1967), Bell and Nalewaja (1968), Wilson and Peters (1982), and O'Donovan et al. (1985) who found non-linearity in yield reductions due to increased wild oat infestation, Carlson et al. (1982) found that yield reductions linearly increased with each increase in wild oat infestation, which was significant at the $p=0.01$ level in all three of their experiments.

When there is sufficient soil moisture, the rate of seeding wheat influences its competitive ability against wild oat (Radford et al. 1980, Martin et al. 1987). When no herbicide was used and wild oat density was high (e.g. 290 mean wild oat plants m^{-2}), net returns were increased when seeding rate was increased (Barton et al. 1992).

Specifically, Radford et al. (1980) recommended increasing wheat-seeding rates to 150 plants m^{-2} as a low-cost method for some wild oat control. Walker et al. (2002) found maximum wheat production when sowing rate was 130 wheat plants m^{-2} and herbicide rate was 75% of the label rate. These benefits were also achieved at a wheat density of 150 plants m^{-2} and a 50% dose of herbicide. However, soil water levels need to be considered because high seeding rates can deplete soil moisture more rapidly than low rates in a dry year, thus lowering yields (Fawcett 1969, Pelton 1969).

Soil fertility is a determining factor in wheat's effectiveness of reducing wild oat growth (Thurston 1962, Chancellor and Peters 1974). Chancellor and Peters (1974)

suggested a weed density threshold above which yield reductions begin to occur. Specifically, they reported that in three of seven field experiments yields were significantly decreased which they directly related to the density of the wild oats. Three experiments showed a reduction in yield with wild oat densities of 156-306 stems m^{-2} at harvest, while stem counts in the other four experiments ranged from 19-102 stems m^{-2} . There was no apparent difference between wild oat's effect on the spring wheat crop and the two spring barley crops. Thus, Chancellor and Peters (1974) found that high densities of wild oats are needed to significantly reduce wheat yield. Similarly Paterson (1969) concluded that yield reductions due to wild oat infestation also depended on the crop-yield potential such that the greatest crop reductions occurred when crop yield potential was highest. These results were drawn using ANOVA as the method of analysis rather than regression.

It must be noted that in four of their seven field experiments, Chancellor and Peters (1974) found wheat yields were not significantly different with varying levels wild oat densities. Likewise, from a field study conducted in Alberta between 1972 and 1983, O'Donovan et al. (1985) reported that the relationship between yield loss and wild oat was typically non-significant within years, but was significant when data was pooled across years. Many wheat and wild oat experiments have not revealed significant trends. Wilson and Peters (1982) found that reductions in spring barley yield were poorly correlated with number of wild oat seedlings, panicles, or seeds produced. These poor correlations were revealed in scatter plots showing a high degree of variability and low R^2 values, as well as no distinction between linearity and non-linearity. Rather, there was a significant correlation between yield loss and biomass of wild oats at harvest (Wilson

and Peters 1982). An additional phenomenon contributing to the difficulty of deciphering significant trends was that the amount of yield loss has shown to vary at similar wild oat densities under different growing and/or regional conditions (Bowden and Friesen 1967, Bell and Nalewaja 1968). Wilson and Peters (1982) found that similar levels of crop losses have resulted from five-fold differences in wild oat densities (Hoepfner 1969). Both Wilson and Peters (1982) and O'Donovan et al. (1985) attributed the lack of relationships between wild oat density and yield to variation caused by other factors such as crop density, time of emergence of the weed relative to the crop, soil type, and yearly effects such as weather.

The previously described studies reveal the fourth main conclusion of wheat-wild oat interference research: variability in crop-wild oat competition experiments makes determining trends difficult and has led to contradictory conclusions from similar studies. While there is question regarding trends between wild oat density and wheat yield loss, it is generally agreed that high densities of wild oat (> 200 seedlings m^{-2}) can reduce grain yield severely (Wilson and Peters 1982). At very low wild oat densities it may be economically difficult to justify the use of herbicides or other weed control methods. Thus, there is a need to estimate the probability of yield loss from low wild oat densities versus yield loss due to high wild oat densities in order to achieve more environmentally and economically efficient wild oat management strategies.

Period of competition and time of emergence

Experiments have investigated the efficiency of wild oat control by specifically investigating the period during which competition from wild oats has biologically

detectable or economically significant reductions in crop yield. These experiments evaluate the necessity of timeliness of weed control. Chancellor and Peters (1974) reported that at high wild oat densities (>150 stems m^{-2}) the competitive effects of wild oat on the crop did not start until the crop was at the four-leaf stage, which was four to five weeks after the crop emerged. In contrast, Bowden and Friesen (1967) and Pavlychenko and Harrington (1935) suggested that the competition between wild oat and wheat might precede crop emergence when roots of both species compete for nutrients and water. It must be noted that plants are generally only drawing on seed reserves to grow prior to emergence (i.e. prior to the beginning of photosynthesis). However, Bowden and Friesen (1967) admit that their experimental methods did not allow for measurement of pre-emergence competition from wild oat in their weed-free plots, where wild oat seedlings were weeded out immediately after they emerged. Bowden and Friesen (1967) reported that the maximum period wild oat could be tolerated without affecting wheat yield is two weeks after emergence. In a later study, Martin and Field (1988) concluded that when wild oat was sown three to six weeks later than wheat, wheat was more competitive than wild oat, and wild oat panicle production was prohibited due to root and shoot competition from the wheat. Thus, they concluded that long-term containment of wild oats requires control of wild oat seedlings within three weeks of sowing the wheat crop. From a viewpoint of density effects along with period of competition, Harper (1961) indicated that the onset of competition from wild oats is inevitably earlier in higher densities of wild oats.

As opposed to the previously described field studies, Chancellor and Peters (1974) performed a greenhouse experiment to investigate the period of competition

between barley and wild oat where both species emerged at approximately the same time. They suggested that competition between these two species occurred at earlier than the two-leaf stage of wild oat. However, they explained that the onset of earlier competition in the greenhouse is likely due to the dense planting and root restriction between the boxes. Furthermore, Chancellor and Peters (1974) were skeptical that results of their greenhouse experiment were applicable to field conditions.

O'Donovan et al. (1985) alluded to varying times of emergence playing a role in the lack of significant yield loss-wild oat density relationships. Two other studies found that when both species emerged at nearly the same time, neither was clearly dominant (Martin et al. 1987, Bubar 1991). While contrary to Martin and Field's (1988) result that wild oat is more competitive due to its greater root competitive ability, the above finding agrees with Martin et al. (1987) and Cudney et al. (1989), who indicated through a replacement series experiment varying wheat and wild oat densities, that spring wheat and wild oat were equivalent in competitiveness. When time of emergence was varied the species that emerged first had greater root growth, and thus greater root competitive ability, and higher relative yields than the other species (Bubar 1991). Additionally, the early emerging species in a two-plant competition system can grow at the expense of the other (Spitters and Aerts 1983). In their study of the emergence of wild oat in spring barley, Peters and Wilson (1983) found that a given density of wild oat emerging at an early stage caused greater barley yield loss than the same density emerging later. Specifically, wild oat must emerge more than two days before wheat seedlings to cause yield reductions (Bubar 1991). Thus, time of emergence plays a dominant role in the outcome of crop and weed competition, and the rate of growth after emergence is

seemingly less important (Peters 1978, Manlove et al. 1982, Peters and Wilson 1983, O'Donovan et al. 1985, Bubar 1991). Thus, a common conclusion has been that crop management that allows for wheat to emerge before wild oat should help reduce competition from wild oats (Bubar 1991).

Models including relative times of emergence as well as weed density were shown to be more predictive than those including weed density alone (Kropff et al. 1984, O'Donovan et al. 1985, Cousens et al. 1987). Roberts (1984) articulated that timing of emergence, however, is dependent on resources available to plants that influence the speed of emergence. Thus, patterns of precipitation and corresponding available soil moisture that vary with site and year account for significant proportions of variation (Firbank et al. 1985). More detailed description of models including time of emergence can be found in the second part of this review.

Nitrogen

Racz (1974) showed that the wheat yield was highly correlated with available nitrogen, which consisted of available soil nitrogen and fertilizer at rates from 10 to 269 kg N ha⁻¹, with R² values of 0.59 to 0.78 (although he did not account for various moisture levels). As expected, the R² values increased when available water and growing degree-days were included in the regression equation; however, nitrogen alone accounted for the greatest amount of variation in yield (Racz 1974). As cited by Henry et al. (1986), Bole (unpublished) showed, with regression analysis, that N fertilizer increased wheat yield 23.3 kg for each added kg of N fertilizer, and yield was increased 16.1 kg ha⁻¹ for

each kg of soil nitrate to 60 cm depth. However, only 34% of the variation (i.e. $R^2 = 0.339$) in yield was accounted for when including N fertilizer, soil nitrogen, and the interaction terms in a regression analysis.

Nitrogen, Wheat Density, and Wild Oat Density

Competition between plants has been defined as an interaction between individuals brought about by a shared requirement for a resource in limited supply, and leading to a reduction in the survivorship, growth, and/or reproduction of the individuals concerned (Begon et al. 1986, Firbank and Watkinson 1990). Implicit in this definition are the effects of shared resources on the resulting species and their population dynamics (Firbank and Watkinson 1986). One of these shared resources is nitrogen –both nitrogen fertilizer in the form of $\text{NH}_4\text{-N}$ and $\text{NH}_4\text{-NO}_3$ – and stored soil nitrogen in the form of nitrate, $\text{NO}_3\text{-N}$. Several studies have explored the influence of nitrogen (N)² on wheat and wild oats, specifically investigating wild oat germination, wild oat seed production, and wheat yields. The research of this thesis is specifically concerned with resulting wild oat density and wheat yields from applied N inputs; however, long-term yield prediction models must consider wild oat germination and seed production effects from N. Thus, following is a description of studies that have investigated germination and seed production effects as well as crop yield effects from N.

Thurston (1959) compared growth of wild oats in pots to that of wheat and barley. She concluded that the addition of N affected the growth of wild oat and the wheat

² “N” refers to nitrogen applied as fertilizer, in the form of ammonium-nitrogen ($\text{NH}_4\text{-N}$) or ammonium-nitrate ($\text{NH}_4\text{-NO}_3$)

similarly, such that wild oat took up the same amount of N per plant as winter wheat. Thurston (1959) added that wild oat seedlings had higher net assimilation rates than the cereal crops, but the cereals soon caught up to the wild oat and outgrew them. Thurston (1959) and Sexsmith and Russell (1963) concluded that N will increase the yields of wheat and wild oat while their proportional densities remain unchanged (Zimdahl 1980). As an aside, phosphorus was found to increase wheat yield and decrease growth of wild oats (Thurston 1959, Sexsmith and Russell 1963).

In wild oat infested fields several studies reported that wheat grain yield generally declined with increased fertilizer beyond a certain level (Sexsmith and Russell 1963, Bell and Nalewaja 1968, Bowden and Friesen 1968, Carlson and Hill 1985b). One explanation offered for this response was that in competition with wheat, wild oat was better able to utilize nitrogen fertilizer and thus gain a competitive advantage over wheat. Supporting this argument, DiTomaso (1985) stated that weeds are often more competitive with crops at higher soil nutrient levels. Similarly, Bowden and Friesen (1967) found that it required 12 - 48 wild oat plants m^{-2} as opposed to 84 - 167 wild oat plants m^{-2} to cause a significant reduction in spring wheat yield when ammonium phosphate fertilizer (16-20-0) was drilled with the seed in a continuous rotation, implying that fertilizer increased the competitive ability of wild oat. It must be pointed out that this experiment was conducted with approximate simultaneous emergence of wheat and wild oat plants. Thus, Molberg (1966) concluded that the crop's optimal benefit from applied fertilizer happens when the weed is "under control". Pande (1953) concluded that wheat was influenced more by weed removal when fertility was low than when it was sufficient.

Bowden and Friesen (1967) also suggested that on stubble land (i.e. annually cropped land without summer fallow), soil fertility was more influential on wheat yield than moderate densities of wild oats. However, Satorre and Snaydon (1992) showed that N reduced the severity of competition of wild oat on two cultivars each of wheat, barley, and oats. Supporting Satorre and Snaydon's finding, Knezevic et al. (2000) argued that insufficient N in corn could lead to a decreased competitive ability of corn against weeds.

Sexsmith and Russell (1963) evaluated germination effects of N. They reported that in early spring when N fertilizer applications were broadcast and disced along with adequate moisture, an increase in germination of wild oat seed was observed. With dry conditions the effect of N fertilizer on increased wild oat germination did not overlap the crop-growing period (Sexsmith and Russell 1963). Sexsmith and Pittman (1963) also found that fertilizer application could stimulate wild oat germination.

Watkins (1971) found that annual fertilization increased wild oat infestation in a continuous wheat rotation since wild oat panicles produced more seed than unfertilized wild oat plants, which led to an overall increase in wild oat infestation. However, wild oat levels decreased when N application was augmented with increased crop seeding rate (Sexsmith 1955, McCurdy 1958). Wright (1993) also reported that seed production of *A.fatua* increased as the amount of added N increased, and that this confirmed the results of Thurston (1959) and Franz et al. (1990). It must be noted that these studies suggest that the influence of fertilizer on wild oat and wheat population dynamics depends on the individual densities of wheat and wild oat and the degree that the resource pools are drawn down to become limiting.

Timing and placement of fertilizer is also critical, leading to N management strategies that increase the competitive ability of wheat while reducing the interference from wild oat (DiTomaso 1985). Specifically, broadcast fertilizer application more effectively enhanced wild oat and broadleaf weed emergence and growth than banded fertilizer application (Kirkland and Beckie 1998). Similarly, Scursoni and Benech Arnold (2002), who studied the effect of N fertilizer timing on the demography of wild oat and barley in field experiments, found that N fertilizer increased wild oat seedling survival rate and fecundity, especially when it was applied at early tillering. Thus, when fertilizer was applied late (i.e. at tillering) wild oat's competitive ability was favored. However, the earlier N was applied, the more beneficial it was to the crop's competitive ability (Scursoni and Benech Arnold 2002). If N is applied at tillering an herbicide application is essential (Scursoni and Benech Arnold 2002).

Unlike the previous studies conducted in the field, Henson and Jordan (1982) conducted a greenhouse experiment to investigate the effect of wild oat competition on two genotypes of wheat at three nitrate concentrations holding water levels constant. Plants were grown to maturity in 28-cm wide × 31-cm deep pots filled with heat sterilized sand, where plants in each pot were either wheat or wild oats alone, or mixtures of 10 wheat and 10, 25, or 50 wild oat plants. Nitrates were supplied with Hoagland's solution with 1.5, 7.5, or 15.0-mM nitrate every four days. Like the findings of Worzella (1943), who found that the first increment of nitrogen in weed-free wheat produces the largest increases in grain yield, Henson and Jordan (1982) found that in monocultures of wild oat, in monocultures of wheat, or in mixtures of wheat and wild oat, individual plant weight increased more when the nitrate concentration was raised from 1.5 to 7.5-mM

nitrate than when raised from 7.5 to 15.0-mM. Wheat in competition with wild oat never increased in weight, and wheat plants with 50 wild oat plants decreased in weight when nitrate concentration was raised from 7.5 to 15.0-mM. Plant weight of wild oat was reduced more than that of wheat at each nitrate concentration (e.g. 1.5, 7.5 and 15-mM) when equal numbers of wild oat and 'Anza' (cv) wheat plants competed. Wild oat plant weight was reduced more than wheat weight at the 1.5 and 7.5-mM nitrate concentrations when equal numbers of 'Mexicali' (cv) wheat and wild oat competed; at the 15.0-mM nitrate concentration both wild oat and wheat weights were reduced equally. Thus, a main conclusion from this highly controlled experiment is that wheat is more competitive for N than wild oat under relatively high moisture conditions.

Nitrogen, Wheat Density, and Water

The interaction between nitrogen fertilizer and water influence on plant growth has been understood since Justus Von Liebig (1803-1873). Water and nitrogen are the two main constraints to cereal production in the Great Plains of North America and in similar climactic regions elsewhere (Henry et al. 1986, Campbell et al. 1993). Water is the driving variable in Great Plains agriculture (Brown and Carlson 1990, Peterson et al. 1996) while nitrogen is the nutrient most limiting wheat yield (Engel et al. 2001). While soil nitrogen can be amended through fertilizer application, available water in dryland agriculture is more difficult to control. Specifically, available soil water at planting is largely determined by growing season precipitation (GSP) during the fallow season and soil properties that determine water holding capacity and evaporation (Fawcett et al.

1974). Many studies have not focused on wheat-wild oat competition for N and/or water, but rather how nitrogen and/or water affect wheat production alone.

Several studies have investigated N management in wheat fields with varying amounts of available water without the influence of wild oat competition (Neidig and Snyder 1924, Fernandez and Laird 1959, Hunter 1958, Warder et al. 1963, Henry 1971, Racz, 1974, Campbell et al. 1993, Engel et al. 2001, Bole, unpublished data). First published by Neidig and Snyder (1924) and later confirmed by Campbell et al. (1993) and Engel et al. (2001), a high available water level and sufficient N will lead to high wheat yields. Low available soil water and excess N will result in low wheat yields but a higher grain protein content (Neidig and Snyder 1924, Campbell et al. 1993, Engel et al. 2001). Hunter et al. (1958) added that wheat yield was reduced from N applications on shallow soils with low moisture holding capacity. As cited in Henry et al. (1986), Hunter et al. (1958) explained that this might be due to stimulation of excessive tillering and vegetative growth early in the season, which would result in decreased available soil water and later desiccation of the crop. Fernandez and Laird (1959) quantitatively concluded that in the lowest moisture treatment the yield increase was $12.8 \text{ kg grain kg}^{-1} \text{ N}$ from 0 to 100 kg N ha^{-1} . Henry et al. (1971) added that under extremely dry conditions where yields are less than 600 kg ha^{-1} and nitrogen fertilizer usually has little effect on yield. Henry et al. (1971) further stated that the relative importance of water and nitrogen will vary from study to study, depending on the degree of stress imposed by the individual factors. In addition, when these two factors were varied the contribution of the interaction was as large or larger than the effects of the individual variables.

Campbell et al. (1993) argued that response to fertilizer depends not only on rate, but also on the method of placement (i.e. seed placed, deep banded, broadcast), time of application, and weather events. In addition to investigating wheat yield response to N fertilizer placement and timing, Campbell et al. (1993) quantified the relationship between spring wheat yield and available soil $\text{NO}_3\text{-N}$ levels, fertilizer rate, and available water via regression analysis, and concluded that placement of N was more important than time of N application on yield. Specifically, deep-banded fertilizer (0.1-0.15m deep) gave better yields than broadcast N application.

Demonstrating that predicting yield is quite difficult due to variability across years and sites, Campbell et al. (1993) found that fertilizer placement influenced grain yields more than timing in their nine-year study. In five of nine years, however, neither factor accounted for significant variation in wheat yield. Rather, water was found to be the overall most important factor on yield and the square of soil $\text{NO}_3\text{-N}$ level was the second most important. Bauer et al. (1965) quantified GSP plus stored soil moisture and found that they accounted for 40.3% of barley and wheat yield response to N fertilizer in their three-year study in North Dakota. The lack of clear trends alludes to Warder et al.'s (1963) suggestion that environmental factors like stored soil moisture and GSP must be considered along with soil tests when studying the results of fertilizer experiments. In addition, effective management of N-fertilizer to optimize net returns is highly dependent on stored soil moisture, which is difficult to measure, and GSP, which is not very predictable at the time of N application. It is interesting that in the face of this uncertainty, the preferred management response is to apply nitrogen under the

assumption of ideal moisture and GSP levels even though this strategy rarely results in profit maximization.

An important consideration when recommending the appropriate N fertilizer rate is that response to nitrogen can decrease over years, presumably due to accumulation of available nitrogen in the soil as a result of tillage and annual fertilization (Campbell et al. 1993, Engel et al. 2001). Thus, N fertilizer requirements need to be based on estimates of available water and residual soil nitrate (Engel et al. 1993).

While Campbell et al. (1993) and Engel et al. (2001) focused on wheat crops, Bole and Pittman (1980) focused on barley. Bole and Pittman (1980) developed barley yield equations with soil water. Soil water (W_s), as an explanatory variable, was defined as soil water percent at May 15, and growing season precipitation was defined as the precipitation received from May 15 to July 31. Overall, GSP had a 3× greater response to N fertilizer than soil water level on May 15. Given this conclusion, a producer should base her/his N fertilizer rate decision on the soil water level tested on May 15 and the GSP probability associated with his/her level of risk aversion (Bole and Pittman 1980). They found that including the GSP received after July 31 decreased the accuracy of the model. Before finalizing a N fertilizer management strategy, soil $\text{NO}_3\text{-N}$ should be measured to the 30-cm depth (Bole and Pittman 1980). Based on the assumption that the relationship between soil $\text{NO}_3\text{-N}$ and fertilizer is additive (Heapy 1976, Zentner and Read 1977), this magnitude of soil N should then be added to the amount of applied N fertilizer. Contrary to the reported positive correlation between effects of nitrogen and water availability (Engel et al. 2001), backwards stepwise regression showed that the term $\text{GSP} \cdot W_s \cdot N$ contributed little to reducing overall variance in Bole and Pitman's study

(1980). Another curious finding of Bole and Pitman's experiment (1980), yet not surprising given the complexity of ecological systems and the difficulty of ecological prediction, was that the main effect of N fertilizer rate was not a significant predictor of wheat grain yield.

Water

Lehane and Staple (1965) concluded that June through July rainfall and available soil moisture below 30 cm significantly influenced wheat yield on all soils in Saskatchewan. A more specific quantitative result by de Jong and Rennie (1967) who concluded that 125 mm of water in Canada was necessary to yield a 600 kg ha^{-1} wheat crop. The relationship between water and grain yield was linear up to 600 kg ha^{-1} . Beyond that threshold, a non-linear asymptotic trend was evident.

GSP vs. soil moisture as a predictor variable

Water's influence on yield is clear such that increased available water increases yield up to a threshold. However, what is not obvious is the role stored soil water and GSP individually play in influencing wheat yield as well as the interactions these two variables have with other variables influencing yield (e.g. wild oat population dynamics, available stored soil nitrogen, applied N fertilizer, and herbicide efficacy). Bole and Pittman (1980) performed a field plot study from 1973-1977 at Lethbridge, Alberta. They found that at mean levels for stored soil water and GSP, and at an applied nitrogen level of 40 kg ha^{-1} , additional water in the form of soil water increased barley yields $12.1 \text{ kg ha}^{-1} \text{ mm}^{-1}$ while in the form of precipitation yields were increased $13.7 \text{ kg ha}^{-1} \text{ mm}^{-1}$.

Thus, the influence of soil water and precipitation was nearly equivalent in their experiment. Similarly, Lehane and Staples (1965) had previously concluded that soil water and GSP had nearly the same influence on yield.

Other studies, however, show unequal influence of precipitation and stored water on yield. Robertson (1974) found that stored soil moisture was only 0.68 times as efficient as GSP in increasing yield. Similarly, Bauer et al. (1965) and Read and Warder (1974) reported that rainfall during the growing season had a greater influence on yield when fertilizer was not added to their plots. When fertilizer was added, Read and Warder (1974) found that stored soil moisture had a greater influence on the effectiveness of fertilizer on the variation in yield than did GSP. Similarly, Williams and Robertson (1965) concluded that wheat yield is more closely related to soil moisture than precipitation, and that rain occurring after the end of July had little effect on final crop yield in their region. Other studies in Canada, which simply investigated weather as a predictor variable, found that more wheat yield variability was explained when regression equations included potential evapotranspiration with precipitation and preseason-conserved precipitation (Williams 1969, 1973), as opposed to including only precipitation.

No studies were found that investigated GSP and soil moisture as shared resources in the competition between wheat and wild oats.

Soil Moisture and Wild Oat

While several studies have investigated the influence of water and/or nitrogen on wheat yield, it is also important to address how water and/or nitrogen affects wild oat without the presence of wheat in order to better understand what makes wild oat such a strong competitor in cereal crops. Thus, Akey and Morrison (1984) conducted a simple experiment investigating the growth of wild oat under different moisture regimes. They explored the influence of water on wild oat growth (e.g. leaf area, dry weight, and number of reproductive tillers) in both a growth chamber and in the field. In both environments they found that growth was significantly reduced in the low versus the high water regime (i.e. 10% vs. 20% soil moisture content). Plus, wild oat growth was more adversely affected by reducing the soil moisture content from 20% to 10% after rather than before the four-leaf stage. Perhaps the most powerful and surprising conclusion from this experiment was that overall, the wild oat plants responded similarly in the field and in the growth chamber, despite differences in soil type, light, temperature conditions, and water regimes. This conclusion alludes to the important contribution of greenhouse experiments identifying first principle relationships, despite their inherent differences from field experiments.

Like Akey and Morrison (1984), Van Wyken (2002) also performed a greenhouse experiment to investigate wild oat growth at different soil matric potentials to elucidate the mechanisms that determine the wide-ranging habitat of wild oat in cereal crops. Specifically, Van Wyken (2002) measured wild oat carbon partitioning and fecundity at a range of soil moisture levels, without interference from wheat plants. The

results of this physiological experiment showed that wild oat allocated about 10% more carbon to roots at the expense of leaf tissue under water stress. Furthermore, seed production decreased fourfold from the wettest to the driest treatments, however, wild oat plants were still able to reproduce at a minimal level under the driest conditions (Van Wychen, 2002). No studies reporting wheat yield response to wild oat densities at different soil moisture levels were found.

Soil Moisture, Wheat Density and Wild Oat

Van Wychen (2004) reported an extensive two-year study undertaken to investigate the predictability of weed spatial distributions from existing weed maps or from correlations with soil properties and edaphic factors. He hypothesized that wild oat habitat-defining variables would be more favorable in weed patches compared to non-patch environments, with water being the most limiting factor. To test this hypothesis, Van Wychen intentionally seeded high monoculture and mixture densities of wild oat and wheat in field areas with and without a history of wild oat infestation in commercially farmed fields. He reported that average soil moisture use of wild oats did not differ between wild oat patch and non-patch areas. Additionally, on a per plant basis, spring wheat always extracted more water than wild oat in both patch and non-patch areas over all sites.

Herbicide

Another economically and environmentally influential agricultural input is herbicide. Increasing economic constraints and environmental concerns have led to a desire to reduce herbicide use on farms (Kim et al. 2002) and to many efforts investigating the consequences of weed-crop competition with reduced herbicide inputs. Several studies have found that herbicide rate, under certain circumstances, can be reduced without any consistent significant reduction in crop yield (Wilson 1979b, Salonen 1992, Grundy et al. 1996, Spandl et al. 1997, Walker et al. 2002). Following are brief descriptions, in chronological order, of several studies supporting reduction in recommended³ herbicide rates while maintaining yield level.

Salonen (1992) found that reduced herbicide doses provided 60-90% control efficacy while giving higher yields than the highest herbicide treated areas. When the highest herbicide dose was applied, weed control was more than 90% (Salonen 1992). The only crop with a significant increase in yield from using herbicide at the 100% label rate, did so at the highest N fertilizer rate (Salonen 1992).

Barton et al. (1992), who investigated variable rate herbicide application to wild oats in barley, found grain yields were greatest when herbicides were used. However, a full herbicide application was not necessary, rather barley grain yield was similar when wild oat biomass was reduced by 65-85% using half or full rate applications. Net return was greatest when a half rate application was used on 100 wild oat plants m⁻². Net return

³ “Recommended”, “label”, or “full” rate refers to the manufacture’s advised herbicide dose.

was also greatest when a full herbicide rate was applied, however this was only when wild oat density was higher or equal to 290 wild oat plants m^{-2} .

Similarly, Grundy et al. (1996), who investigated several weed species in cereal crops but not wild oats, found that no weed control or half rate applications gave significantly better yields than the full rates. However, this may have been due to the lack of competitive weeds in their fields, such that yield received little to no benefit from applied herbicides. Additionally, spring wheat showed a significant increase in yield from using the full herbicide rate but only at the highest application rate of N (i.e. 200 kg ha^{-1}) (Grundy et al. 1996).

Spandl et al. (1997) did not investigate crop-seeding rate along with efficacy of herbicides but rather focused on herbicide rates and application timings of post-emergence herbicides (i.e. difenzoquat, imazamethabenz, and fenoxaprop plus MCPA plus thifensulfuron plus tribenuron, and fenoxaprop plus MCPA) for wild oat control in spring wheat and barley crops. Wild oat control sprayed with 50% of the label rate of the previously listed herbicides was less effective than the same herbicides applied at the 75% rate. Wild oat control at the 75% rate of the herbicides listed above was lower than or similar to wild oat control at their full rates. Reducing herbicide rates generally did not influence crop yields or net economic returns; however, grain yields and net economic returns were generally greater when some level of herbicide rate was used as compared to the non-treated control plots (Spandl et al. 1997).

Walker et al. (2002) stated that maximum wheat yield and reduction in *Avena ludoviciana* seed production was found when crop density was 130 wheat plants m^{-2} with herbicides applied at 75% of the label rate. These benefits were also found when crop

density was raised to 150 plants m⁻² and herbicide was applied at the 50% rate.

Alternately, at high crop density the 100% herbicide rate led to reductions in yield, which ultimately favored wild oat seed production (Salonen 1992, Walker et al. 2002).

Several studies have advocated decreasing recommended herbicide doses in order to maintain or increase yields and profit (Gerowitt et al. 1984, Erviö et al. 1991, Fykse 1991). In Finland, Erviö et al. (1991) recounted that the average yield increase with herbicide in spring cereals was 123 kg ha⁻¹ and that 60% of the treatments were profitable. In Germany, over half of the herbicide applications (presumably at full label rate) have been unprofitable (Gerowitt et al. 1984).

Not only are full label rates of herbicides expensive, leading to unprofitable yields as mentioned above, full label rates can have harmful effects on the crop, thus reducing yield (Fykse 1991, Grundy et al. 1996). For example, in Norway, herbicides decreased the cereal crop yield in 25% of their fields (Fykse 1991). When considering variable rate management strategies of herbicides in drought-stressed crops or when there is a lack of weed competition, it is critical to note that herbicides can have harmful effects on crop yields (Grundy et al. 1996). Thus, it is critical to have a precise knowledge of the mode of action of the herbicide and the mechanism that determines differential selectivity between the crop and weed in order to predict the conditions that may contribute to crop injury.

Illustrating the difficulty of revealing universal trends in ecology, Davies et al. (1989) concluded in contrast to the previously described studies, an advantage from reduced or variable-rate herbicide applications. Field experiments in Scotland consistently showed little or no response to applications of diflufenican + isoproturon

(55% wt/V flowable formulation 'Panther') in wheat, and spring post emergence application of metsulfuron-methyl (20% wt/wt w.d.g., 'Ally') + mecoprop (57% w/b a.c. 'Iso-Cornox' 57) in wheat and spring barley at a wide range of weed densities (Davies et al. 1989). Their preliminary results for 1988-89 revealed no consistent herbicide effect on crop yields down to 12.5% of the recommended label rate. It must be noted that wild oats was not one of common weeds in this experiment.

When considering long-term management and likelihood of future infestations, it must be considered that herbicides have varying degrees of effectiveness, as illustrated by Davies et al. (1989) and Grundy et al. (1996), who concluded that wheat and barley response to herbicide rate was less than predictable. In an experiment of wheat-wild oat competition with applications of post-emergence herbicides, difenzoquat, flamprop-methyl and diclofop-methyl, Wilson (1979b) concluded that these herbicides generally did not provide complete control of wild oats. There are several specific factors influencing herbicide efficacy and resultant net returns including crop yield potential and the ratio of weed and crop densities (Radford et al. 1980). Crop yield potential and the ratio of weed and crop densities is further influenced by available water at planting (Fawcett 1967), planting date (Doyle and Maracellos 1974), corresponding time of emergence (Peters and Wilson 1983, Spitters and Aerts 1983, O'Donovan et al. 1985, Bubar 1991) or growth stage of the weed (Kudsk 1989), soil type (Jensen 1985), and crop nutrition (Colwell and Esdaile 1966). Given this level of complexity, making herbicide management decisions remains challenging (Martin et al. 1987).

Crop rotation is perhaps more influential than herbicides when controlling wild oat infestations. In an economic analysis Wilson (1979b) showed that a crop rotation of

wheat and sorghum was the most profitable cropping system, as well as being the most profitable method of controlling wild oats. Thus, considering the cost of herbicides is crucial since negative net returns can be devastating due to ineffective herbicide applications (Martin et al. 1987). McNamara 1972 within-year control of wild oat in the range of 70-90% did not deplete the wild oat seedbank .

Economic thresholds

The previously described studies allude to the idea of an economic threshold such that there is a population density of wild oat infestation where herbicides should be applied in small grain production, resulting in increased crop yield to the extent that net return is positive. This concept has emerged from the fact that weed-free fields or even maximum yields are not the goal (Jensen 1985), rather, the goal is an optimization of economic returns and environmental health. The idea of an economic threshold is logical from a management perspective; however, determining a threshold is quite difficult and highly debated and therefore rarely performed by highly risk averse land managers (Cousens 1987). Thresholds can be calculated for within a growing season (“Economic Injury Level”) or over several seasons that include a much more detailed knowledge of weed population dynamics.

Carlson and Hill (1982) concluded that wheat densities affected the economic threshold for wild oat herbicide application. For example, in their study, it would be economically advantageous to control wild oats above a population of 14 wild oat plants m^{-2} if the wheat density was equal to/or greater than approximately 520 plants m^{-2} . However, if the wheat stand were only half as dense at 260 plants m^{-2} , herbicide

application would be warranted with a much lower wild oat density of approximately seven plants m^{-2} . Another challenge in determining thresholds is that they are strongly affected by the yield potential and the price of the crop. For example, given average environmental conditions, wheat density, and yield potential, plus a \$7 cwt^{-1} wheat price, the economic threshold for difenzoquat application is approximately ten wild oat plants m^{-2} (Carlson and Hill 1982). In another study, however, no reliable threshold density for chemical weed control was found (Salonen 1992).

Herbicide and population dynamics

Scursoni et al. (1999) and Walker et al. (2002) found that less herbicide was needed when crop density was increased. Scursoni et al.'s (1999) investigation focused on wild oat demography in barley fields rather than wheat yields. They found that by increasing barley sowing rate from 160 plants m^{-2} to 280 plants m^{-2} the number of wild oat seeds entering the seed bank was reduced by 50% by decreasing fecundity. With the application of diclofop-methyl, the number of wild oat seeds that entered the seed bank was reduced from 1050 to 140 seeds m^{-2} through a reduction in seedling survivorship and reproductive rate. Interestingly, their study found that half the number of wild oat seeds entered the seed bank in a barley crop than in a wheat crop, implying that barley has a greater competitive ability against wild oat. Overall, they advocated control of wild oat through herbicide treatment, crop selection and sowing rate.

Martin and Felton (1993) studied the demography of wild oats but with emphasis on the effects of crop rotation and tillage practices along with herbicide use. In the third and fourth years of their study they found that a continuous wheat rotation using

cultivated fallow increased wild oat density and reduced crop yield as compared with no tillage fallow. Thus, the number of wild oat seeds in the seed bank at the end of their 4-year experiment was less under no tillage than cultivated fallow. They also reported that triallate or fomprop-methyl in four successive wheat crops did not decrease the number of wild oat seeds in the seed bank. However, poor performance of these herbicides was somewhat due to dry conditions. A more diverse crop rotation of wheat and sorghum, as opposed to continuous wheat using herbicides, was more effective in reducing the wild oat seed bank. Since wild oat is well-adapted to continuous wheat cropping systems, only 3-6% of the wild oat seed reservoir maintained the wild oat population (Martin and Felton 1993).

Herbicide and soil properties

While surprisingly few published papers exist concerning the efficacy of herbicides in wild oat-infested fields as influenced by soil properties, it is nonetheless worthwhile to note the findings of those authors who have addressed this topic for other weeds. Blackshaw et al. (1994) found that herbicide efficacy on downy brome (*Bromus tectorum*) was highly correlated with soil organic and soil water content.⁴ Specifically, soil organic matter accounted for over 50% of the herbicide efficacy variation. For all herbicides used in this study, the rate of each herbicide required to reduce downy brome dry weight by 50% was 1.5-2 times greater in dry soils (-1.53 MPa) than in moist soils (-0.03 MPa). Herbicide efficacy did not decrease ($p>0.05$) with decreased soil water

⁴ Herbicides studied were metribuzin, BAY SMY 1500, cinmethylin, and napropamide (Blackshaw et al. 1994).

content from -0.03 MPa to -0.01 MPa. This finding, as cited by Blackshaw et al. (1994), was in agreement with Moyer (1987) who concluded that the efficacy of many herbicides is reduced in dry soil conditions. Blackshaw et al. (1994) explained that herbicide adsorption to soil particles increased and herbicide mobility decreased in low moisture soils, which resulted in decreased plant uptake of herbicide (Calvet 1980, Moyer 1987).

Soil Properties

While soil properties, such as water holding capacity, clearly influence plant growth and crop-weed interference (Buchanan et al. 1975, Hamblin 1985), and need to be considered important predictors of wheat yield (Firbank et al. 1990), identifying relationships between yield and soil properties remains difficult especially given the site-specific nature of these relationships (Walter et al. 2002). The challenge of revealing yield-soil property relationships is illustrated by the lack of literature in this area, particularly concerning spring wheat yield and wild oat competition. Van Wychen's account (2002) was one of the only references found that specifically investigated soil property influence on wild oat. After an intensive two-year study he found that site property correlations with wild oat patch areas differed for each of the three fields considered; thus, he concluded that no site properties were correlated with historic wild oat patches across all three sites. Likewise, Boyd (2002) classified wild oat as a generalist since it can successfully grow in various soil types and soil moisture levels. These findings led Van Wychen (2002) to conclude that overall wild oat habitat may be unlimited by soil properties commonly found in cereal grain-growing regions of the

Northern Great Plains. The only other reference found concerning soil properties and crop competition with wild oat was by Thurston (1962) who found that wild oat in competition with winter barley grew better in soil with low pH while the crop grew worse in these patches.

Like the ambiguous findings of Van Wychen (2002), Walter et al. (2002) who investigated the spatial correlation between weed species densities and six soil properties concluded that weed pattern is field-specific and that the spatial variation in soil properties is one of several variables affecting weed patchiness and subsequent crop-weed competition. Walter et al. (2002) did not study wild oat specifically, 10 and 11 dominant weed species were investigated in two fields sown to winter barley and winter wheat, respectively.

Some authors, who have investigated crop-weed competition other than between wheat and wild oat have found significant trends between weeds and soil properties. For example, different soil types have been shown to affect the competition between wheat and *Agrostemma githago* L. (Gajic 1966) and between winter wheat and *Bromus sterilis* (Cousens et al. 1988, Firbank et al. 1990). However several studies have resulted in inconclusive findings like those of Van Wychen (2002) and Walter et al. (2002). Following are descriptions of a few important studies between soil properties and crop-weed competition other than between wheat and wild oat.

Firbank et al. (1990) studied the effects of soil type on crop yield-weed density relationships between winter wheat and *Bromus sterilis* by conducting a pot experiment with two different soils. In a corresponding field experiment Cousens et al. (1988) grew *B. sterilis* in a range of densities with winter wheat on fields used as the sources for the

different soil types in Firbank et al.'s (1990) experiment. Taking the results of Cousens et al. (1988) along with theirs, Firbank et al. (1990) concluded that differences in crop variety and weather between field sites seem to have overridden the influence of soil type alone.

Dieleman et al. (2000a, b) identified associations between site properties and weed species abundance in corn using canonical correlation analysis. Specifically they investigated 12 site properties including total N, Bray-1 P, percent organic carbon (OC), pH, percent silt, percent sand, and elevation. They concluded that there were associations across years for topography and/or soil texture with weed presence. However, there was significant yearly variation in these relationships, which they attributed to cropping practices, weed management, and weather. Drawing any causative conclusion from correlation must be done with caution that presence of a weed population can influence the soil properties and thus provide the illusion that those properties are attracting the weed.

Dille et al. (2002) determined the probabilities of *Setaria* spp., *Solanum ptycantum*, *Helianthus annuus*, and *Abutilon theophrasti* occurrence in maize and soybean fields based on three site properties and weed presence the previous year. The general site properties they investigated were topography, soil type, and soil fertility status. They concluded that the difficulty of predicting weed occurrence indicates that there are other abiotic and biotic variables that influence weed presence and that adding biological variables could increase the predictive power of their model.

Spratt and McIver's study (1972) did not include soil property effects on wild oat populations, but focused on the effects of topographical positions, soil test values, and

fertilizer use on wheat yields. They concluded that microclimate and pedological factors affected wheat yields more than applied fertilizer. This study reveals the importance of considering soil properties such as topography and soil fertility as predictor variables in a yield prediction model, although, the ease of collecting input data on topography and soil fertility may be the biggest reason why these variables have not been frequently included in yield models. Other references that have investigated the relationships between soil properties and weed distributions in agricultural crops include Weaver and Hammill (1985), Andreasen et al. (1991a,b), Dale et al. (1992), Bowes et al. (1994), Hausler and Nordmeyer (1995), and Heisel et al. (1999).

Overall, it seems that soil type and other pedological effects may be overridden by differences in local weather patterns, which suggests the sizeable influence weather has as a predictor variable on yield, and the interaction between soil type characteristics and weather (Firbank et al. 1990, Dieleman 2000a,b). Firbank et al. (1990) further conclude that prediction models only based on weed density and time of emergence are weak without the integration of soil type variability and local weather patterns, upon which weed density and time of emergence depend.

Variation in Experimental Studies

The yields on annually cropped fields vary greatly from year to year and from site to site due to differences in stored soil moisture, GSP, climate, available nitrogen, and/or a combination of these factors (Read and Warder 1974, Wilson and Peters 1982). These factors also affect crop yield-weed density relationships by influencing time of

emergence (Firbank et al. 1985, O'Donovan et al. 1985, Bubar 1991) and the availability of resources (Sexsmith and Russell 1963, Bell and Nalewaja 1968, Bowden and Friesen 1968, Carlson and Hill 1985, Campbell 1993). Williams (1973) concluded that weather-based estimates (i.e. precipitation and evapotranspiration) could be used to explain a major portion of annual variability in wheat yields in the three provinces of Canada. For example, nearly 90% of the differences between the smallest and largest yields in Saskatchewan from 1952-1967 were due to weather differences (Williams 1973). Thus, one may conclude that any hope of predicting current or future year dryland wheat yields will be diminished until reliable weather predictions can be made.

Not only do soil properties and weather play an important role on the variability of yield, and thus the difficulty of prediction, but also the morphological and physiological variations in the wild oat species play a role. Several studies report the variation in wild oats germination (Lindsay 1956, Thurston 1957, Baker and Leighty 1958, Somody et al. 1984b), dormancy (Toole and Coffman 1940, Naylor and Jana 1976, Seeley 1977, Sawhney and Naylor 1979, Miller et al. 1982), and susceptibility to herbicides (Jacobsen and Anderson 1968, Seeley 1977, Somody et al. 1984b). Wilson and Peters (1982) reported that growth and competitive ability of wild oat varied between the two years of their field experiments with spring barley. Irregular germination throughout the growing season (Sharma and Vanden Born 1978) and the varying proportion of dormant seeds within each wild oat population (Auld and Coote 1990) contribute to the persistence of wild oats and illustrate the variability in wild oat morphology. Dormancy has been shown to vary between wild oat accessions and is influenced by year and location effects such as weather (Miller et al. 1982).

Additionally, Miller et al (1982) concluded that there is potential for particular accessions of the wild population to become weedier than others. Variation in the competitiveness of wild oats can also be attributed to the wheat cultivar growing with the wild oat, N fertilizer strategies, and available soil moisture as well as the previously reported morphological and physiological variation within the wild oat species (Carlson and Hill 1985).

Conclusions of Experimental Studies

Following are the main conclusions drawn from this literature review of experiments of yield as the dependent variable:

1. Individual plant densities of wheat and wild oat govern the outcome of their interference.
2. Nitrogen fertilizer will increase wheat yield to a threshold level in wild oat infested fields.
3. Low wild oat densities caused yield reductions that compared to those caused by high wild oat densities with added N fertilizer,.
4. Both GSP and soil moisture affect wheat yield, although there is disagreement about which factor has more influence.
5. Lack of yield response to nitrogen fertilizer and herbicide has been shown, which is most likely due to environment and other site-specific factors.
6. Herbicide, in many cases, can be decreased without a decrease in the current year's yield. No studies were found that investigated long-term effects of

reducing current-year herbicide rates or assessed the potential risk (i.e. increased variability in yield) associated with herbicide application rates below label rates.

7. Soil properties influence yield and yield-weed interference; however no studies specifically reported the influence of soil properties on spring wheat-wild oat interference.
8. Field experiments have illustrated the high degree of variability in wheat yield-wild oat competition studies and the subsequent difficulty in crop yield prediction.
9. Results of several independent field experiments indicate spatial and temporal variability in crop yield response, which suggests economic potential for variable-rate and site-specific management of N fertilizer and herbicide.

Part II. Modeling Plant Competition and Predicting Yield—Empirical Models

This section of the literature review focuses on models used to predict wheat yield in response to wheat density, wild oat density, available nitrogen, herbicide rate, and available water. Since several authors have espoused the importance of time of emergence (Manlove et al. 1982, Peters and Wilson 1983, Spitters and Aerts 1983, O'Donovan et al. 1985, Bubar 1991) and soil type (Thurston 1962, Buchanan 1975, Hamblin 1985, Cousens et al. 1988, Firbank et al. 1990) in predicting yield, these two potential predictors are also addressed. For a review of prediction models concerning weed population dynamics see Cousens (1987b) and van Groenendael (1988). Here we start by reviewing the simplest yield prediction models that only include one predictor variable, and progress sequentially to the more complex models.

Cousens et al. (1984) acknowledged that competition between weeds and crops is one of the most studied topics in weed biology worldwide. Many experiments have been conducted investigating every major crop and the weeds that compete with them (Zimdahl 1980). However, experiments can only investigate a small range of the combinatorial factors influencing crop and weed interactions. To explore circumstances not investigated by experiments, predictive mathematical models must play a critical role (Cousens et al. 1984).

Wild Oat Density or Crop Density as a Predictor Variable

Some of the earliest models in weed ecology focused on crop density or weed density alone as predictor variables of crop yield (Zimdahl 1980). Many of these models are shown in Table 1.2, Parts I and II.

Zimdahl (1980) suggested a biologically logical sigmoidal model response between weed density and crop yield, but few experiments have included enough low weed densities to statistically select the sigmoidal form. Thus, the most accepted yield-weed density model in the history of weed ecology is the rectangular hyperbolic equation. There are a few different forms of this equation. Cousens (1985b) provided convincing evidence that the following form adequately describes the relationship between crop yield loss and weed density:

$$y_L = \frac{i\rho_w}{1 + i\rho_w / a} \quad (1.1)$$

where y_L is percent yield loss, ρ_w is weed density, i is the percent yield loss per weed plant per unit area as weed density approaches zero, and a is the upper limit to percent yield loss as ρ_w becomes very large. The parameters a and i can be interpreted as high and low indices of competitiveness (Cousens et al. 1984). The hyperbolic model has 3 important properties: 1) percent yield loss increases monotonically towards a maximum with increasing weed density, 2) the model approaches a straight line through the origin at low weed densities (Wells 1979, Cousens et al. 1987), and 3) a single weed plant is most competitive when it is at a low density and its competitive ability decreases as weed density increases (Cousens et al. 1984).

An alternative form of the hyperbolic model is

$$y = \frac{y_0}{1 + \beta x_0} \quad (1.2)$$

where y is yield, y_0 is the weed-free crop yield, β is the aggressiveness of the weed in reducing crop yield (i.e. a weed density of $1/\beta$ will reduce the crop yield by 50%), and x_0 is the initial weed density. This model assumes the crop is grown at a single density.

Cousens et al. (1984) found that the rectangular hyperbolic model is sufficient for describing yield at low weed density and a departure from this model is not necessary. Cousens et al. (1987b) reported that the rectangular hyperbolic model provides a slightly improved description of experimental data over O'Donovan et al.'s (1985) multiple regression model, and lacks the biologically unrealistic characteristics implicit in the simple multiple regression approach (i.e. regression models implicitly assume biological phenomena are additive linear processes). However, only including one predictor variable (i.e. weed density) for yield was a weakness of this family of models (Dew

1972). Thus, the hyperbolic model, as well as other models have been revised to include crop density as well as wild oat density as predictor variables for yield (Table 1.2).

Wild Oat and Wheat Density as Predictor Variables

While the rectangular hyperbolic model is inherently flexible to include crop density as well as weed density in explaining yield, it should be pointed out that the history of weed ecology is rich with models that have included these two predictors since the 1950's with the work of Shinozaki and Kira (1956), Carter et al. (1957), and Baeumer and deWit (1968). Many more forms of yield prediction equations were developed in the 1950's through the present (Table 1.2).

While models for yield that included crop density and weed density were being developed in the 1950's, it seems that a considerable number of experiments testing the strength of these predictors were not published until later, with the work of Zimdahl (1980) and Cousens et al. (1984) who showed that crop density plays a significant role in yield loss and should be added as a predictor variable. In 1985, with the addition of crop density to the hyperbolic model, Cousens (1985a) reported on the comparison made between his model and several others found in the literature (Shinozaki and Kira 1956, Carter et al. 1957, Baeumer and de Wit 1968, Moore 1979, Carlson and Hill 1981, Watkinson 1981, Wright 1981, Wiener 1982, de Wit 1983, Håkasson 1983, Spitters 1983a, Spitters 1983b, Firbank 1984, Jolliffe et al. 1984). Much of the theory of these models has been based upon data from a replacement series experimental design (Cousens 1985a). Cousens (1985a) concluded that the model developed by Baeumer and

deWit (1968) adequately describes the data and analysis, assuming the parameters are interpreted with agronomic explanations. Baeumer and deWit's (1968) model is

$$y = \frac{a\rho}{1 + b\rho + f\rho_w} \quad (1.3)$$

where y is yield, ρ is crop density, ρ_w is weed density, and a , b , and f are indices of competition for the crop and weed. Given certain assumptions, the double hyperbolic model becomes identical to the models of deWit and Baeumer (1967), Suehiro and Ogawa (1980), Wright (1981), and Spitters (1983a).

In 1985 Cousens reported that an increase in complexity beyond the model

$$y = c \left(1 - \frac{1}{(1 + a\rho_w)^b} \right) \quad (1.4)$$

was hardly justified. More complex models will only be worthwhile if data become more abundant and less variable than that which he had collected. This model was not exclusive to competition between wheat and wild oat but was also parameterized with data investigating other weeds (Mercado and Talatala 1977, Poole 1979).

To examine how much complexity in models can be supported by “typical” data, Cousens tried to fit 14 models of varying forms to previously published data. Cousens (1985a) reported that it was evident at an early stage in his study that there were very few published data “of the appropriate form” to compare a model including crop and weed density with other models. Thus, he conducted an experiment that seeded wheat and barley together at various combinations and at a range of seeding rates for each species. The dependent variable was above ground biomass and each crop was considered as a

weed of the other (Cousens 1985a). His experiment supported the following hyperbolic three-parameter model including crop and weed density:

$$y = \frac{aC}{1+bC+fD} \quad (1.5)$$

Equation 1.5 is a version of the Beverton-Holt model growth model (Brown and Rothery 1993) where a is the intrinsic growth rate of the crop, C is the density of the crop, D is the density of the weed, and b and f are intra-specific and inter-specific coefficients of competition respectively. More complex models were not supported statistically.

Another important model that includes crop and weed density is Maxwell and Jasieniuk's double hyperbolic model (Jasieniuk et al. 2000), which is based on the standard rectangular hyperbolic yield loss function developed by Cousens (1985b). One weakness of the hyperbolic model and the other models cited above that included crop density and/or weed density as predictor variables, was that they do not allow for an interpretation of parameter values in terms of space occupied by individual plants, as in the original application to a replacement series design. This model is the product of two hyperbolic components:

$$y = \left(\frac{j \rho}{1 + j \rho / y_{\max}} \right) \left(1 - \frac{i \rho_w}{1 + i \rho_w / a} \right) \quad (1.6)$$

where y is the crop yield per unit area, $y_{\max}$ is the maximum crop yield (the maximum value observed in the data set), ρ is crop density, ρ_w is weed density, and a, i, j are estimated parameters. Specifically, a is the asymptote of yield loss at high weed density, i is the slope through the origin of the curve of yield loss versus wild oat density, and j is an index of competition between the crop and the weed.

Wild Oat Density and Time of Emergence as Predictor Variables

Given the number of field studies that demonstrated the importance of the period of time emergence between the crop and the weed as influencing crop yield (Manlove et al. 1982, Peters and Wilson 1983, Spitters and Aerts 1983, O'Donovan et al. 1985, Kropff 1988, Bubar 1991), yield modelers began to incorporate relative time of emergence as a predictor variable. Cousens et al. (1987) aimed to develop a yield loss model that would include relative time of emergence of wild oat plants as well as the density of wild oats as an explanatory variable. The resulting model was

$$y_L = \frac{gD}{1 + e^{f(T+h)} + gD/a} \quad (1.7)$$

where D is wild oat density, T is relative time of emergence, and g , f , h , and a are parameters. Cousens et al. (1987) determined the accuracy of their model by fitting it to 15 previously collected data sets. It was concluded that even when relative time of wild oat emergence is added to the yield loss model, there is still a large amount of unexplained variance and significant differences in parameter estimates between years. Cousens et al. (1987) attributed this to the likelihood of factors other than relative time of emergence and weed density that significantly effected yield. Firbank et al. (1990) further added that a yield prediction model based only on weed density and time of emergence would have little economic value because of the large variability in weather and soil type. They concluded, "A practical model must address the effects of variation in soil, weather, and management on the parameters of weed-crop competition on the rate

of increasing the weed species. It must have a clearly defined area within which it would be expected to work” (Firbank et al. 1990). Firbank et al. (1990) describe a potential model in which farmers would enter information on current weed densities, fall weather, soil type, and soil condition to predict an optimal weed management strategy for future years.

Herbicide as a Predictor Variable

Brain and Cousens (1989) and Streibig et al. (1989) argued that when herbicide is used to manipulate crop and weed competition, the herbicide effects should be included in a yield prediction model. However more complex yield prediction models, specifically models including wheat density and wild oat density along with variable-rate herbicide effects, are largely absent from the literature with the exception of Brain et al.’s (1999) and Kim et al.’s (2002) models. Many yield prediction models that include herbicide effects rely on dose-response curves or the threshold concept. Dose-response models typically focus on the decision to spray or not to spray, rather than a recommended variable rate (Kim et al. 2002).

The most commonly used dose-response curve is a sigmoidal form (Streibig 1980, Brain and Cousens 1989), such that yield is a function of the applied herbicide dose and plant production at the minimum and maximum herbicide rates. The most common equation for herbicide dose response, according to Brain and Cousens (1989) is

$$y = \frac{k}{1 + ae^{b \log x}} + d \quad (1.8)$$

where y is plant yield; x is herbicide dose; and a , b , d , and k are parameters (Streibig 1980). The ED_{50} (i.e. the dose that kills 50% of the plant population) when $y=d+k/2$ is given by

$$ED_{50} = a^{-1/b} \quad (1.9)$$

(Brain and Cousens 1989). Due to typical high correlation between a and b , Brain and Cousens (1989) advise to use the following form instead of eqn 1.8:

$$y = \frac{k}{1 + e^{bg} x^b} + d \quad (1.10)$$

Brain and Cousens (1989) provided an additional equation that describes the relationship between yield effects to herbicide dose where there is plant response at low doses. Their motivation for including plant response at low doses is in criticism to many herbicide studies that show that low herbicide doses can stimulate plant growth. Brain and Cousens (1989) explained that this conclusion may often be the result of experimental error due to the standardization of yield values, where any low dose whose mean yield is greater than the control appears to stimulate growth. Brain and Cousens' (1989) equation introduced a peak by incorporating the parameter f such that

$$y = \frac{k + fx}{1 + e^{bg} x^b} + d \quad (1.11)$$

where f measures the initial rate of increase in plant yield at low herbicide rates. While this equation (1.11) seems to accurately describe the data assessed, Brain and Cousens (1989) note that this is a first approximation that may need revision.

Jensen and Kudsk (1988) showed that the shape of the dose-response curve of herbicide was dependent only on the mode of action of a herbicide. Additionally, the

efficacy of herbicides can be described by a parallel displacement of the curve depending on temperature, humidity, soil moisture, weed species, and stage of development of the weed. Thus, the performance of a herbicide under different climatic conditions results in a vertical displacement of the dose-response curve while the same sigmoidal shape is retained.

Brain et al. (1999) criticized the simplest models by Wilson (1986), Cussans and Rolph (1990), and Rydahl (1995), which investigate herbicide effects and crop-weed competition, and rely on the threshold concept. Wilson (1986) and Cussans and Rolph (1990) studied herbicide effects in winter crops. Their models recommend herbicide application if weeds reach a threshold density, but assume that the full herbicide application is used and will reduce the effect of the weed on crop yield to an insignificant amount. Brain et al. (1999) criticized this method because it focused on the decision to spray or not to spray at a specified weed threshold as opposed to focusing on variable rate herbicide decisions. Brain et al. (1999) also criticized decision support systems developed by Heitefuss et al. (1987) and Gerowitt and Heitefuss (1990) that found negative net returns in many herbicide application scenarios. Brain et al. (1999) suggested that a model that would allow for variable rates of herbicide would reduce negative net returns outcomes

Herbicide, Wheat Density, and Wild Oat Density/Biomass as Predictor Variables

Recently field studies have investigated crop-weed interaction with variable-rate herbicide effects (Salonen 1993, Courtney 1994, Davies et al 1995), although there

remains a lack of models that have been developed using these concepts (Brain et al. 1999). Exceptions are Brain et al.'s (1999) and Kim et al.'s (2002) proposed models that describe crop-weed interference and the effects of variable-rate herbicide application. However, even these two models do not specifically address spring wheat and wild oat interference with the effects of variable-rate herbicide applications. Brain et al.'s (1999) model, and Kim et al.'s (2002) updated version of Brain et al.'s (1999) model of winter wheat and cultivated oats is nonetheless included in this review because it illustrates the most recent advance in a three-predictor variable wheat model. Both papers are useful references for describing model development.

Specifically, Brain et al.'s (1999) empirical model is a combined model of three submodels, which are assumed to be independent; the submodels are: 1) the rectangular hyperbolic model, i.e. the function for crop yield at harvest and initial weed density, 2) the dose-response curve, i.e. the relationship for the competitive ability of the weed and the amount of weed biomass at a chosen date; and 3) the relationship for weed biomass at a chosen date after a variable-rate herbicide application. The three submodels are combined for yield prediction in terms of herbicide rate and weed biomass.

Explicitly, submodel 1 is

$$y = \frac{y_0}{1 + \mu w^\theta} \quad (1.12)$$

where y is yield, y_0 is the weed-free crop yield, w is the chosen assessment date for weed biomass. This model assumes that weed competitiveness is linearly related to leaf area of an individual weed (Kropff and Spitters 1991) such that $\mu = \lambda\gamma$. The parameter λ is the increase in competitiveness per unit increase in leaf area, and γ and θ are parameters that are

likely to change with the date of measurement. A second assumption is that total leaf area and weed biomass are allometric (Jolliffe et al. 1988).

Submodel 2, the weed biomass-herbicide dose submodel, is based on Streibig's (1980) standard dose-response curve such that

$$w = \frac{w_0}{1 + \left(\frac{Dose}{e^{LD_{50}}} \right)^B} \quad (1.13)$$

w is weed biomass, parameter w_0 is the untreated weed biomass at the chosen date, LD_{50} is the log of the dose required to reduce weed biomass by 50%, and B is the response rate of the herbicide (i.e. the steepness of the slope of the curve). As Brain et al. (1999) explain, the LD_{50} value is logged because it is easier to estimate with nonlinear regression, and the log dose has a less skewed distribution, thus, it is more easily compared with other doses.

Submodel 3, combines equations 1.11 and 1.12 to achieve a relationship between crop yield and herbicide dose such that

$$y = \frac{y_0}{1 + \mu \left(\frac{w_0}{1 + \left(\frac{Dose}{e^{LD_{50}}} \right)^B} \right)^\theta} \quad (1.14)$$

where the parameters are the same as in the above models. Brain et al. (1999) make assumptions concerning the combined model. First, changing crop density will only affect w_0 but not the parameters LD_{50} and B . Secondly, the dose-response curve for the weed in the presence of the crop is the same as in a monoculture of weeds. Thirdly, the parameters will change with differing densities of the crop. Brain et al. (1999) add that equation 1.13 reduces to submodel 1 (equation 1.11) in the unsprayed treatment. The

combined model (equation 1.13) is empirical, but it is based on the underlying biological processes inherent in its components (Brain et al. 1999)

To determine the appropriate herbicide dose given a specified threshold of an acceptable percent yield loss, Brain et al. (1999) rework equation 1.14 into the following form:

$$d_p = e^{LD_{50}} \left(\frac{w_0}{\left(\frac{1}{\mu} \left(\frac{p}{100-p} \right) \right)^{1/\theta}} - 1 \right)^{1/B} \quad (1.15)$$

where d_p is the dose required to give the assumed percentage yield loss, p .

After conducting an experiment of three winter wheat densities, one seeded rate of cultivated oats (similar to wild oat but with a more uniform emergence), and five rates of imazamethabenz-methyl, Brain et al. (1999) fit their combined model to the data. Oat biomass was measured on three assessment dates: at the seedling stage (April 21 1992), at mid-growth stage (June 15 1992) and near full maturity (July 29 1992). Their results were as follows:

1. No evidence was given that parameters μ or θ , which alter the shape of the dose-response curve, were affected by crop density.
2. y_0 was significantly higher at higher wheat densities.
3. According to the residual sum of squares, the agreement between predicted and observe yield values were closest when the predictive dose curve was based on the first assessment date, although there was evidence that the first date does not predict the untreated case as well as it should.

4. Using equation 1.14, the herbicide dose of $0.1 \text{ kg a.i. ha}^{-1}$ or greater would allow yield loss to be kept below 10% for oat biomass observed at 175 g m^{-2} at the first assessment date.

Brain et al. (1999) conclude that further experimentation is necessary to evaluate this model for different weed and herbicide combinations and in different environmental conditions. In order for environmental conditions to be included in the model, Brain et al. (1999) argue that realistic growth models for the crop and weed need to be incorporated into the combined model. However, they stated there are serious flaws in the many models of winter wheat growth plus there are very few if any models of wild oat growth (Brain et al. 1999).

In 2002 Kim et al. published a revised version of Brain et al.'s (1999) model, which included weed density in addition to weed biomass not density, by starting with an alternate form of the rectangular hyperbolic model. The fact that Brain et al.'s (1999) model relied on weed biomass was a weakness since measuring biomass is expensive and impractical for farmers (Kim et al. 2002). Additionally, weed biomass is variable since it depends on temperature and soil fertility, and it changes throughout the growing season, which makes determining an assessment data difficult. In contrast, weed density remains relatively constant throughout the growing season (Kim et al. 2002). Unlike Brain et al.'s approach, Kim et al. (2002) used the following equation form of the rectangular hyperbolic equation:

$$y = \frac{y_0}{1 + \beta_i x_0} \quad (1.16)$$

where y_0 is the weed-free crop yield, β_i is a parameter for weed competitiveness which changes with herbicide dose i , and x_0 is the initial weed density. Assuming that weed biomass and herbicide dose can be well described by the standard dose-response curve, Kim et al. (2002) established the following equation:

$$\beta_i = \frac{\beta_0}{1 + \left(\frac{Dose_i}{e^{LD_{50}}} \right)^B} \quad (1.17)$$

where β_0 is weed competitiveness at zero herbicide dose, LD_{50} is the log of the dose required to reduce weed biomass by 50%, and B is the response rate of the herbicide (i.e. the steepness of the slope of the curve). The right-hand side of equation 1.16 is replaced in equation 1.15 for β_i to produce the following function:

$$y = \frac{y_0}{\frac{1 + \beta_0 x_0}{1 + \left(\frac{Dose}{e^{LD_{50}}} \right)^B}} \quad (1.18)$$

Equation 1.18 is analogous to Brain et al.'s model (equation 1.13) except that it includes weed density instead of weed biomass.

In the same manuscript Kim et al. (2002) (in which Brain is a co-author) proceeded to develop another model based on weed biomass by including the following relationship of biomass as reported by Wilson et al. (1995):

$$w_0 = Cx_0 / (1 + Ax_0) \quad (1.19)$$

where C is the parameter for biomass of an individual weed plant without inter-specific competition, A is a measure of intra-specific competition of the weed, x_0 is the initial weed density, and w_0 , as defined above, is the weed biomass at zero-herbicide treatment at the chosen assessment date (Kim et al. 2002). Equation 1.19 was combined with

equation 16 to produce the following model, which describes the relationship between weed biomass and herbicide dose at different weed densities simultaneously:

$$w = \frac{Cx_0}{\left(1 + \left(\frac{Dose}{e^{LD_{50}}}\right)^B\right)(1 + Ax_0)} \quad (1.20)$$

Based on the rectangular hyperbolic models and the leaf area model of Kropff and Spitters (1991) the weed-crop prediction equations 1.17 and 1.19 have wide applicability (Kim et al. 2002). Kim et al. (2002) parameterized their model with a mock weed, *Brassica napus* L., in one year at a single site; thus, more experimentation needs to be done before fully assessing these models.

Brain et al. (1999) suggested that data are also needed to determine the long-term effects of decreased rates of herbicide on seed fecundity. However, Andersson (1992) concluded, as cited by Brain et al. (1999), that reduced herbicide rates may not lead to increased weed infestation. Andersson (1992) showed that weeds treated with a sub-lethal herbicide doses produced fewer viable seeds; fewer seeds than would be expected from the corresponding reductions in biomass. Additionally, Rasmussen (1993) investigated seed production of two *Polygonum* species and concluded that 1/2 to 1/16 of the label rate reduced weed seed production by 85%.

Soil Properties and Available Water as Predictor Variables

While wild oat-wheat yield prediction models incorporating available water and/or soil properties as predictor variables were not found, both variables arguably play a significant role in wheat-wild oat competition. The importance of water to modeling

studies was illustrated by the findings of Auld and Coote (1990) who concluded that the growth rate of wild oat was significantly affected by the variation between yearly rainfall amounts. For completeness, a brief description of wheat yield models that included weather and/or soil factors but did not include weed competition is given.

In 1973 Williams et al. attempted to explain wheat yield based on precipitation. Williams et al. (1973), included potential evapotranspiration (PE), as well as precipitation, which led to the conclusion that regression equations based on precipitation and PE were more accurate than those based on precipitation alone. Performing macro-scale regression analyses on cereal yields from 1961–1972 in Alberta, Saskatchewan, and Manitoba, Williams et al. (1973) concluded that 57% to 86% of yield variation was explained by precipitation, PE, soil texture, and topography; however, less variation was explained for wheat than oats and barley. Additionally, a small portion of the yield variability was attributed to soil texture and topography. Williams et al. (1973) also concluded that the relationship between yield and texture seemed to be non-linear with course-textured soils producing the lowest yield and medium-textured soils producing the highest yields. In 1974 Haun reported on the predictability of wheat yield using the independent predictor variables temperature and precipitation. Haun (1974) developed his model by deriving a daily growth index for spring wheat as a function of temperature and precipitation and regressed county yield estimates on accumulated daily values to generate a single yield equation. While Haun (1974) was optimistic that using the environmental variables was a promising approach for predicting wheat yield, the R^2 value for his regression equation was only 0.249. After adjusting yield values to account for yield magnitudes in different regions in Canada, the R^2 value was 0.780.

In contrast Williams (1973), and Haun (1974) included only variables related to weather. Feyerherm and Paulsen (1981) attempted to build a wheat prediction model using regression analysis that was based on agronomic as well as climatic variables. Specific variables included in Feyerherm and Paulsen's (1981) model were precipitation, evapotranspiration, plant-available water, mean daily maximum temperature, mean number of degree days, amount of applied N fertilizer over the growing season, percent of soil organic matter, and soil texture. Data to parameterize this large regression model was obtained from varietal trials conducted on agricultural experiment stations in the U.S. Great Plains and in the Cornbelt region from 1920–1973. The authors provide a root mean square error value of 120-130 kg ha⁻¹ between their model and and USDA estimates of yield. The authors' interpretation of their data was that the relatively small r.m.s.e. showed wide-ranging climatic and agronomic conditions can be used to estimate model parameters for wide-ranging wheat yield. Nonetheless, their goal was not to predict site-specific yields for the optimal application of agricultural inputs but rather to predict large-scale regional wheat production.

Stewart and Dwyer (1990) also developed a crop growth model that included a non-linear response factor for temperature influence on yield. Eighty percent of yield variation was explained by using daily maximum and minimum air temperature, precipitation, and soil type.

Shatar and McBratney (1999) developed empirical models for sorghum yield and soil properties such as pH; available phosphorus; percent clay, silt and sand; gravimetric moisture content of air-dry soil; and percent organic carbon (OC). Only a small percentage of the observed variation could be explained by a single measured soil

variable, which indicated that a collection of variables contributed to yield variation. Shatar and McBratney (1999) investigated several models and the one derived from percent OC fit the data most accurately by explaining 35% of the observed yield variation.

Overall, no papers were found that described a model of wheat-wild oat competition that included soil moisture, GSP, and/or soil type as predictor variables; despite Firbank et al.'s (1990) conclusion 14 years ago that predictions of crop yield based on the densities of the crop and weed are likely to be imprecise unless soil type and climate effects are included.

Available Nitrogen and Water as Predictor Variables

Beckie et al. (1995) tested the effectiveness of four simulation models (e.g. CERES, EPIC, NLEAP, and NTRM) for estimating soil nitrates and water in two soils. These simulation models illustrate a different modeling approach based on crop growth simulation, as compared with models by Williams (1973), and Haun (1974) that relied on linear regression analysis. These simulation models are not “empirical” models, but are nonetheless included in this review because they have described the step before yield prediction which is the determination of the levels of available soil nitrogen and water that are then input into a yield prediction model. Thus, Beckie et al.'s evaluation of these simulation models illustrates complexity of the factors influences on yield. Not only does the current season's application of nitrogen and growing season precipitation influence yield but so does the amount of nitrate and water stored in the soil. The amount

of stored soil water and nitrate is also fundamentally influenced by soil type, as well as tillage practices and cropping rotation. Some of the input parameters in the above listed simulation models are values for precipitation, air temperature, solar radiation, spring $\text{NO}_3\text{-N}$, spring moisture, spring labile phosphorus, runoff curve number, crop residue, carbon/nitrogen ratio, seeding date, fertilizer rate, fertilizer application date, and fertilizer placement.

Chipanshi et al. (1997) used the CERES-Wheat model ("Crop Estimation through Resource and Environment Synthesis wheat) model to predict wheat yield using climate data from the start of the growing season up to the prediction date (i.e. harvest) and historical weather data. CERES-Wheat was developed by Ritchie and Otter (1985) and Godwin et al. (1990) uses input variables based on weather data (e.g. daily maximum and minimum temperatures, solar radiation, and total rainfall), soil data (physical and chemical), crop data, and management data. Chipanshi et al. (1997) locally parameterized the model with the following phenological data: dates of emergence, anthesis and maturity, grain yield, aboveground biomass, and grain density and weight. Soil data was collected including soil water availability at 0.03 and 1.5 MPa, bulk density; total carbon in the soil profile; and soil pH. They concluded that this method allowed predictive values to agree well with measured data. By using ratios of simulated to observed values, it was found that ratios between all sites varied from 0.76 to 1.35 with an overall average of 1.08. While the model described by Chipanshi et al. (1997) is an advancement in the development of a procedure to monitor climate/weather affects on yield, it does not incorporate the very influential effects from weeds and herbicide application.

Available Nitrogen, Weather, and Soil Type as Predictor Variables

Chipanshi et al. (1997), Moore and Tyndale-Biscoe (1999) used the CERES-Wheat simulation model to investigate wheat growth over a range of weather conditions, fertilizer rates, and soil types. Data were used to predict long-term benefits from spatially managing N applications when fertilizer rates were matched to soil type. According to their predictive model, Moore and Tyndale-Biscoe (1999) concluded that benefits from spatially variable N fertilizer applications were “modest on average”. Furthermore, a large proportion of the yield variability was attributed to weather events and the different soil water holding capacities. Moore and Tyndale-Biscoe (1999) concluded that there is a need to devise strategies that manage for yield variability due to weather and soil types.

Modeling Competition for Resources

Very little literature exists on models of crop-weed competition in light of resources, with the exception of Carlson and Hill’s (1985b) model for yield with wheat density, wild oat density, and applied nitrogen rate as predictor variables. Several papers detail experiments of crop–wild oat competition with varying levels of nitrogen, however, the results are presented in table form, typically using ANOVA and p-values, and do not employ any modeling techniques, let alone regression analysis (Sexsmith and Russell, 1962, Bell and Nalewaja, 1968, Di Tomaso, 1995, Scursoni and Bencech Arnold, 2002⁵). Brain et al. (1999) modeled the effect of crop and weed on herbicide efficacy in

⁵ Scursoni and Bencech Arnold (2002) studied barley and wild oat competition with varying levels of nitrogen; the other authors studied wheat and wild oat competition.

wheat, as previously described in the section (i.e. Herbicide, crop density, and wild oat density as predictor variables). No papers were found on models of crop-weed competition for water.

Taking a different approach from most of the papers discussing competition for resources, Tollenaar (1992) describes competition for resources using simple descriptive models for weed-crop interference and theorizes about “one-sided” and “two-sided” competition. Two-sided competition refers to equal partitioning of available resources while one-sided competition, also described as “asymmetric competition” or “dominance and suppression”, is based on unequal uptake of resources by the weed and the crop (Weiner and Thomas 1986, Wilson 1988, Tollenaar 1992). Like Cousens et al. (1987), Tollenaar (1992) advocates the importance of biologically meaningful models, however, the models Tollenaar (1992) describes do not consider the ease of data collection and model validation.

Tollenaar (1992) describes the following models. First, the two-species inverse yield law is

$$y = \frac{\lambda \rho}{1 + a(\rho + \alpha \rho_w)} \quad (1.21)$$

where y is yield per unit area, ρ is crop density, ρ_w is weed density, λ is crop yield per plant in the absence of weed competition, a is the ecological neighborhood area (Antonovics and Levin 1980) and α is the niche overlap or the equivalence of weed species with respect to crop species in terms of effect on y , yield per unit area. The second model, based on equation 1.21, is called the Hassell-Commins model:

$$y = \frac{\lambda\rho}{(1 + a(\rho + \alpha\rho_w))^b} \quad (1.22)$$

where the parameter b describes the competition for resources (Hassell and Commins 1976) or the efficiency of resource utilization by the population (Watkinson 1981). The third model by Farazdaghi and Harris (1968) and Vandermeer (1984) is slightly different:

$$y = \frac{\lambda\rho}{1 + a(\rho + \alpha\rho_w)^d} \quad (1.23)$$

where d is a measure of the rate at which competition decays as a function of distance between plants (Vandermeer 1984). These models describe crop-weed interference for resources, which is necessary for determining crop-weed competition with applied fertilizer, applied herbicide and available water. It is questionable, however, that a farmer or crop consultant will be able to easily and *accurately* parameterize α , the niche overlap and d , the quantification of the rate at which competition decays as a function of distance between plants. Overall, these models are a step in the right direction in terms of adding competition for resources into the yield prediction equation. However, further consideration needs to be given to practical models that will enable optimal N and herbicide management decisions to be made.

Conclusions of Modeling Studies

The following are the main conclusions drawn from this literature review of yield modeling studies:

- 1) Biologically meaningful yield prediction models are essential (Cousens 1985b, Willey and Heath 1969, Tollenaar 1992).

In their thorough literature review of yield and crop density equations, Willey and Heath (1969) stated that to describe yield/density relationship from a minimum amount of data, “it would clearly seem to be desirable to use equations that have a better biological foundation”. However, Cousens (1985b) points out that many of the models found in the literature are plainly unreasonable biologically. One example is Dew’s (1972) model which approaches an infinite slope at low density and an infinite upper limit to yield at high weed density, as is only appropriate for making decisions over a set range of weed densities.

- 2) The dynamics of species in competition can be modeled, but the parameters of these models vary across sites and years.

When predicting plant competition and the influence of resources, general equations need to be sought; data will provide the site-specific parameter values. Empirical-based competition models, which originate in sound underlying biological principles can include biologically meaningful parameters whose magnitudes account for each particular setting (Tollenaar 1992). Firbank and Watkinson (1990) are somewhat more pessimistic, stating that because parameters of these models vary across sites and years, predicting plant competition dynamics remains inaccurate. Acknowledged slightly differently, Firbank et al. (1990) state, “If the relationship between yield loss and weed density is used for prediction, then it must be either approximately constant or be predictable from year to year and from site to site.” Nonetheless, there is agreement that parameters of models will vary across sites and years.

3) Linear and non-linear trends have been observed for wheat yield as a function of some of the identified predictor variables (e.g. wheat density, wild oat plant density, wild oat biomass, and herbicide rate).

The following specific trends were observed:

- Cousens (1985b) concluded that most models describe a linear relationship between crop yield and weed density at low weed densities, although with increasing density most models become curvilinear. In most agricultural fields, where weed density is kept under control at relatively low levels, a linear model may suffice (Cousens, 1985b).
- Martin et al. (1987) reported that under sufficient moisture conditions, the yield-density relationship was asymptotic; however, when soil water was limiting a parabolic model was more accurate.
- Poole and Gill (1987) found that there is typically a linear relationship between weed biomass and loss in crop biomass; and crop biomass translates to crop yield if there is sufficient moisture during grain-filling (Hawton, 1990).
- Cudney et al. (1989) found that wheat yield was linearly proportional to wild oat density.
- Walker et al. (2002) report that although herbicide rate for both weed and crop density had significant linear effects on yield, there was a significant non-linearity of the response surface.

4) A widely used generalized model of wheat-wild oat interference including the effects of nitrogen, herbicide and water has not been developed.

Concerning such a model, Firbank et al. (1990) stated, “A generalized linear model would have little economic value because variation in weather and soil type is too great. A practical model must address the effects of variation in soil, weather and management on the parameters of weed-crop competition and on the rate of increase of weed species. It must have a clearly defined area within which it would be expected to work.”

My conclusions

After reading the above review of modeling studies, the two most important questions I find myself asking are:

- 1) is it *even* possible to predict yield?
- 2) if yield prediction is possible, what variables should be included in a yield prediction model?

I ask the first question because the complexity of ecological prediction is undeniable. Yield prediction is so challenging that even today yield prediction models remain inadequate. For example, despite the nonlinear yield models Cousens et al. (1987a) developed to describe the effects of weed density and time of emergence, a large amount of unexplained variance persisted. The unexplained variance was probably due to other important influences on yield other than time of emergence and weed density, which was reflected in the significant differences in parameter estimates among years (Cousens et al. 1987a). In the fields of agronomy and ecology, *accurate* yield prediction models including predictor variables beyond crop density and weed density, and sometimes relative time of emergence, remain underdeveloped and inadequate for farmers needing to make variable-rate and site-specific management decisions for

application of inputs. The fact that farmers need to make decisions remains the simple practicality, thus the prediction model that can provide this needs to be attempted.

So, if yield prediction modeling needs to be attempted, what variables should be included in the model? After all, the number of influences on yield is countless. One approach to this simple fact is addressing the threshold number of variables that have the majority of influence on yield, beyond which adding predictor variables will not add a significant increase in prediction. Discovering the most important predictors is the next step. Martin et al. (1987) reported that the four most influential factors affecting cereal grain yield in northern New South Wales, Australia are available water at sowing, available soil nitrate at sowing, planting date, and wild oat infestation. As previously discussed, these variables are then influenced by a long list of other environmental variables. For example, available water at sowing, according to the EPIC model, is influenced by site latitude, air temperature, precipitation, solar radiation, spring moisture, hydrologic group, and runoff curve number to just name a few of the many predictor variables included in this model to estimate available soil water (Williams et al. 1990). Again, a similar approach needs to be taken: only consider the small collection variables that constitute the majority of influence.

When determining the small number of predictor variables that are crucial, another essential consideration is the undoubted insufficiency of data (Cousens 1985a, Martin et al. 1987). Yield prediction modeling remains in its current general state, that predictors beyond crop density and weed density have not been included in models determining yield, because of the lack of data by which to develop such a succinct yet appropriately complex and accurate model. There are a few exceptions to this statement,

for example, Kim et al.'s (2002) yield model that calculates crop yield by investigating weed density and herbicide rate. Another exception is O'Donovan et al.'s (1985) yield model that includes weed density and time of emergence. However, these models are still very simple such that they do not include the influence other important variables, namely crop density and available nitrogen and water.

Another complication to this lack of data is consideration for reasonable predictor variables, specifically those variables for which data can feasibly be collected by farmers for site-specific model parameterization. For example, consider the feasibility of collecting wild oat biomass versus wild oat density. Both predictor variables are arguably influential and necessary to a yield prediction model, however, wild oat density is a more practical measurement for growers (Kim et al. 2002). The lack of data has been by far the biggest challenge to developing a yield prediction model based on crop and weed density, available nitrogen and water, and herbicide rate. Given the continual advancements of precision agricultural technology, more comprehensive and detailed information is continually collected by computer software installed on agricultural machines during planting, fertilizer and herbicide application, cultivation, and harvest. Most likely ease of data collection due to precision agriculture technologies will enable future yield model development.

The Problem of Insufficient Data

In order to reveal significant trends within ecological systems and to develop corresponding prediction models, adequate data are critical. However, when managing

numerous predictor variables and/or deciding which predictor variables should be included in a yield prediction model—crop density, planting date, wild oat density, time of emergence, stored soil nitrogen, N fertilizer, N fertilizer placement, herbicide rate, GSP, stored soil moisture, soil type, etc. —data sets which have measured all of these variables are non-existent. Also, experimental designs do not typically cover the entire possible response surface area, even if such experiments exist (Cousens 1985b).

Combining data sets

To embark upon the problem of lacking data and the site-specific nature of ecological data, some researchers have gathered independent data sets in hope of uncovering common trends across data sets and/or augmenting and verifying a model derived from their experiment. For example, Martin et al. (1987) conducted a field experiment where wheat and wild oat density, and corresponding crop yield were measured. With their data the following model was parameterized:

$$y = \left(\frac{\rho_c}{\alpha + \beta + \gamma \rho_c^2} \right) \cdot \left(1 - \frac{\rho_w}{i_0 + B\rho_c + \rho_w / A} \right) \quad (1.23)$$

where ρ_c is crop density, ρ_w is weed density, and α , β , and γ are parameters. The portion of the model in the right parenthesis relates to yield loss (Cousens, 1985a), where i is the initial slope of the hyperbolic yield loss curve at low weed densities and A is the asymptotic yield loss and B is a yield loss parameter. To determine the predictive ability of their model, parameterized by their own experimental data, Martin et al. (1987) gathered seven independent data sets which included wheat and wild oat yield-density measurements. Then, they gathered 36 independent data sets to investigate the variation

in the model (equation 1.23) attributed to sowing date, available water, phosphate fertilizer rate, and wheat cultivar, all of which they did not explicitly vary nor measure. Specifically, parameters α , β , and γ were investigated for their relation to these variables (e.g. sowing date, available water, phosphate fertilizer, and wheat cultivar). A thorough test of the predictive model (equation 1.23) was excluded because reliable available soil water data was not available. Therefore, the yield-density parameters (e.g. α , β , and γ) were estimated for each of the 36 data sets and the yield loss parameters (e.g. A and B) were estimated from Martin et al.'s (1987) two experiments and then compared to the A and B estimates from the seven independently data sets. Since wheat and wild oat were deemed near equal competitors, A and B were similar in value and i_0 was near one.

Martin et al. (1987) described the resulting model (equation 1.23) as a “combined” yield loss model because there was a crop density component (e.g. the first set of parenthesis) and a yield loss component (e.g. the second set of parenthesis). The basis for the yield loss component was the allowance of relating parameters in the weed-free wheat yield-density model to environmental variables. This allows prediction of wheat yield potential, which is essential for expressing yield loss due to wild oats in economic terms. Also, the model can be considered as “combined” since it was based on information from their collected data as well as independent, previously gathered data sets.

Tollenaar (1992) reported a similar exercise. His experimental design did not include observations at very low and very high wheat densities. In order to check the ends of the yield curve, he included low and high plant density points from other experiments.

Obtaining previously collected data sets for parameterization and modeling

Empirical models can be developed and parameterized with historically collected data, originally collected for some other purpose (Cousens et al. 1987). Cousens (1985b) compared and evaluated 18 models through application to 22 data sets developed by Bowden and Friesen (1967), Bell and Nalewaja (1968), Mercado and Talatala (1977) and Poole (1979). Only the data sets of Bowden and Friesen (1967) and Bell and Nalewaja (1968) investigated wheat and wild oat competition. (Poole (1979) investigated crop competition with ryegrass and Mercado and Talatala (1977) investigated competitive ability of *Echinochloa colonum* L. against rice.)

Summary

Within the field of agronomy model building is critical even if data is inadequate and the investigated system is infinitely complex. Models will always be wrong such that they will never describe full reality, but *good* models can approximate the system leading to more sustainable management decisions. Thus, this literature review represents the state of knowledge in agronomy in terms of experimental results and consequential development of models. The assessment of prior knowledge is the first step of model development. From this point independently collected field data sets will be obtained for further investigation. Model development based on observations from the data and the information presented in this literature will follow.

Table 1.1. A list of experimental field and greenhouse studies and their corresponding investigated predictor variables. While barley experiments were included in the literature review, they are not included in this table. "N fertilizer" refers to fertilizer "Herbicide" refers to herbicide rate, unless otherwise noted. "sw" is spring wheat, "ww" is winter wheat, and "wo" is wild oat.

$y = f(\text{sw density, wo density})$	
Author • Description of Experiment	Results
Chancellor and Peters 1974 *field and greenhouse expt	• 3 of 7 sites showed significant yield reductions due to wild oat; these sites all had wild oat densities of 150 stems m^{-2} or greater at harvest. • No significant reductions were observed when wild oat were at lower densities of 28-100 stems m^{-2}. • In a glasshouse experiment (also included in this paper) to test competition prior to crop and weed emergence, it was found that no competition was indicated during this stage.
Carlson and Hill 1985a	• Wheat yield increased in wild oat infested plots as wheat plant density increased. • Wheat yields were best described by a nonlinear regression equation using the relative density of wild in a weed-crop stand as the dependent variable. • Including crop density improved the fit of the regression models. • Wild oat was more competitive in this experiment than others previously reported.
Martin et al. 1987 *7 seeding rates from 11 to 88 kg ha^{-1} *6 wild oat densities from 0 to 448 kg ha^{-1}	• The best model to describe the data included a parabolic wheat yield-density component and a hyperbolic yield loss component. • Wheat and wild oat were near-equal competitors.
Wilson et al. 1990	• At average crop density, wild oat infestation is likely to cause a 1% yield reduction for each wild oat plant m^{-2}.
Kirkland and Hunter, 1991 *one seeding rate (100 kg ha^{-1})	• Wheat yields of all three cultivars studied were decreased as wild oat density increased.
$y = f(\text{sw density, wo density, wo time of emergence})$	
O'Donovan et al. 1985	• At a given wo density, % yield loss increased the earlier wild oat emerged relative to the crop and gradually diminished the later it emerged. • Relationships between yield loss and wo density were non-significant for most years. The low R^2 values in some years allude to other important factors not measured and yearly effects. • Crop density did not significantly alter the extent of yield loss due to wo density or time of wo emergence.

Table 1.1. Continued

Bubar, 1991 *greenhouse expt	• Wild oat must emerge more than 2 days before wheat seedlings to cause yield reductions. Crop management strategies show allow for early wheat emergence. • Time of emergence is a major determinant of competition between wo and wheat. • When wild oat and wheat emerged synchronously, neither species was competitively dominant. • Relative growth rates did not show any differences between wild oat and wheat
$y = f(\text{sw density, wo density, } N \text{ fertilizer})$	
Sexsmith and Russell 1963 *one seeding rate (2.2 kg ha ⁻¹) *N and P rates: 0, 22, and 45 kg ha ⁻¹ *only in 1960 were wo stand counts taken	• N fertilizer increased wheat yield but at the expense of increasing the number of reproductive wo tillers and seed yield.
Bell and Nalewaja 1968 *one seeding rate (100 kg ha ⁻¹) *only one N rate (68 kg ha ⁻¹)	• In 1965 70 and 160 wo seedlings yd⁻² reduced wheat 22.1% and 39.1% respectively. The addition of N at 68 kg ha⁻¹ and P at 44 kg ha⁻¹ reduced yield loss caused by wo 2 out of 3 years. • On fertilized plots wo densities in the seedling stage of 35 and 80 plants yd⁻² reduced wheat yield 8.4 and 11.6 bu/A respectively, compared to weed-free plots. With no fertilizer, similar wild oat densities decreased wheat yield 2.8 and 5.3 bu ac⁻¹ respectively. • Yield loss was greater on fertilized plots than the unfertilized plots but the fertilized plots containing 65 or less wild oat plantsyd⁻² yielded as much or more than the unfertilized weed-free plots. • In sparse wo infestation, fertilizer is likely to increase wheat yields; as wo density increases less benefit from fertilizer is realized by the wheat. • Averaged over all wo densities, fertilized plots yielded 23.3 bu ac⁻¹ of wheat that was significantly higher than the 16.8 bu ac⁻¹ yield of the unfertilized plots.
Hensen and Jordan 1982 *greenhouse expt *sw and wo densities: 10 wheat and 10 wild oat plants/pot; mixtures of 10 wheat and 10, 25, or 50 wild oat plants	• When nitrate concentration was increased from 7.5 to 15.0 mM (as opposed to 1.5 to 7.5mM), wheat in competition never increased in weight, and weight in competition with the high wild oat density decreased in weight.
Carlson and Hill 1985b *preplant N trt: 84 and 168 kg ha ⁻¹ ; postplant N trt: 84 kg ha ⁻¹ ; split N trt: 84 and 84 kg ha ⁻¹	• Yield in wild oat-infested fields generally declined with fertilization. • In competition with wheat, wo was better able to utilize added nitrogen and gain a competitive advantage over wheat.

Table 1.1. Continued

Farahbakhsh et al. 1987 *greenhouse expt *one sw density (8 plants, 25-cm dia pot, equivalent to 160 plants m⁻²) *wo densities: 0,1,2,4, and 8 plants, 25-cm dia pot, equivalent to 0, 20, 40, 80, and 160 plants m⁻²) *4 N dressings were applied at rates equivalent to 10, 20, and 30 kg N ha⁻¹ at tillering (GS 21), stem elongation (GS 30), booting (GS 40), and wheat anthesis (GS 70)	• Goal of this expt was to investigate the relative competitiveness of <i>A.fatua</i>, <i>Alopecurus myosuroides</i>, and <i>Stellaria media</i>. • Linear (Dew 1972, Carlson et al. 1981) and non-linear (Wilson and Cussans 1983, Cousens 1985) models of yield loss-weed density were evaluated with the greenhouse data: • Best fit of the data was given by Dew's (1972) model (yield loss as the square root of weed density) with Cousens (1985) model (non-linear hyperbolic model) the second-best fit.
Cudney et al. 1989 *only one N rate (urea at 100 kg N ha⁻¹ as a pre-plant application and 75 kg N ha⁻¹ at tillering)	• Yield of wheat grain was linearly proportional to relative density of wild oat. • Wheat and wild oat were equivalent in their competitiveness.
Tollenaar 1992 • 2 N rates: 80,160 kg ha⁻¹	• 4 data sets from this experiment were used to select the most appropriate of 4 mathematical models describing weed-crop interference.
$y = f(\text{sw density, wo density, GSP})$	
Murphy, unpublished data *GSP is from May-Oct	• Scatter plots of yield vs. wild oat density showed high degree of variability, slight • Negative trend yield vs. wheat density showed slight curvilinear response and much variability
$y = f(\text{sw density, wo density, N fertilizer, GSP})$	
Kirkland and Beckie, 1998 *one crop seeding rate (90 kg ha⁻¹) * N treatments: 45 kg ha⁻¹ (1994); 66 kg ha⁻¹ (1995); 69 kg ha⁻¹ (1996) * 3 N placement strategies: broadcast, banded, side-banded * this study focused on tillage and N placement, not plant densities and GSP *GSP is from May-Aug	• Generally no significant tillage by fertilizer interactions when analyzed by site-year and across site-years. • The addition of fertilizer rather than placement more often affected wild oat density, biomass, and N uptake. • Weed emergence, growth and N uptake were greater ($P \leq .05$) in fertilized than unfertilized plots. • Broadcast-applied fertilizer had twice the probability of promoting wo emergence, growth, or N uptake. Plots where fertilizer had been banded had 22% fewer wo plants than plots with broadcast fertilizer.
Blackshaw and Molnar, 2001[†] *N rates: 0,50 kg ha⁻¹ *included a N banded trt *GSP is from Apr-Aug	• Large amount of variability across years made any linear and non-linear trends difficult to decipher.

Table 1.1. Continued

Lenssen, unpublished data *sw and wo density was measured with a visual rating *Nitrate (ppm) were measured 0-2' of soil. *GSP is from Apr-Aug	• All 4 sites revealed large variability in the scatter plots of yield vs. wheat density and yield vs. wild oat density that any linear and non-linear trends within and across sites were not evident.
Rew, unpublished data *N rates: 0, 50 kg N ha⁻¹ *GSP is from Apr-Oct	• Scatter plot yield vs. wild oat density showed linear decreased trend. • No trend in yield vs. wheat density plot was evident.
Maxwell, unpublished data *yearly N rates: either 68 kg ha⁻¹ or 0 kg ha⁻¹ *GSP is from Apr-Aug	• Scatter plots of yield vs. wild oat density showed a declining curvilinear response with a high degree of variability. • Yield vs. wheat density showed a linear increasing response with a high degree of variability.

$$y = f(\text{sw density, wo density, wo time of emergence, N fertilizer})$$

Bowden and Friesen, 1967 *seeding rate: 40 kg ha⁻¹ *wo densities: 0, 10, 40, 70, 100, 130, 160, 190 plants/yard² *2 ammonium phosphate rates: 0 and 56 kg ha⁻¹ of 11-48 0 on the summerfallow land; 0 and 100 kg ha⁻¹ of 16-30-0 on stubble land	• Competition from wo might precede crop emergence. • 10-40 wo plants yd⁻² decreased yield when wheat was grown on summer fallow or when N fert. was added; 70-100 wild oat plants yd⁻² were needed to decrease yield when wheat was grown on annually cropped land without a fertilizer treatment. This suggests soil fertility is more influential on yield than average wo densities.
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$$y = f(N \text{ fertilizer, GSP and soil water})$$

Bauer et al. 1965	• GSP and stored soil water accounted for 40.3% of yield response. • R-values were higher for total moisture (GSP + stored soil moisture) than for either moisture category alone. • Total moisture accounted for 46.5% and 40.3% of the yield response to NP and N fertilizer, respectively (NP is nitrogen and phosphorus). • The magnitude of yield response to a given N rate increased when rainfall was also increased (e.g. the 23 kg N ha⁻¹ produced greatest yields on soil with less than 2" of stored moisture, the 45 kg ha⁻¹ treatment produced greatest yields with 2-3.99" stored soil moisture, and the 68 kg N ha⁻¹ on soils 10 or more cm.
Jackson, unpublished data *N treatments were applied (0, 85, 170, 255 kg ha⁻¹) * percent soil moisture was measured at 24, 48, and 72 cm depths * 36 site-years	• Results are unpublished.

Table 1.1. Continued

$y = f(N \text{ fertilizer, soil } N, \text{ GSP and soil water})$	
Read and Warder 1974	• Rainfall during the growing season had a greater influence on yield when fertilizer was not added to their plots. When fertilizer was added, soil moisture had a greater influence on the effectiveness of fertilizer on the variation in yield than did GSP.
Engel et al. 1999 *includes irrigational water	• Nitrogen requirements increased by 22.5 kg ha⁻¹ for each inch of additional available water. • Available water and soil N must be used to calculate N fertilizer requirements.
$y = f(N \text{ fertilizer, soil } N, \text{ GSP and soil water})$	
Campbell et al. 1993a *N fert includes rate, timing, and placement	• Fertilizer placement influenced yields more than timing, but in 5 of 9 years neither factor was significant
Campbell et al. 1993b *N fert includes rate, timing, and placement	• In SW Saskatchewan, available water was by far the most influential variable on yield. • Deep banding was more influential on yield than broadcast N in 1 of 9 years.
$y = f(\text{GSP, pre-season precipitation, potential evapo-transpiration})$	
Williams 1973 *GSP is May-July	• Most variability in wheat yields in Saskatchewan is attributed to weather variability. • Lack of uniformity in climate and soils contributed to inconclusive results. • Regression equations based on GSP and potential evapo-transpiration were more explanatory than those only including precipitation.
$y = f(\text{sw density, } N \text{ fertilizer, herbicide})$	
Salonen 1992 *crop seeding rates: 200,400,600,800,1000 kernels m ⁻² *one N rate: 90 kg ha ⁻¹ *herbicide rates: .33x, 0.5x, 1x	• Weeds other than wild oat were dominant. • The benefit of using reduced herbicide rates was illustrated even at high weed densities. • At one site reduced herbicide rates provided weed control efficacy of 70-90% and overall, gave greater yields than the highest herbicide rates (which controlled weeds at 90% efficacy).
$y = f(\text{wo density, herbicide})$	
Spandl et al. 1997 *herbicide trt: included rate and timing	• Wild oat control at 0.5x rates was generally less than at the 0.75x rate, which was lower or similar to the 1.0x rate. • Reducing herbicide rate typically did not influence grain yield or net economic return. • Yield and net return was greater in herbicide

Table 1.1. Continued

$y = f(\text{wo population dynamics, herbicide, crop rotation, tillage})$

Martin and Felton 1993

*see this paper for methods of
cropping sytem x herbicide
type x herbicide rate x tillage

- Poor performance of herbicides was due to dry moisture conditions.
- Continuous wheat rotations with herbicide for control was less effective than a diverse rotation for reducing the wild oat seedbank.
- Wild oat seed reservoir was smaller under a no-tillage regime.

$y = f(\text{sw density, wo density, herbicide})$

Walker et al. 2002

- In *A. ludoviciana*-infested plots, maximum crop yield was achieved at 130 wheat plants m^{-2} with 75% herbicide rate. Maximum yield was also achieved at 150 wheat plants m^{-2} with 50% herbicide rate.
- At high crop density, 100% herbicide rate tended to decrease yield.

$y = f(\text{sw density, wo density, herbicide, GSP})$

Blackshaw and Molnar 2003

*herb. rates: 0,1/2,1x label
*GSP is from Apr-Aug

- Herbicide rate effects showed great variability, such that the full rate did not give significant yield increase over the half label rate.
- Scatter plots of yield vs. wild oat density and yield vs. wheat density revealed such great variability that any linear and/or non-linear trends were not apparent.

$y = f(\text{sw quality, N fertilizer, herbicide})$

Grundy et al. 1996

- Lack of weeds at the study site gave little benefit from herbicide.
- Grain yields were positively correlated with N rate, but the yield response to herbicide rate was less predictable.
- Grain nitrogen was the only aspect of grain quality to show a decline with moderate reductions in N application.

$y = f(\text{sw density, wo density, N fertilizer, herbicide, GSP})$

Van Wychen, unpublished
data

*N. rates: 0, 23, 45, 90, 112 kg ha^{-1}
*herb. rates: 0, 0.125, 0.5,
0.75, 1x label
*3 herb applied: Achieve,
Assert, and Puma
*GSP is from May-Aug

- Overall very little or no response to N fertilizer was observed, possibly because of stored soil N and/or extremely dry conditions.
- Herbicide rate was the most influential predictor for application of Assert. It was the second most influential predictor variable after GSP for Puma and Achieve applications.
- It was impossible to separate GSP from generalized year-location effects.

Table 1.1. Continued

Experiments with winter wheat	
<i>y = f(ww growth, wo growth, N fertilizer)</i>	
Thurston 1959 *pot expt	• N fertilizer affected wheat and wild oat plants similarly, i.e. they took up the approx. same amount of N per plant.
<i>y = f(ww density, wo density, N fertilizer)</i>	
Thurston 1962 *crop density was measured but not included in this paper *only one N rate (68 kg ha ⁻¹)	• Generally, there were too few wild oats to affect the yield of the crop so this paper reported the effect on crop growth by wild oats. • N fertilizer increased the weight of the both the crop and wild oats. • N fertilizer does not alter the proportion of wild oats to the crops (e.g. winter wheat, winter rye, winter and spring barley) in an infested field, but increased the yield of both. • Beyond a certain crop density dependent on soil fertility, further increase in wheat did not decrease the size of the wild oats.
<i>y = f(ww density, wo density, N fertilizer, herbicide)</i>	
Wilson et al. 1990 *one N treatment *only herbicide treatment	• The competitiveness and wild oat significant less at higher crop density (0.7% yield loss per wild oat plant m⁻²) than at low crop density (1.2% loss per wild oat plant m⁻²) • The present study shows the problem of generalizing between different studies where varying levels of competitiveness exist and exact experimental details are unknown. (Wilson et al. compared various estimates of the parameters <i>i</i> from Cousens (1985) hyperbolic model for 7 different experiments cited in the literature investigating wo density and wtr wheat or spr wheat. Carlson and Hill (1985a,b) had very different results (high <i>i</i> values) from the other studies due to fert. treatments. • Low densities of wo are likely to cause yield losses of 1% for every wild oat plant m⁻². This is in agreement with models that have used values of 0.75% and 1% as economic thresholds (Cousens et al. 1985, Cousens 1987) and 1% as a long-term weed control threshold (Cousens et al. 1986).

Table 1.2. Yield prediction equations based largely on reviews by Willey and Heath (1969), Cousens (1985a), Cousens (1985b), and Firbank and Watkinson (1990).

I. Yield - crop density equations		
• grouped according to equation type, then chronologically • y is yield unless otherwise noted; w is yield per plant; ρ is crop density; a, b, c are parameters.		
Author	Model	Description
1. Hudson 1941	$y = a + b\rho + c\rho^2$ * c is negative	• polynomial equation attempting to describe relation between grain yield and crop seeding rate • yield rises to a maximum then decreases at higher densities
2. Sharpe and Dent 1968	$y = a + b\rho + c\rho^{1/2}$ * b is negative	• polynomial equation which avoids symmetric nature of Hudson's (1941) equation by using a square root • yield rises to a maximum then decreases at higher densities
3. Duncan 1958	$y = \rho K 10^{b\rho}$ * K is a constant * b is negative, slope of the regression line	• exponential equation describing relation between yield and crop density • yield increases to a maximum
4. Carmer and Jackobs 1965	$y = \rho A K^\rho$ * A, K are constants	• exponential equation analogous to equation 3
5. Warne 1951	$y = A \rho^{1-b}$ * y is yield per unit area	• geometric equation which assumes linear relationship between the logarithm of yield per plant and the logarithm of crop density • this equation proposes a linear relation between the logarithm of yield per plant and the logarithm of distance between plants in a row where row width is constant • Warne assumed the higher value of b, the more the plant was dependent on the space available to it
6. Kira et al. 1953	$w = K / \rho^a$ * K, a are constants	• geometric equation which assumes linear relationship between the logarithm of yield/plant and the logarithm of crop density • a is the "competition-density index"; Kira <i>et al.</i> assumed the higher the value of a the more thorough utilization of the space available to the plant • analogous equation 5
7. Shinozaki and Kira 1956	$1/w = a + b\rho$	• reciprocal equation which assumes a linear relationship between the reciprocal of yield per plant and density

Table 1.2. Continued

8. Holliday 1960	$1/w = a + b\rho + c\rho^2$	- reciprocal equation assuming the relationship between the reciprocal of yield per plant and density is non-linear - unlike Hudson's equation 1, Holliday's equation is a flexible yield/ density curve which is not symmetric about the maximum yield and does asymptote at high densities
9. De Wit 1960	$y = PQ / Q + s$ *1/P and Q are the points where the regression line cuts the 1/y and s axes *s is the space available per plant	- reciprocal equation - unlike equations 7 and 8, 1/w at zero density is defined by two constants (e.g. 1/PQ) where P is the asymptote of yield per area - like eqn. 7 this equation can only describe an asymptotic yield/density relationship and not a parabolic one
10. Bleasdale and Nelder 1960	$1/w^\theta = a + b\rho$ * θ is a constant	- reciprocal equation derived from a generalization of the logistic growth curve described by Richards (1959) - describes an asymptotic yield/density relationship
11. Farazdaghi and Harris 1968	$1/w = a + b\rho^\gamma$	reciprocal equation that can describe either an asymptotic situation when $\gamma = 1$, or a parabolic yield/density situation, when $\gamma > 1$
12. Watkinson 1980	$w = w_m(1 + a\rho)^{-b}$ * w_m is mean weight of isolated plants *a is the area a plant requires to grow to w_m *b is the efficiency of the use of resources by the population	

II. Yield - weed density equations

* y is yield; ρ_w is weed density; i, a, are parameters.

Author	Model	Description
13. Hammerton 1964	$y = ab + b\rho_w$	describes weed competition in kale
14. Zakharenko 1968	$y = 1 - e^{-ad}$	
15. Weise 1971	$y = a\rho_w + a\sqrt{\rho_w}$	
16. Dew 1972	$y = a\sqrt{\rho_w}$	
17. Schweizer 1973	$y = ab + b\rho_w + d\rho_w^3$	predicts sugarbeet root losses due to kochia densities
18. Chiskaka 1977	$y = \frac{a\rho_w}{1 + a\rho_w}$	
19. Wilcockson 1977	$y = \frac{a\rho_w}{1 + b\rho_w}$	describes weed competition in sugar beet

Table 1.2. Continued

20. Carlson et al. 1981	$y = \frac{a\rho_w + b\rho_w^2}{(1 + c\rho_w)^2}$	
21. Håkasson 1983	$y = \frac{a\rho_w^b}{1 + a\rho_w^b}$	
22. Håkasson 1983	$y = \frac{a\rho_w + b\rho_w^2}{1 + a\rho_w + b\rho_w^2}$	
23. Marra and Carlson 1983	$y = a\rho_w^b$	• describes economic thresholds of weeds in soybean
24. Wilson and Cussans 1983	$y = b(1 - e^{-ad})$	
25. Covarelli 1984	$y = a\rho_w$	• describes competition between <i>Chenopodium album</i> and sunflower
26. Cousens 1985b	$y = y_{wf} \left(1 - \frac{i\rho_w}{1 + i\rho_w} \right)$ * y_m is weed-free yield	• this model gave the best fit out of 17 other tested models (see Cousens 1985b) • describes relationship between crop yield and weed density as hyperbolic

III. Yield - weed density - crop density equations

• y is yield; ρ is crop density; ρ_w is weed density; a, b, f, g, h, j are arbitrary parameters.

Author	Model	Description
27. Shinkzaki and Kira 1956	$y = \frac{a\rho(1 + b\rho)}{(1 + f\rho)(1 + b\rho + g\rho_w)}$	
28. Shinkzaki and Kira 1956	$y = \frac{a\rho(1 + b\rho + h\rho_w)}{(1 + f\rho)(1 + b\rho + g\rho_w)}$	
29. Carter et al. 1957	$y = a(1 - e^{-b\rho})e^{-f\rho_w}$	
30. Baeumer and deWit 1968 Wright 1981 Weiner 1982 de Wit 1983a Jolliffe et al. 1984	$y = \frac{a\rho}{1 + b\rho + f\rho_w}$	
31. Moore 1979	$y = \frac{a\rho}{\rho + b\rho_w}$	
32. Carlson and Hill 1981	$y = a + \frac{b\rho}{\rho + \rho_w} + \frac{f\rho_w^2}{(\rho + \rho_w)^2}$	
33. Watkinson 1981 Firbank 1984	$y = \frac{a\rho}{(1 + b\rho + f\rho_w)^g}$	
34. Håkasson 1983	$y = \frac{a\rho}{1 + b(\rho + \rho_w)}$	

Table 1.2. Continued

35. Håkasson 1983	$y = \frac{a\rho}{1 + b(\rho + \rho_w) + f(\rho + \rho_w)^2}$	
36. Håkasson 1983	$y = \frac{a\rho}{1 + b\rho + f\rho_w + g\rho\rho_w + h\rho^2 + j\rho_w^2}$	
37. Spitters 1983a	$y = a \log \rho + b \log \rho_w$	• this model was applied to mixed cropping of groundnut and maize • additivity of the log of crop density and the log of weed density is difficult to interpret
38. Spitters 1983a	$y = \frac{a\rho}{1 + b\rho + f\rho_w + g\rho\rho_w}$	• this model is parameterized to reveal the competition characteristics between maize and groundnut • investigates intra- and inter-specific competition and niche differentiation
39. Spitters 1983b	$y = \frac{a\rho}{(1 + b\rho + f\rho_w)(1 + g(1 + b\rho + f\rho_w))}$	
40. Jasieniuk et al. 2000	$y = \left(\frac{j\rho}{1 + j\rho/y_{\max}} \right) \left(1 - \frac{i\rho_w}{1 + i\rho_w/a} \right)$	

IV. Yield - crop density – resource equations

• y is yield per unit area; ρ is crop density; a, b, c, f are arbitrary parameters.

Author	Model	Description
41. Farazdaghi and Harris 1968	$y = \frac{\lambda\rho}{1 + a(\rho + \alpha\rho_w)^d}$	• λ is crop yield per plant in the absence of weed competition • a is the ecological neighborhood area • α is the niche overlap • d is a measure of the rate at which competition decays as a function of distance between plants
42. Hassell and Commins 1976	$y = \frac{\lambda\rho}{(1 + a(\rho + \alpha\rho_w))^b}$	• λ, a, α are the same as above
43. Carlson and Hill 1985	$y = 100 + b\sqrt{\frac{N}{\rho + N}} + cA\sqrt{\frac{N}{\rho + N}} + fA$	• on average a negative yield response to nitrogen fertilization occurred when wild oat density exceeded 1.6% of the total stand
44. O'Donovan et al. 1985	$y = a + bT + c\sqrt{\rho_w}$	• T is the interval between weed and crop time of emergence

Table 1.2. Continued

45. Cousens et al. 1987	$y = \frac{b\rho_w}{e^{ct} + b\rho_w/a}$
	• T is the interval between weed and crop time of emergence

* I have not included models that were later updated by the same authors. Rather, I have included their final models.

**According to Willey and Heath (1969), exponential equations (3 and 4, Table 1.2) are more flexible than the polynomial equations (1 and 2) but cannot fit data which asymptote. Exponential equations have another advantage over polynomial equations—at high densities the curve does not cut the density axis but gradually approaches it. Also, the curve can pass through the origin. A criticism of geometric and reciprocal equations (5 and 6) is the failure of the equation to describe the asymptotic nature of yield per plant at densities too low for competition to occur (Shinozaki and Kira, 1956), thus it cannot describe a parabolic yield/density relationship (Willey and Heath, 1969). The reciprocal equations are based on the relationship of the reciprocal of mean yield per plant and density (Willey and Heath, 1969).

References Cited

- Akey, W.C., and I.N. Morrison. 1984. Effects of soil moisture on the vegetative growth of wild oat (*Avena fatua*). *Weed Science* 32:625-630.
- Andersson, R.L., D.L. Tanaka, A.L. Black, and E.E. Schweizer. 1998. Weed community and species response to crop rotation, tillage, and nitrogen fertility. *Weed Technology* 12:531-536.
- Andreasen, C., Jensen, J.E., and J.C. Steibig. 1991a. Soil properties and plant nutrients affecting the occurrence of *Poa annua*, *Stellaria media*, and *Viola arvensis* on arable land. In *British Crop Protection Conference-weeds*, Brighton, Great Britain.
- Andreasen, C., J.C. Steibig, and H. Haas. 1991b. Soil properties affecting the distribution of 37 weed species in Danish fields. *Weed Research* 31:181-187.
- Antonovics, J., and D.A. Levin. 1980. The ecological and genetic consequences of density-dependent regulation in plants. *Annu. Rev. Ecol. Syst.* 11:411-452.
- Auld, B.A., and B.G. Coote. 1990. INVADE: Towards the simulation of plant spread. *Agriculture, Ecosystems and Environment* 30:121-128.
- Baeumer, K., and C.T. DeWit. 1968. Competitive interference of plant species in monocultures and mixed stands. *Netherlands Journal of Agricultural Science* 16:103-122.
- Baker, L.O. and D.H. Leighty. 1958. Wild oat germination and dormancy. *Proceedings of the Western Weed Control Conference*, Vol. 16, pp.69-74.
- Barton, D.L., D.C. Thill, and B. Shafii. 1992. Integrated wild oat management affects spring barley yield and economics. *Weed Technology* 6:129-135.
- Bauer, A., R.A. Young, and J.L. Ozbun. 1965. Effects of moisture and fertilizer on yields of spring wheat and barley. *Agronomy Journal* 57:354-356.
- Beckie, H.J., A.P. Moulin, C.A. Campbell, and S.A. Brandt. 1995. Testing the effectiveness of four simulation models for estimating nitrates and water in two soils. *Canadian Journal of Soil Science* 75:135-143.
- Begon, M., J.L. Harper, and C.R. Townsend. 1986. *Ecology, Individuals, Populations, and Communities* Blackwell, Oxford, England.
- Bell, A.R., and J.D. Nalewaja. 1968. Competition of wild oat in wheat and barley. *Weed Science* 16:505-508.

- Blackshaw, R.E., L.J. Molnar, and H.H. Janzen. 2003 (submitted). Nitrogen fertilizer timing and application method affects weed competition and spring wheat yield. *Weed Science*.
- Blackshaw, R.E., J.R. Moyer, and K.N. Harker. 2002. Integration of cultural practices for sustainable weed management in direct seeding systems. Alberta Agricultural Research Institute Final Report, Edmonton, AB.
- Blackshaw, R.E., J.R. Moyer, and G.C. Kozub. 1994. Efficacy of downy brome herbicides as influenced by soil properties. *Canadian Journal of Plant Science*.
- Bleasdale, J.K.A., and J.A. Nelder. 1960. Plant competition and crop yield. *Nature* 188:342.
- Bole, J.B., and U.J. Pittman. 1980. Spring soil water, precipitation, and nitrogen fertilizer: Effect on barley yield. *Canadian Journal of Soil Science* 60:461-469.
- Bowden, B.A., and G. Friesen. 1967. Competition of wild oats (*Avena fatua* L.) in wheat and flax. *Weed Research* 7:349-359.
- Bowes, G.G., D.T. Spurr, A. Thomas, G. D.P. Pechken, and D.W. Douglas. 1994. Habits occupied by scentless chamomile (*Matricaria perfoata* Merat) in Saskatchewan. *Canadian Journal of Plant Science* 74:383-386.
- Boyd, N.S., R.V. Acker, M. Entz, and P. Bullock. 2002. The relative importance of seed and microsite limitation on annual and perennial weed populations. *WSSA Abstracts* 42:81.
- Brain, P., and R. Cousens. 1989. An equation to describe dose responses where there is stimulation of growth at low doses. *Weed Research* 29:93-96.
- Brain, P., B.J. Wilson, K.J. Wright, G.P. Seavers, and J.C. Caseley. 1999. Modeling the effect of crop and weed on herbicide efficacy in wheat. *Weed Research* 39:21-35.
- Brown, P.L., and G.R. Carlson. 1990. Grain yields related to stored soil water and growing season rainfall. *Agricultural Experiment Station* 35.
- Brown, D., and P. Rothery. 1993. *Models in Biology: mathematics, statistics and computing* John Willey and Sons, Chichester.
- Bubar, C.J. 1991. Competition between *Avena fatua* L. and *Triticum aestivum* L. with varying time of emergence. Ph. D. Thesis, University of Saskatchewan.

- Buchanan, G.A., C.S. Hoveland, and M.C. Harris. 1975. Responses of weeds to soil pH. *Weed Science* 23:473-477.
- Calvet, R. 1980. Adsorption-desorption phenomena, p. pp. 1-30, In R. J. Hume, ed. *Interactions between herbicides and the soil*. Academic Press, New York, NY.
- Campbell, C.A., R.P. Zentner, F. Selles, B.G. McConkey, and F.B. Dyck. 1993. Nitrogen management for spring wheat grown annually on zero-tillage: yields and nitrogen use efficiency. *Agronomy Journal* 85:107-114.
- Carlson, H., Hill, J., and Baghott, K. 1982. Wild oat competition in spring wheat. *In* 33rd Annual Californian Weed Conference, pp. 13-24.
- Carlson, H.L., and J.E. Hill. 1985a. Wild oats (*Avena fatua*) competition with spring wheat: plant density effects. *Weed Science* 33:176-181.
- Carlson, H.L., and J.E. Hill. 1985b. Wild oat (*Avena fatua*) competition with spring wheat: effects of nitrogen fertilization. *Weed Science* 34:29-33.
- Carmer, S.G., and J.A. Jackobs. 1965. An exponential model for prediction optimum plant density and maximum corn yield. *Agronomy Journal* 57:241-244.
- Carter, H.W., H.W. Norton, and G.H. Dungan. 1957. Wheat and cheat. *Agronomy Journal* 49:261-267.
- Chancellor, R.J. and N.C.B. Peters. 1970. Seed production by *Avena fatua* populations in various crops. *Proceedings of the 10th British Weed Control Conference*, pp. 7-11.
- Chancellor, R.J., and N.C.B. Peters. 1974. The time of the onset of competition between wild oats (*Avena fatua* L.) and spring cereals. *Weed Research* 14:197-202.
- Chipanshi, A.C., E.A. Ripley, and R.G. Lawford. 1997. Early prediction of spring wheat yields in Saskatchewan from current and historical weather data using CERES-Wheat model. *Agricultural and Forest Meteorology* 84:223-232.
- Chisaka, H. 1977. Weed damage to crops: yield loss due to competition, p. 1-16, In J. D. Fryer and S. Matsunaka, eds. *Integrated control of weeds*. University of Tokyo Press, Tokyo.
- Colwell, J.D., and R.J. Esdaile. 1966. The application of production function analysis for the estimation of fertilizer requirements of wheat in northern New South Wales. *Australian Journal of Experimental Agriculture and Animal Husbandry* 6:418-424.

- Courtney, A.D. 1994. Density dependent relationships to herbicide response. 1994 BCPC Monograph no. 59: Comparing glasshouse and field pesticide performance II., 35-36:35-46.
- Cousens, R. 1985a. An empirical model relating crop yield to weed and crop density and a statistical comparison with other models. *Journal of Agricultural Science* 105:513-521.
- Cousens, R. 1985b. A simple model relating yield loss to weed density. *Annals of Applied Biology* 107:239-252.
- Cousens, R., P. Brain, J.T. O'Donovan, and P.A. O'Sullivan. 1987. The use of biologically realistic equations to describe the effects of weed density and relative time of emergence on crop yield. *Weed Science* 35:720-725.
- Cousens, R., L.G. Firbank, A.M. Mortimer, and R.G.R. Smith. 1988. Variability in the relationship between crop yield and weed density for winter wheat and *Bromus Sterilis*. *Journal of Applied Ecology* 25:1033-1044.
- Cousens, R., Peters, N.C.B., and C. J. Marshall. 1984. Models of yield loss-weed density relationships. *Proceeding of the 7th International Symposium on Weed Biology, Ecology and Systematics*, pp. 367-374. Columa-EWRS, Paris
- Covarelli, G. 1984. Competition between *Chenopodium album* and sunflower. *Proceedings of EWRS 3rd Symposium on Weed Problems in the Mediterranean*, pp. 117-120.
- Cudney, D.W., L.S. Jordan, J.S. Holt, and J.S. Reints. 1989. Competitive Interaction of Wheat (*Triticum aestivum*) and Wild Oats (*Avena fatua*) Grown at Different Densities. *Weed Science* 37:538-543.
- Cussans, G.W. and J. Rolph. 1990. Herbmast-A herbicide selection system for winter wheat. *Proceedings of the 7th EWRS Symposium: Integrated Weed Management Cereals*, pp. 451-457, Helsinki.
- Dale, M.R.T., A.G. Thomas, and E.A. John. 1992. Environmental factors including management practices as correlates of weed community composition in spring seeded crops. *Canadian Journal of Botany* 70:1931-1939.
- Davies, D.H.K., Fisher, N.M., Proven, M.J., Whytock, G.P., and A.D. Courtney, A.D. 1995. Risk evaluation of reduced dose approaches to weed control in cereals. *Proceedings of the 9th EWRS Symposium: Challenges for Weed Science in a Changing Europe*, pp. 459-466, Budapest.
- Davies, D.H.K., Whiting, A.J., and G.M. Whytock. 1989. Yield responses to herbicide

- use and weed levels in winter wheat and spring barley in Scottish trials and consequences for economic models. *Proceedings of the Brighton Crop Protection Conference--Weeds*, pp. 955-960.
- deJong, E., and D.A. Rennie. 1967. Physical soil factors influencing the growth of wheat. *Can. Cent. Wheat Symp. Pub. Western Co-op Fertilizers Ltd., Calgary, Canada.*
- Dew, D.A. 1972. An index of competition for estimating crop loss due to weeds. *Canadian Journal of Plant Science* 52:921-927.
- DeWit, C.T. 1960. Development of a pure peat mixture for raising plants with blocks. *Verslag Lankbouwk Onderzoek* 66:1-81.
- Dieleman, J.A., D.A. Mortensen, D.D. Buhler, C.A. Cambardella, and T.B. Moorman. 2000a. Identifying associations among site properties and weed species abundance. I. Multivariate analysis. *Weed Science* 48:567-575.
- Dieleman, J.A., D.A. Mortensen, D.D. Buhler, and R.B. Ferguson. 2000b. Identifying associations among site properties and weed species abundance. II. Hypothesis generation. *Weed Science* 48:576-587.
- Dille, J.A. 2002. Predicting weed species occurrence based on site properties and previous year's weed presence. *Precision Agriculture* 3:193-207.
- DiTomaso, J.M. 1985. Approaches for improving crop competitiveness through the manipulation of fertilization strategies. *Weed Science* 43:491-497.
- Duncan, W.G. 1958. The relationship between corn population and yield. *Agronomy Journal* 50:82-84.
- Engel, R., D. Long, and G. Carlson. 2001. Nitrogen requirement and yield potential of spring wheat as affected by water. *MSU Extension Service Agricultural Experiment Station.*
- Ervio, L.-R., T. Tanskanen, and J. Salonen. 1991. Profitability of chemical weed control in spring cereals. *Annales Agriculturae Fenniae* 30:199-206.
- Farazdaghi, H., and P.M. Harris. 1968. Plant competition and crop yield. *Nature* 217:289-290.
- Fawcett, R.G. 1967. Factors influencing the development and grain yield of spring wheat grown on the North-West plains of New South Wales, with special reference to soil-water-plant relationships. Ph.D. Thesis, University of East Anglia.

- Fernandez, R., and R.J. Laird. 1959. Yield and protein content of wheat in central Mexico as affected by available soil moisture and nitrogen fertilization. *Agronomy Journal* 51:33-36.
- Feyerherm, A.M., and G.M. Paulsen. 1981. Development of a wheat yield prediction model. *Agronomy Journal* 73:277-282.
- Firbank, L.G. 1984. The population biology of *Agrostemma githago*. Ph. D. Thesis, University of East Anglia.
- Firbank, L.G., and A.R. Watkinson. 1986. Modelling the population dynamics of an arable weed and its effect upon crop yield. *Journal of Applied Ecology* 23:147-159.
- Firbank, L.G., and A.R. Watkinson. 1990. On the effects of competition from monocultures to mixtures. *In: Perspectives on Plant Competition.* pp.165-193.
- Franz, K., F. Kaiser, and B. Gerowitt. 1990. Effects of different levels of nitrogen fertilization on development and seed production of three weed species in winter wheat. *Zeitschrift fur Pflanzenkrankheiten und Pflanzenschutz* 95:225-240.
- Freckleton, R.P., and A.R. Watkinson. 2001. Nonmanipulative determination of plant community dynamics. *TRENDS in Ecology and Evolution* 16:301-307.
- Fykse, H. 1991. Skadetersklar for vgas. *Norsk Landbrukforskning*, suppl 10:40-43.
- Gajic, D. 1966. Interference among wheat (*Triticum vulgare*) and corn cockle (*Agrostemma githago*) on brown soil and smonitsa. *Arhiv za Poljoprivredne Nauke, Beograd* 19:63-96.
- Gerowitt, B., H. Bodendorfer, and R. Heitefuss. 1984. Zur Wirtschaftlichkeit des Herbizideinsatzes im Getreide-Auswertung von versuchen des Pflanzenschutzdienstes den Jahren. 1977-1981. *Zeitschrift fur Pflanzenkrankheiten und Pflanzenschutz, Sonderheft X*:127-135.
- Gerowitt, B., and R. Heitefuss. 1990. Weed economic thresholds in cereals in the Federal Republic of Germany. *Crop Protection* 9:323-331.
- Godwin, D., J.T. Ritchie, U. Singh, and L. Hunt. 1990. User's Guide to CERES Wheat-V2.10 International Development Center, Muscle Shoals, AL.
- Grundy, A.C., N.D. Boatman, and R.J. Foud-Williams. 1996. Effects of herbicide and nitrogen fertilizer application on grain yield and quality of wheat and barley. *Journal of Agricultural Science* 126:379-385.

- Håkansson, S. 1983. Competition and production in short-lived crop-weed stands. Density effects. Sveriges Lantbruksuniversitet Rapport 127. Institutionen for vaxtodling.
- Hamblin, A.P. 1985. The influence of soil structure on water movement, crop root growth and water uptake. *Advances in Agronomy* 38:95-158.
- Hammerton, J.L. 1964. Aspects of weed competition in kale. *Proceedings 7th British Weed Control Conference*, pp. 389-395.
- Harper, J.L. 1961. Approaches to the study of plant competition. In *Mechanisms in biological competition: Symposium Soc. Exp. Biol.*, Vol. 15, pp. 1-39.
- Hassell, M.P., and H.N. Comins. 1976. Discrete time models for two-species competition. *Theoretical Population Biology* 9:202-221.
- Haun, J.R. 1974. Prediction of spring wheat yields from temperature and precipitation data. *Agronomy Journal* 66:405-409.
- Hausler, A. and H. Nordmeyer. 1995. Impact of soil properties on weed distribution. *Proceedings of a seminar on site specific farming* (ed S.E. Olesen), Vol. SP-report 26, Danish institute of Plant and Soil Science.
- Heapy, L.A., J.A. Roberston, D.K. McBeath, V.M.V. Maydell, H.C. Love, and G.R. Webster. 1976. Development of a barley yield equation for central Alberta. I. Effects of soil and fertilizer N and P. *Canadian Journal of Soil Science* 56:233-247.
- Heisel, T., A.K. Ersboll, and C. Andreasen. 1999. Weed mapping with co-kriging using soil properties. *Precision Agriculture* 1:39-52.
- Heitefuss, R., Gerowitt, B., and W. Wahmhoff. 1987. Development and implementation of weed economic thresholds in the F. R. Germany. *Proceedings 1987 British Crop Protection Conference--Weeds*, pp. 1025-1034, Brighton.
- Henry, J.L. 1971. The effect of soil zone, available soil nitrogen level and nitrogen fertilization on the yield and quality of stubble seeded cereal grains. In *Soil Fertility Workshop, Ext. Div.*, pp. 22pp., University of Saskatchewan.
- Henry, J.L., J.B. Boole, and R.C. McKenzie. 1986. Effect of nitrogen water interactions on yield and quality of wheat in Western Canada, In A. E. Slinkard and D. B. Fowler, eds. *Wheat Production in Canada: a Review*. University of Saskatchewan, Saskatoon.

- Henson, J.F., and L.S. Jordan. 1982. Wild oat (*Avena fatua*) competition with wheat (*Triticum aestivum* and *T. turgidum durum*) for nitrate. *Weed Science* 30:297-300.
- Hoepfner, K.H. 1969. Beeinträchtigung des Ertrages der Sommergerste durch Wildhafer (*Avena fatua* L.). *Berl* 49:139-140.
- Holliday, R. 1990. Plant population and crop yield: Part I and Part II. *Field Crop Abstract* 13.
- Holliday, R. 1990. Plant population and crop yield: Part I and Part II. *Field Crop Abstract* 13.
- Hudson, H.G. 1941. Studies with wheat. *Journal of Agricultural Science* 31:138-144.
- Hunter, A.S., C.J. Gerard, H.M. Waddoups, W.E. Hall, H.E. Cushman, and L.A. Alban. 1958. The effect of nitrogen fertilizers on the relationships between increases in yields and protein content of pastry type wheats. *Agronomy Journal* 50:311-314.
- Jacobsohn, R., and R.N. Anderson. 1968. Differential response of wild oat lines to diallate, triallate and barban. *Weed Science* 16:491-494.
- Jensen, P.K. (1985) Review of yield responses to weed control in one thousand spring barley experiments. *Proceedings 1985 British Crop Protection Conference--Weeds*, pp. 687-692.
- Jensen, P.K., and P. Kudsk. 1988. Prediction of herbicide activity. *Weed Research* 28:473-478.
- Johnson, G.A., D.A. Mortensen, and A.R. Martin. 1995. A simulation of herbicide use based on weed spatial distribution. *Weed Research* 35:197-205.
- Jolliffe, P.A., G.W. Eaton, and M.V. Potdar. 1988. Plant-growth analysis--allometry, growth, and interference in orchardgrass and timothy. *Annals of Botany* 62:31-42.
- Jolliffe, P.A., A.N. Minjas, and V.C. Runeckles. 1984. A reinterpretation of yield relationships in replacement series experiments. *Journal of Applied Ecology* 21:227-243.
- Kim, D.S., P. Brain, E.J.P. Marshall, and J.C. Caseley. 2002. Modelling herbicide dose and weed density effects on crop:weed competition. *Weed Research* 42:1-13.

- Kira, T., H. Ogawa, and N. Shinozaki. 1953. Intraspecific competition among higher plants. I. Competition-yield-density interrelationships in regularly dispersed populations. J. Inst. Polytech. D4.
- Kirkland, K.J., and H.J. Beckie. 1998. Contribution of nitrogen fertilizer placement to weed management in spring wheat (*Triticum aestivum*). Weed Technology 12:507-514.
- Kirkland, K.J., and J.H. Hunter. 1991. Competitiveness of Canada prairie spring wheats with wild oat (*Avena fatua* L.). Canadian Journal of Plant Science 71:1089-1092.
- Knezevic, S., Evans, S., Shapiro, C., and J. Lindquist. 2000. Effect of nitrogen on critical period of weed control in corn. Abstracts of the III International Weed Science Congress, pp. p. 52, Foz do Iguassu, Brazil.
- Kropff, M.J. 1988. Modelling the effects of weeds on crop production. Weed Research 28:465-471.
- Kropff, M.J., and C.J.T. Spitters. 1991. A simple model of crop loss by weed competition from early observation on relative leaf area of the weeds. Weed Research 31:97-105.
- Kropff, M.J., F.J.H. Vossen, C.J.T. Spitters, and W. DeGroot. 1984. Competition between a maize crop and a natural population of *Echinochloa crus-galli* (L.). Netherlands Journal of Agricultural Science 32:324-327.
- Kudsk, P. 1989. Experiences with reduced herbicide doses in Denmark and the development of the concept of factor-adjusted doses. 1989 Proceedings Brighton Crop Protection Conference--Weeds, pp. 545-554.
- Lehane, J.J., and W.J. Staple. 1965. Influence of soil texture, depth of soil moisture storage and rainfall distribution on wheat yields in southwestern Saskatchewan. Canadian Journal of Soil Science 45:207-219.
- Lindsay, D.R. 1956. Taxonomic and genetic studies on wild oat (*Avena fatua* L.). Weeds 4:1-10.
- Manlove, R.J., Mortimer, A.M., and P.D. Putwain. 1982. Modelling wild oat populations and their control. In 1982 British Crop Protection Conference--Weeds, pp. 749-756.
- Marra, M.C., and G.A. Carlson. 1983. An economic threshold model for weeds in soybean. Weed Science 31:604-609.

- Martin, M.P.L.D., and R.J. Field. 1988. Influence of time of emergence of wild oat on competition with wheat. *Weed Research* 28:111-116.
- Martin, R.J., B.R. Cullis, and D.W. McNamara. 1987. Prediction of wheat yield loss due to competition by wild oats. *Journal of Agricultural Research* 38:487-499.
- Martin, R.J., and W.L. Felton. 1993. Effect of crop rotation, tillage practice, and herbicides on the population dynamics of wild oats in wheat. *Australian Journal of Experimental Agriculture* 33:159-165.
- McCurdy, E.V. 1958. The effect of crop competition on the number of wild oats in the crop. In *Res. Rep. West Sect. Nat. Weed Comm. Can.*, pp. p. 34.
- McNamara, D.W. 1972. Wild oats in wheat, *The Agricultural Gazette of New South Wales*. pp.157-159
- Mercado, B.L. and Talatala, R.L. (1977) Competitive ability of *Echinochloa colonum* L. against direct-seeded lowland rice. *Proceedings of the 6th Asian-Pacific Weed Science Society Conference*, pp. 161-165.
- Miller, S.D., J.D. Nalewaja, and C.E.G. Mulder. 1982. Evaluation of morphological and physiological variation in wild oat. *Agronomy Journal* 74:771-775.
- Molberg, E.S. 1966. Triallate, 2,4-D and fertilizer combinations for *Avena fatua* and broad-leaved weed control in wheat. *Res. Rept. Nat. Weed Comm. (Canada) Western Sect.*:p. 80.
- Moore, G.A., and J.P. Tyndale-Busoe. 1999. Estimation of the importance of spatially variable nitrogen application and soil moisture holding capacity to wheat production. *Precision Agriculture* 1:27-338.
- Mortensen, D.A., VonBargen, K., Meyer, G.E., Merritt, S.J., and D.M. Woebbecke. 1993. Evaluation of a vertical view intermittent herbicide applicator. *Proceedings of the Weed Science Society of America*, Vol. 33, pp. 44.
- Moyer, J.R. 1987. Effect of soil moisture on the efficacy and selectivity of soil-applied herbicides. *Rev. Weed Science* 3:19-34.
- Navas, M.L. 1991. Using plant population biology in weed research: a strategy to improve weed management. *Weed Research* 31:171-179.
- Naylor, J.M., and S. Jana. 1976. Genetic adaptation for seed dormancy in *Avena fatua*. *Canadian Journal of Botany* 54:306-312.

- Neidig, R.E., and R.S. Snyder. 1924. The relation of moisture and available nitrogen to the yield and protein content of wheat. *Soil Science* 18:173-179.
- O'Donovan, J.T., E.A.d.S. Remy, P.A.O. Sullivan, D.A. Dew, and A.K. Sharma. 1985. Influence of the relative time of emergence of wild oat (*Avena fatua* L.) on yield loss of barley (*Hordeum vulgare*) and wheat (*Triticum aestivum*). *Weed Science* 33:498-503.
- Pande, H.K. 1953. Effect of weeding on the yield of wheat (India). *Empire J. Expt. Agric.* 21:297-303.
- Paterson, J.G. 1969. How important are wild oats. *Journal of Agric., Western Australia* 10:162.
- Pavlychenko, T.K. 1937. Quantitative study of the entire root system of weed and crop plants under field conditions. *Ecology* 18:62-79.
- Pavlychenko, T.K., and J.B. Harrington. 1935. Root development of weeds and crops in competition under dry farming. *Scientific Agric.* 16:151-160.
- Pavlychenko, T.K., and J.B. Harrington. 1967. Competitive efficiency of weeds and cereal crops. *Can. J. Res* 10:77-94.
- Pelton, W.L. 1969. Influence of low seeding rates on wheat yield in South Western Saskatchewan. *Canadian Journal of Plant Science* 49:607-614.
- Peters, N. 1978. Factors influencing the emergence and competition of *Avena fatua* L. with spring barley. Ph.D., University of Reading.
- Peters, N.C.B., and B.J. Wilson. 1983. Some studies on the competition between *Avena fatua* L. and spring barley. II. Variation of *Avena fatua* emergence and development and its influence on crop yield. *Weed Research* 23:305-311.
- Peterson, G.A., A. J. Schlegel, D.L. Tanaka, and O.R. Jones. 1996. Precipitation use efficiency as affected by cropping and tillage systems. *J. Prod. Agric.* 9:180-186.
- Poole, M.L. 1979. Competition between crops and ryegrass. *Proceedings Western Australian Weeds Conference*, pp. 95-97.
- Racz, G.J. 1974. Effect of nitrogen supply, water supply and temperature on the yield and protein content of cereal grains. *Proceedings of 18th Man. Soil Sci. Soc. Meetings*, Dec. 1974, pp. 219-228, Winnipeg.

- Radford, B.J., B.J. Wilson, O. Carthedge, and F.B. Watkins. 1980. Effect of wheat seeding rate on wild oat competition. *Aust. Journal of Experimental Agriculture and Animal Husbandry* 20:77-81.
- Read, D.W.L., and F.G. Warder. 1974. Influence of soil and climatic factors on fertilizer response of wheat grown on stubble land in southwestern Saskatchewan. *Agronomy Journal* 66:245-248.
- Ritchie, J.T., and S. Otter. 1985. Description and performance of CERES-Wheat: a user-oriented wheat yield model, In W. O. Willis, ed. *ARS Wheat Yield Project, Vol. ARS-38*. Agricultural Research Service, US Department of Agriculture, Temple, TX.
- Roberston, G.W. 1974. Wheat yields for 50 years at Swift Current, Saskatchewan, in relation to weather. *Canadian Journal of Plant Science* 54:625-650.
- Roberts, H.A. 1984. Crop and weed emergence patterns in relation to time of cultivation and rainfall. *Annals of Applied Biology* 105:263-275.
- Rydahl, P. 1995. Computer-assisted decision making. *Proceedings of the 9th EWRS Symposium: Challenges for Weed Science in a Changing Europe*, pp. 29-37, Budapest.
- Salonen, J. 1992. Yield responses of spring cereals to reduced herbicide doses. *Weed Research* 32:439-499.
- Salonen, J. 1993. Reducing herbicide use in spring cereal production. *Agricultural Science Finland* 2:42pp.
- Satorre, E.H., and R.W. Snaydon. 1992. A comparison of root and shoot competition between spring cereals and *Avena fatua* L. *Weed Research* 32:44-45.
- Sawhney, R., and J.M. Naylor. 1979. Dormancy studies in seed of *Avena fatua*. A demonstration of genetic variability affecting the response to temperature during seed development. *Canadian Journal of Botany* 57:59-63.
- Schweizer, E.E. 1973. Predicting sugarbeet root losses based on kochia densities. *Weed Science* 19:125-128.
- Scursoni, J., R. Benech-Arnold, and H. Hirchoren. 1999. Demography of wild oat in barley crops: effect of crop, sowing rate, and herbicide treatment. *Agronomy Journal* 91:478-485.

- Scursoni, J.A., and R.B. Arnold. 2002. Effect of nitrogen fertilization timing on the demographic processes of wild oat (*Avena fatua*) in barley (*Hordeum vulgare*). *Weed Science* 50:616-621.
- Seeley, C.I. 1977. Seed dormancy in wild oats. *Proceedings of Western Society of Weed Science*, Vol. 30, pp. 33-35.
- Sexsmith, J.J. 1955. Delayed seeding of wheat and barley for control of wild oats. *Proceedings of Res. Rep. 12th N. Cent. Weed Cont. Cof. Can.*, pp. 80-82.
- Sexsmith, J.J., and U.J. Pittman. 1963. Effect of nitrogen fertilizers on germination and stand of wild oats. *Weeds* 11:99-101.
- Sexsmith, J.J., and G.C. Russell. 1963. Effect of nitrogen and phosphorus fertilization on wild oat and spring wheat. *Canadian Journal of Plant Science* 43:64-70.
- Sharma, M.P., and W.H.V. Born. 1978. The biology of Canadian weeds 27. *Avena fatua* L. *Canadian Journal of Plant Science* 58:141-157.
- Sharpe, P.R., and J.B. Dent. 1968. The determination and economic analysis of relationships between plant propagation and yield of main crop potatoes. *Journal of Agricultural Science* 70:123-129.
- Sharpe, P.R., and J.B. Dent. 1968. The determination and economic analysis of relationships between plant propagation and yield of main crop potatoes. *Journal of Agricultural Science* 70:123-129.
- Shatar, T.M., and A.B. McBratney. 2000. Empirical modeling of relationships between sorghum yield and soil properties. *Precision Agriculture* 1:249-276.
- Shinozaki, K., and T. Kira. 1956. Intraspecific competition among higher plants VII. Logistic theory of the C-D effect. *Journal of Institute of Polytechnics, Osaka City Univ* D7:35-72.
- Somody, C.N., J.D. Nalewaja, and S.D. Miller. 1984a. Wild oat (*Avena fatua*) and *Avena sterilis* morphological characteristics and response to herbicide. *Weed Science* 32:353-359.
- Somody, C.N., J.D. Nalewaja, and S.D. Miller. 1984b. Wild oat (*Avena fatua*) seed environment and germination. *Weed Science* 32:502-507.
- Spandl, E., B.R. Durgan, and D.W. Miller. 1997. Wild oat (*Avena fatua*) control in spring wheat (*Triticum aestivum*) and barley (*Hordeum vulgare*) with reduced rates of postemergence herbicides. *Weed Technology* 11:591-597.

- Spitters, C.J.T. 1983a. An alternative approach to the analysis of mixed cropping experiments. 1. Estimation of competition effects. *Neth. Journal of agricultural Sciences* 31:1-11.
- Spitters, C.J.T. 1983b. An alternative approach to the analysis of mixed cropping experiments. 2. Marketable yield. *Netherlands Journal of Agricultural Science* 31:143-155.
- Spitters, C.J.T., and R.Aerts. 1983. Simulation of competition for light and water in crop-weed associations. *Aspects of Applied Biology* 4:467-483.
- Spratt, E.D., and R.N. McIver. 1972. Effects of topographical positions, soil test values, and fertilizer use on yields of wheat in a complex of black Chernozemic and Gleysolic soils. *Canadian Journal of Plant Science* 52:53-58.
- Stewart, D.W., and L.M. Dwyer. 1990. A model of spring wheat (*Triticum aestivum*) for large area yield estimations on the Canadian prairies. *Canadian Journal of Plant Science* 70:19-32.
- Streibig, J.C. 1980. Models for curve-fitting herbicide dose response data. *Acta Agriculturae Scandinavica* 30:59-64.
- Streibig, J.C., J.H. Combellack, and G.H. Pritchard. 1989. Estimation of thresholds for weed control in Australian cereals. *Weed Research* 29:117-126.
- Streibig, J.C., M. Rudemo, and J.E. Jensen. 1993. Dose-response curves and statistical models, In J. C. Streibig and P. Kudsk, eds. *Herbicide Bioassays*. CRC Press, Boca Raton.
- Thornton, P.K., R.H. Fawcett, J.B. Dent, and T.J. Perkins. 1990. Spatial weed distribution and economic thresholds for weed control. *Crop Protection* 9:337-342.
- Thurston, J.M. 1957. Morphological and physiological variation in wild oats (*Avena fatua* L. and *A. ludoviciana* Dur.) and in hybrids between wild and cultivated oats. *Journal of Agricultural Science* 49.
- Thurston, J.M. 1959. A comparative study of the growth of wild oats (*Avena fatua* L. and *A. ludoviciana* Dur.) and of cultivated cereals with varied nitrogen supply. *Annals of Applied Biology* 47:716-739.
- Thurston, J.M. 1962. The effect of competition from cereal crops on the germination and growth of *Avena fatua* L. in a naturally infested field. *Weed Research* 2:192-207.

- Tollenaar, H. 1992. Reinterpretation and evaluation of some simple descriptive models for weed-crop interference in terms of one-sided and two-sided competition. *Oikos* 65:256-264.
- Toole, E.H., and F.A. Coffman. 1940. Variations in the dormancy of seeds of the wild oat, (*Avena fatua*). *J. of Am. Soc. Agron.* 32:631-638.
- Torner, C., C. Fernandez-Quintanilla, L. Navarrette, and M.J. Sanchez. 1985. Tolerance and competitive ability of different cultivars of wheat and barley in the presence of *Avena sterilis* L. subsp. *ludoviciana* (Durieu) Nyman. *Tecnica y Economica Agraria* 16:65-71.
- van Genuchten, M.T. 1980. A closed-form equation for predicting the hydraulic conductivity of unsaturated soils. *Soil Science American Journal* 44:892-898.
- Vandermeer, J. 1984. Plant competition and the yield-density relationship. *Journal of Theoretical Biology* 109:393-399.
- VanGroenendaal, J.M. 1988. Patchy distribution of weeds and some implications for modelling population dynamics: a short literature review. *Weed Research* 28:437-441.
- VanWychen, L.R., B.D. Maxwell, A.J. Bussan, L.R. and E.C. Luschei. 2004. Wild oat (*Avena fatua*) habitat and water use in cereal grain cropping systems. *Weed Science* 52:352-358.
- VanWychen, L.R. 2002. Field-scale spatial distribution, water use, and habitat of wild oat in the semiarid Northern Great Plains, Montana State University, Bozeman, Montana.
- VanWychen, L.R., E.C. Luschei, A.J. Bussan, and B.D. Maxwell. 2002. Accuracy and cost effectiveness of GPS-assisted wild oat mapping in spring cereal crops. *Weed Science* 50:120-129.
- Walker, S.R., R.W. Medd, G.R. Robinson, and B.R. Cullis. 2002. Improved management of *Avena ledoviciana* and *Phalaris paradoxa* with more densely sown wheat and less herbicide. *Weed Research* 42:257-270.
- Walter, A.M., S. Christensen, and S.E. Simmelsgaard. 2002. Spatial correlation between weed species densities and soil properties. *Weed Research* 42:26-38.
- Warder, F.G., J.J. Lehane, W.C. Hinman, and W.J. Staple. 1963. The effect of fertilizer growth, nutrient uptake and moisture use of wheat on two soils in southwestern Saskatchewan. *Canadian Journal of Soil Science* 43:107-116.

- Warne, L.G.G. 1951. Spacing experiments on vegetables. *Journal of Horticultural Science* 26:84-97.
- Watkins, F.B. 1971. Effects of annual dressings of nitrogen fertilizer on wild oat infestations. *Weed Research* 11:299-301.
- Watkinson, A.R. 1980. Density-dependence in single-species populations of plants. *Journal of Theoretical Biology* 83:345-357.
- Watkinson, A.R. 1981. Interference in pure and mixed populations of *Agrostemma githago*. *Journal of Applied Ecology* 18:967-976.
- Weaver, S.E., and A.S. Hamill. 1985. Effects of soil pH on competitive ability and leaf nutrient content of corn (*Zea mays* L.) and three weed species. *Weed Science* 33:447-451.
- Weiner, J. 1982. A neighborhood model of annual-plant interference. *Ecology* 63:1237-1241.
- Weiner, J., and S.C. Thomas. 1986. Size variability and competition in plant monocultures. *Oikos* 47.
- Weise, A.F. 1971. Method No. 62, In L. Chhilarappa, ed. *Crop Loss Assessment Methods*, FAO Manual on the Evaluation and Prevention of Losses by Pests, Disease and Weeds. CAB, Farnham Royal, Slough.
- Wilcockson, S.J. 1977. Competitive effects of weeds on the sugar beet crop. Ph.D. Thesis, University of Nottingham.
- Wiles, L.J., G.W. Oliver, A.C. York, H.J. Gold, and G.G. Wilkinson. 1992. Spatial distribution of broadleaf weeds in North Carolina soybean (*Glycine max*) fields. *Weed Science* 40:554-557.
- Willey, R.W., and S.B. Heath. 1969. The quantitative relationships between plant population and crop yield. *Advances in Agronomy* 21:281-321.
- Williams, G.D.V. 1973. Estimates of prairie provincial wheat yields based on precipitation and potential evapotranspiration. *Canadian Journal of Plant Science* 53:17-30.
- Wilson, B.J. 1979a. The cost of wild oats (*Avena* spp.) in Australian wheat production. *Proceedings 7th Asian-Pacific Weed Science Society Conference*, pp. 441-444.

- Wilson, B.J. 1979b. Post-emergence control of wild oats in Queensland with difenzoquat, flamprop-methyl, dichlofop methyl and barban. *Australian Journal of Experimental Animal Husbandry* 19:108-117.
- Wilson, B.J. 1986. Yield responses of winter cereals to the control of broad-leaved weeds. *Proceedings from the 5th EWRS Symposium: Economic Weed Control, Stuttgart-Hohenheim.*
- Wilson, B.J., R. Cousens, and K.J. Wright. 1990a. The response of spring barley and winter wheat to *Avena fatua* population density. *Annals of Applied Biology* 116:601-609.
- Wilson, B.J. and G.W. Cussans. 1983. The effect of weeds on yield and quality of winter cereals in the U.K. *Proceedings of the 10th International Congress of Plant Protection*, pp. 121.
- Wilson, B.J., and N.C.B. Peters. 1982. Some studies of competition between *Avena fatua* and spring barley. I. The influence of *Avena fatua* on yield of barley. *Weed Research* 22:143-148.
- Worzella, W.W. 1943. Response of wheat varieties to different levels of soil productivity: I. Grain yield and total weight. *Agronomy Journal* 35:114-124.
- Wraith, J.M., J.M. Baker, and T.K. Blake. 1995. Water uptake resumption following soil drought: a comparison among four barley genotypes. *Journal of Experimental Botany* 46:873-880.
- Wright, A.J. 1981. The analysis of yield-density relationships in binary mixtures using inverse polynomials. *Journal of Agricultural Science* 96:561-567.
- Wright, K.J. 1993. Weed seed production as affected by crop density and nitrogen application. In *Brighton Crop Protection Conference--Weeds--1993*. pp. 275-280, Brighton, UK.
- Zakharenko, V.A. 1968. Investigating the competitive ability of weed and crop plants in relation to herbicide application. *Khimiya Sel Khozyaishe* 6:447-452.
- Zenter, R.P., and D.W.L. Read. 1977. Fertilizer decisions and soil moisture in the Brown soil zone. *Can. Farm Econ.* 12:8-13.
- Zimdahl, R.L. 1980. *Weed-Crop Competition: A review* International Plant Protection Center, Oregon State University, Corvallis, Oregon, USA.

CHAPTER 2

WHEAT YIELD MODELING FOR SITE-SPECIFIC FERTILIZER AND HERBICIDE
MANAGEMENT BASED ON INDEPENDENTLY COLLECTED DATAAbstract

Our interest was to bridge the tools for site-specific agronomic management (e.g. yield monitors, variable rate sensors, etc.) with the ecological factors underlying crop production. Herbicide and fertilizer applications can be made more cost effective with deeper knowledge of the variables influencing yield. Site-specific agriculture technologies can be employed in experimentation to understand the variance in wheat yield caused by the interaction of management inputs and natural factors. With this knowledge precision agriculture technologies can be employed in the most efficient site-specific experimentation and management of farm inputs. We explored the development of an empirical yield prediction model based on five predictor variables: wheat density, wild oat density, nitrogen rate, herbicide rate, and growing season precipitation. The three best-fitting models (in order) from the candidate set of models we explored were a multiple regression equation including all five predictor variables, a double-hyperbolic equation including three input predictor variables, and a nonlinear model including all five predictor variables. The nonlinear three-predictor model which did not include herbicide and fertilizer influence on yield performed slightly better than the 5-variable nonlinear model including these predictors, illustrating the large amount of variation in wheat yield and the lack of concrete knowledge upon which farmers base their fertilizer and herbicide management decisions, especially when weed infestation causes

competition for limited nitrogen and water. Although these data sets represent the combined efforts of an entire discipline over the last several decades, more data collection is necessary for further elucidating the underlying ecological first principles of plant competition with varying combinatorial levels of inputs, specifically including nitrogen and herbicide as well as available water into a yield prediction model for increased management efficiency.

Introduction

Management decisions made by farmers are still based mainly on varying combinations of tradition, personal observations, and interaction with crop consultants, industry salesmen, and university extension agents. Precision agriculture technologies may provide a means to integrate farmer knowledge with tools to manage in a site-specific manner, allowing for increased efficiency of resource use and optimized net returns. On-farm and on-research station experiments have suggested improved economic gain with spatially targeted variable application rates of fertilizer (Barton 1991, Li and Yost 2000, Long et al. in press) and herbicide (Johnson et al. 1995, Grundy et al. 1996, Walker et al. 2002). In addition, by recommending the variable-rate applications of fertilizer and herbicide only when previous site histories (i.e. if a specific location in the field is known to be nitrogen rich or poor, for example) and threshold weed densities warrant their use, environmental pollution and selection for herbicide resistance can be reduced (Christensen et al. 1998, Jasieniuk et al. 1999).

Mechanical tools for site-specific management (e.g. yield monitors, variable rate sensors, etc.) are under development but there is a critical need to further understand the underlying ecological processes involved in optimizing grain yield. With deeper knowledge of the variables influencing yield, more accurate herbicide and fertilizer prescriptions can be made. Our research has attempted to increase the understanding of the variables influencing yield and their interactions, such that precision agriculture technologies can be employed in site-specific parameterization of input optimization in models that will increase the most efficient site-specific management of farm inputs.

Modeling studies

Historically, studies addressing the generality (i.e. ecological first principles regardless of site) and predictive power of relationships have not been thoroughly explored in agronomy or agroecology (Beck 1997). Some yield prediction modeling in agronomy has made significant progress, specifically in terms of quantifying crop/weed interactions. Early yield models, resembling simple linear regression equations that included weed density, were developed by Bleasdale and Nelder (1960), Holliday (1960), and Farazdaghi and Harris (1968), among many others reviewed by Willey and Heath (1969), Cousens (1985a,b), and Firbank and Watkinson (1990). In recent decades more commonly used models include the yield-weed density and the yield loss models described by Cousens (1985a,b).

An alternative body of yield models emerged that included crop density as well as weed density, with one of the first by Shinozaki and Kira (1956). Later, Firbank and

Watkinson (1985) developed a two-species competition model, and Maxwell and Jasieniuk (Jasieniuk et al. 2000) developed a double-hyperbolic yield prediction equation.

Taking another approach, several studies have included the population dynamics of weed impacts on crops to capture the multiple year effects of the weeds (Wilson et al. 1984, Cousens et al. 1986, Mortimer 1987, Gonzalez-Andujar and Perry 1995). Other researchers have considered how well climate and historical weather data can predict wheat yield (Williams 1973, Haun 1974, Chipanshi et al. 1997, Brooks et al. 2001, Hammer et al. 2001), however weed competition was not considered. The previously described empirical, mechanistic, and population dynamics models have not included the combined effects and interactions of uncontrolled environmental resources and controlled agricultural inputs on yield.

Recently Brain et al. (1999) and Kim et al. (2002) have reported models that include herbicide application with weed density as predictor variables of crop yield. While these two models added herbicide rate as a predictor variable, which is an important advancement in yield model development, they do not include crop density or other inputs, such as fertilizer and water, as predictor variables. The only yield models that have included agricultural inputs such as fertilizer, and environmental variables such as weather, are crop growth models such as CERES (“Crop Estimation through Resource and Environment Synthesis”), developed by Ritchie and Otter (1985) and Godwin et al. (1990). Later Beckie et al. (1994), Chipanshi et al. (1997), and Moore and Tyndale-Biscoe (1999) used CERES to investigate wheat growth over a range of weather conditions, fertilizer rates, and soil types. Beckie et al. (1994) also tested the effectiveness of three other simulation models (e.g. EPIC, NLEAP, and NTRM) for

estimating soil nitrates and water in two soils. While mechanistic models are extremely valuable to the investigation of physiological and phenological processes, they are generally not as suitable as empirical models for management in agriculture because they require more parameters for growers to estimate and they have not necessarily been shown to be better predictors than empirical models (Barnett et al. 1997). However, there are no known empirical models that account for resource competition between wheat and wild oat.

Experimental studies

While yield models typically include a small number of predictor variables, an analogous problem exists in experimental studies from which models are developed. Many field studies in agronomy have investigated how available nitrogen (Racz 1974, Henry et al. 1986), available water (Lehane and Staple 1965, deJong and Rennie 1967, Bauder et al. 1987, Brown and Carlson 1990), and herbicide (Salonen 1992, Spandl et al. 1997) individually influence wheat yield. Many other studies have explored the influence of 2 or more of these predictor variables together on yield, specifically, wheat density and wild oat density (Thurston 1962, Chancellor and Peters 1974, Carlson et al. 1982, Wilson et al. 1990); nitrogen rate and wild oat density (Sexsmith and Russell 1963; Bell and Nalewaja 1968, Bowden and Friesen 1968, Carlson and Hill 1985b); nitrogen rate, wheat density, and wild oat density (Henson and Jordan 1982, Carlson and Hill 1985b, Farahbakhsh et al. 1987, Tollenaar 1992, Blackshaw and Molnar 2002); nitrogen rate and available water (Neidig and Snyder 1924, Fernandez and Laird 1959, Hunter 1958, Warder et al. 1963, Henry 1971, Racz 1974, Campbell et al. 1993, Engel et al.

2001); soil moisture, wheat density, and wild oat density (Van Wychen 2002); and herbicide rate, wheat density, and wild oat density (Van Wychen 2002, Blackshaw and Molnar 2002). Other field studies have investigated other site factor and soil property predictor variables such as topography, soil type, soil pH, gravimetric moisture content, and soil fertility (Mortensen et al. 1993, Shatar and McBratney 1999, Dieleman 2000a, 2000b, Dille et al. 2002) to predict weed occurrence and its influence on yield. However, no field studies exist that have explored the combined influence of nitrogen, herbicide, and available water specifically on spring wheat-wild oat interference.

Objectives

In contrast to the previously described modeling and experimental studies, our objective was to explore the influence of spring wheat density, wild oat density, nitrogen rate, herbicide rate, and growing season precipitation on wheat yield as a model system to quantify the influence of a large number of variables on crop yield. We have chosen these five specific predictors with the understanding that many other predictor variables could be considered (and perhaps should be considered in future studies), such as soil nitrogen content, early season soil moisture, and time of emergence of the wild oats in relation to the crop. However, we have chosen this particular collection of five predictor variables for two main reasons; first, after an extensive literature search, this collection of predictor variables were believed to be the five most influential on dryland wheat yield production. Adding more predictors beyond these five would arguably not add to model prediction accuracy but would threaten model convergence. Secondly, these five

variables are relatively easy to measure in comparison to predictors such as site-specific soil pH and moisture content.

This paper describes the procedure we employed for the development of an empirical yield prediction model, the trends revealed in our accumulation of wheat studies from throughout the world, and an assessment of the current status of wheat yield prediction. Specifically, the objectives of this research were to: 1) gather as many data sets as five possible where spring wheat yield was the dependent variable and where as many of the designated independent variables were included, 2) explore individual data sets using scatter plots and regression analysis such that important biological first principles were revealed, i.e. that all predictor interactions were exposed as well as each variable's influence on yield, and 3) develop and parameterize an empirical yield prediction model based on the five selected variables using a combined data set created from the independent data sets. As a future goal, the best fitting and most biologically meaningful model will be the core of a decision support system that farmers and crop consultants will use to develop site-specific and variable management strategies for crop seeding, nitrogen, and herbicide rate.

Materials and Methods

We are interested in identifying a five-variable empirical model in order to improve input management. However, no data sets exist in which managed inputs and environmental variables have been simultaneously manipulated, measured, or modeled. It would take a huge experiment to create empirical characterizations of the multiple

interacting inputs involved in most cropping systems. For example, a full factorial experiment comparing crop response to four levels of nitrogen fertilizer, four herbicide rates, four weed densities, four crop-seeding rates, and three moisture levels would require 768 treatments. If this experiment were replicated only four times, 3072 plots would be required and this is for only one site!

Although the ideal data set including all five predictor variables measured at several levels and sites, and replicated adequately does not exist, empirical models can be developed from the numerous historical on-farm and experiment station trials that have been conducted for different purposes (Cousens et al. 1987). Thus, we have obtained and utilized data sets where subsets of the five specified variables were manipulated and measured. Studies that included as many of the factors (e.g. spring wheat density, wild oat density, nitrogen rate, herbicide rate, and growing season precipitation) in combination and at varying levels were chosen for our analysis. Currently we have accumulated experiment station small plot and on-farm large-plot data sets from wheat regions of California, Minnesota, Montana, Alberta Canada, and western Australia (Table 2.1).

Table 2.1. Collected spring wheat data sets in Canada, United States and Australia. All data sets (except #15) include corresponding growing season precipitation (GSP) values. Engel et al’s study includes supplemental irrigational water. “x” denotes that measurements of that specified variable were collected at more than one level. “1” refers to application of only 1 rate.

	Author(s)	Year(s)	Location	crop density	Variables Included wild oat density	nitrogen rate	herbicide rate
1	Blackshaw and Molnar	1998-2001	Lethbridge, CAN	x	x	x	1
2	Blackshaw and Molnar	1998-2001	Lethbridge, CAN	x	x	x	x
3	Carlson and Hill	1978-1981	Davis, CA, USA	x	x		
4	Carlson and Hill	1980-1982	Davis, CA, USA	x	x	x	
5	Engel et al.	1996-1998	Havre, MT, USA	1		x	1
6	Jackson	1986, 1993-96	Havre, MT, USA			x	
7	Lenssen	1998-2000	Big Sandy, MT, USA ^a	x	x*	x [†]	
8	Lenssen	1998-2000	Big Sandy, MT, USA ^b	x	x*	x [†]	
9	Lenssen	1998-2000	Box Elder, MT, USA ^a	x	x*	x [†]	
10	Lenssen	1998-2000	Box Elder, MT, USA ^b	x	x*	x [†]	
11	Martin and Riordan	1969,	Tamworth, AUS	x	x		
12	Martin	1968, 1982-83	Tamworth, AUS	x	x	1	1
13	Maxwell	1998-2001	Bozeman, MT, USA	x	x		
14	Murphy	1997-1999	Wagga Wagga, AUS	x	x		
15	O’Donovan et al.	1975-1976	Lacombe, CAN	1	x	1	1
16	Rew	1997-1999	Tamworth, AUS	x	x	1	1
17	Spandl et al.	1994-1996	Crookston, MN, USA		x*		x
18	Van Wychen et al.	1999-2000	Sun River, MT, USA	x	x	x	x [‡]
19	Van Wychen et al.	1999-2000	Sun River, MT, USA	x	x	x	x [‡]
20	Van Wychen et al.	1999-2000	Sun River, MT, USA	x	x	x	x [‡]

‘a’ and ‘b’ refer to spring wheat within different cropping rotations. ‘a’ refers to a conventional wheat-fallow system and ‘b’ refers to a diverse rotation including chickpeas, lentils and barley.

* These data sets included a visual rating for weed infestation instead of actual quadrat counts of wild oat plants.

† Nitrogen treatment in this experiment was measured in terms of nitrate (ppm) in the top 2 feet of soil instead of kg/ha (or lb/ac) applied.

‡ Three different herbicides were used at this site (e.g. fenoxaprop, imazamethabenz, and triasulfuron); therefore, this experiment was performed three times on three different fields, one for each herbicide used.

We have used data sets where wheat and wild oat densities were typically measured in quadrats at the seedling stage, specifically before herbicide application (if herbicide was applied). All density measurements were converted to the units of plants m⁻² or reproductive tillers m⁻². Yield was measured by a plot combine or by a farmer-owned combine with yield mapping capabilities. Unlike the other four variables, which

were typically an administered treatment within the respective experiment, growing season precipitation (GSP) has also been included in all data sets due to the ease with which this information can be acquired from local weather stations, although with the realization that because there is only one GSP value per year, GSP is arguably more a predictor of year effects than an *accurate* predictor of water availability. Specifically, GSP for U.S. and Canadian data sets was calculated by summing monthly totals of current year precipitation from April through August. GSP for data collected in Australia was calculated by totaling monthly precipitation from April through October, due to the increased length of the Australian growing season (L. Rew, personal communication). Although other studies may use different months for GSP calculation, such as rainfall from the start of the calendar year up to the date of herbicide application (Pannell 1994), we have used spring rainfall, not including winter precipitation, assuming spring rainfall is most influential on crop yield (P. Miller, personal communication).

A method for making inferences from each experiment was developed. The first step of this method included making two-way scatter plots of all combinations of variables, grouped by a third variable, for each individual data set (see Figure 1 for example). This procedure was fundamental to understanding the interactions among variables and the shape of the scatter plot for each variable's influence on yield (Cousens et al. 1987, Neter et al. 1996). Grouping by a third variable further helped reveal the causes and effects among the predictors and possible underlying ecological processes.

After a visual representation of each variable's influence and possible interactions was given by the scatter plots, a second analysis performed on each individual data set was a standardized regression on wheat yield. Standardizing was accomplished by

subtracting the average of a variable's observations from each observation then dividing by the variable's standard deviation (Brown and Rothery 1993). By examining the magnitude of the coefficients, this analysis revealed the strength of each predictor variable on yield as well as the strength of the predictor interactions. R^2 values, correlations, and residual plots were also explored. Given the volume of analysis output only a general representation and summary of what was revealed within and between data sets is presented.

For the purpose of exploring variation in the data across sites and years, a third analysis combined all independent and previously collected data sets to create two-way scatter plots grouped by a third variable. While combining data sets has been done previously by Cousens (1985b), Martin et al. (1987), and Tollenaar (1992) for investigating model variation, the history of amalgamating agronomic data has been quite recent. Specifically, a more *accurate* amount of model variation can be revealed when there is a greater measured range of predictor and response variables, accounting for a greater representation of the entire response surface.

After scatter plots were investigated, objective 3—developing and parameterizing a five-variable yield prediction model—was undertaken. Model development, including model selection of four historically used agronomic models, as well as three of the authors' development, was dually based on the history of agronomic and competition models and the search for first principles. The following seven candidate models were fit

to the “combined” data set (i.e. the data set that pooled all¹ independent data sets into one) to assess the predictability of the best-fitting model(s).

Model 1, called the “rectangular hyperbolic model” is:

$$y = y_{wf} \left(1 - \frac{\iota \rho_w}{1 + \iota \rho_w / \alpha} \right) \quad \text{MODEL 1} \quad (2.3)$$

where y is yield, y_{wf} is the weed-free yield, ρ_w is weed density, ι is a fitted parameter that estimates percent yield loss per weed as weed density decreases to 0, and α is a fitted parameter that estimates percent yield loss as weed density increases (Cousens 1985b). Equation 2.3 is referred to the rectangular hyperbolic model because it describes the following curve (Figure 2.1).

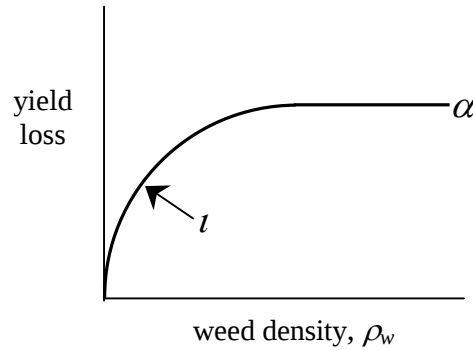


Figure 2.1 Hyperbola of yield versus weed density with yield loss saturating at the maximum weed density.

Model 1 (equation 2.3) was chosen for this analysis because it was shown to fit a large number of data sets more consistently than 17 other functional forms, as investigated by Cousens (1985b). Consequentially, the rectangular hyperbolic model gained acceptance

¹ Not every data set shown in Table 2.1 was included in the combined data set because at least one of the variable measurements was missing. All other independent data sets that included all five variables, even if a variable had only one rate, such as a broadcast nitrogen, herbicide and/or crop seeding rate, was included in the combined data set.

for estimating crop yield response to varying densities of a single weed species (Swanton et al. 1999), as employed by Stoller et al. (1987), Wilson and Wright (1990), Weaver (1991), Coble and Mortensen (1992), Norris (1992), Sattin et al. (1992), Berti and Zanin (1994), and Lindquist et al. (1996).

Model 2 is:

$$y = \frac{r\rho_c}{1 + b\rho_c + f\rho_w} \quad \text{MODEL 2} \quad (2.4)$$

where ρ_c is crop density, and r , b , and f are fitted parameters (and y and ρ_w are defined above) (Baeumer and deWit 1968, Wright 1981, Weiner 1982, Jolliffe et al. 1984). This model is also known as the Beverton and Holt model, which is a modification (that includes inter-specific competition) of the Hassel model for limited population growth in discrete time (Brown and Rothery 1993). In this case, r describes the crop's intrinsic growth rate, b is an intra-specific competition coefficient, and f is an inter-specific competition coefficient. Specifically, as b and f increase due to intra- and inter-specific competition, yield will decrease. Model 2 has gained popularity due to including crop density as well as weed density (Baeumer and deWit 1968, Wright 1981, Weiner 1982, Jolliffe et al. 1984).

Model 3 is:

$$y = \frac{y_{wf}}{1 + \beta_{R_0} \rho_{w_0} \frac{1 + \left(\frac{R}{e^{R_{50}}}\right)^B}{1 + \left(\frac{R}{e^{R_{50}}}\right)^B}} \quad \text{MODEL 3} \quad (2.5)$$

where β_{R_0} is weed competitiveness at zero herbicide dose, ρ_{w_0} is initial weed density, R is herbicide dose, R_{50} is the herbicide dose required to reduce the weed population by 50%,

and B is the response rate of the herbicide (Kim et al. 2002). Model 3 (Kim et al. 2002) was included in this analysis because it is of very few models that include an input (in this case herbicide) as a predictor variable. Graphically, Model 3 is represented below (Figure 2.2).

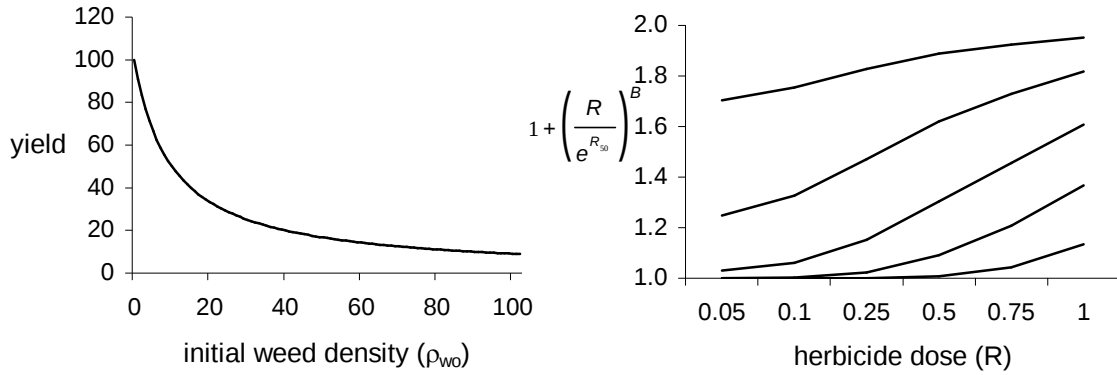


Figure 2.2. Yield, calculated by Model 3, is represented in the left-side graph assuming $R=0$. When herbicide rate is greater than 0, $y_{wf} / \left(1 + \beta_{R_0} \rho_{w_0}\right)$ is divided by the trend shown by the right hyperbola. The trendlines in the right graph assume that $R_{50} = 0.50 \times$ the label rate; top to bottom curves are for values of B from 0.1 to 2, illustrating the vertical shift of this curve depending on B 's value.

Model 4, called the “double hyperbolic model” is:

$$y = \left(\frac{\varphi \rho_c}{1 + \varphi \rho_c / y_{\max}} \right) \left(1 - \frac{\iota \rho_w}{1 + \iota \rho_w / \alpha} \right) \quad \text{MODEL 4} \quad (2.6)$$

where $y_{\max}$ is the asymptotic maximum yield, and φ , ι , and α are fitted parameters (Jasieniuk et al. 2000). Specifically, φ estimates the initial rate of yield increase as crop density increases from zero, ι estimates the initial rate of yield loss as weed density increases from zero, and α is the asymptote for maximum % yield loss as weed density increases to its maximum. Because α describes a proportion, it cannot be greater than 1. Equation 6 is referred to as the double hyperbolic model because of the two hyperbolas

that form the two main components of the model. The first hyperbola describes the nonlinear increase of yield as crop density increases. Yield increases to a maximum, which is defined by y_{max} . The second hyperbola, based on Cousen's (1985b) rectangular hyperbolic model (equation.2.3), describes the nonlinear increase of yield loss as weed density increases to a maximum of α . Graphically the two components of Model 4 are represented by the following two hyperbolas.

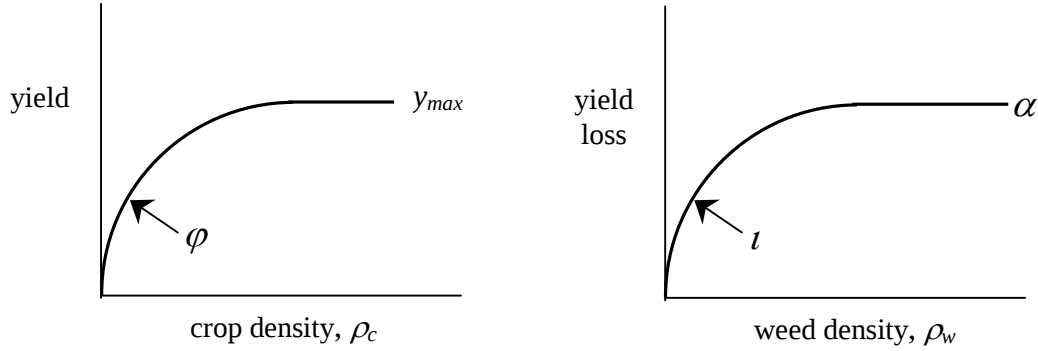


Figure 2.3. The yield and yield loss trends of the double hyperbolic model.

Model 5, an amended version of Model 4, includes the inputs of nitrogen, herbicide and water. Model 5 is:

$$y = \left(\frac{\varphi \rho_c}{1 + \varphi \rho_c / (\beta_0 + \beta_1 f(W) + \beta_2 f(N) + \beta_{12} f(W * N))} \right) \left(1 - \frac{\iota \rho_w}{1 + \iota \rho_w / \left(\alpha_{\min} + \frac{\alpha_{\max} - \alpha_{\min}}{1 + e^{B(R - R_{50})}} \right)} \right)$$

MODEL 5 (2.7)

where W is water, N is nitrogen rate, and $\beta_0, \beta_1, \beta_2$, and β_{12} are fitted parameters describing the magnitude of influence water, nitrogen, and their interaction have on the maximum yield in the field. Based on Model 4, the double-hyperbolic equation of

Jasieniuk et al. (2000), Model 5 was modified to include nitrogen rate and available water through the parameters $\beta_0, \beta_1, \beta_2$ and β_{12} . The inclusion of these variables was made by regressing y_{max} (i.e. weed-free yield) on water level and nitrogen level. This y_{max} regression equation assumes water and nitrogen contribute to the maximum yield value in a field where there is little to no competition from weeds. Water (i.e. growing season precipitation) and nitrogen are written as “ $f(W)$ ” and “ $f(N)$ ” to imply that the functions of these main effects are not assumed, but rather, transformations of these variables were explored for the best fit and biological reality. α_{min} is a parameter between 0 and 1 that describes the minimum herbicide rate response, α_{max} describes the maximum herbicide dose response between 0 and 1, and B affects the slope of the curve. The component of Model 5 which includes these two parameters and herbicide rate, is based on the herbicide dose-response equation of Streibig et al. (1993):

$$\alpha = \alpha_{min} + \frac{\alpha_{max} - \alpha_{min}}{1 + e^{B(R - R_{50})}} \quad (2.8)$$

where R_{50} is the herbicide rate (i.e. LD_{50}) required to obtain a result half way between the upper limit, α_{max} , and the lower limit, α_{min} . On a log dose scale, the slope is maximal at the point $R=R_{50}$. Graphically, the herbicide dose rate curve is shown in Figure 2.4.

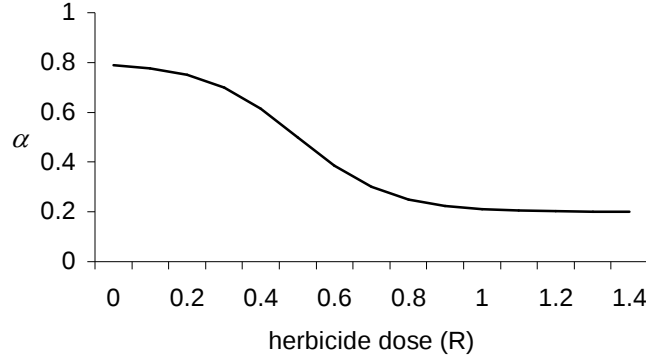


Figure 2.4. Sigmoidal herbicide dose response curve assuming $B = 8$, $R_{50} = 0.5$, $\alpha_{min} = 0.2$, and $\alpha_{max} = 0.8$.

Because Model 5 is relatively difficult to interpret, specifically that the multiplication of the two hyperbolas of the model is complex, Model 6 was developed. Model 6 makes the same assumptions of the double hyperbolic model, that yield increases nonlinearly with increased crop density to a asymptote, and that yield loss increases nonlinearly with increased weed density to an asymptote; Model 5, however, is an alternative functional form. Additionally, Model 6 was developed for possible increased parameter convergence. Model 6 is:

$$y = \frac{\varphi \rho_c}{1 + \left(\frac{\varphi \rho_c}{(\beta_0 + \beta_1 f(W) + \beta_2 f(N) + \beta_{12} f(W * N))} \right)} + \left(\frac{\iota \rho_w}{1 + \iota \rho_w / \left(\beta_{00} + \beta'_1 f(W) + \beta_3 f(H) + \beta_{13} f(W * H) \right)} \right)$$

MODEL 6 (2.9)

where φ is also known as the intrinsic growth rate of the crop, and all other variables and parameters are previously defined. Instead of splitting the effects of crop density and weed density on yield into two hyperbolas, Model 6 adds the effect of crop density, as influenced by water (β_1) and nitrogen (β_2) and their interaction (β_{12}), to the effect of weed density, as influenced by water (β_1') and herbicide (β_3) and their interaction (β_{13}). The negative influence of herbicide on wheat yield in the form of crop injury and fertilizer's positive influence on wild oat density was explored as well as all possible variable interactions, however, the model did not converge with these additional terms. Thus, the version of Model 6 (equation 2.9) presented here did converge and provided the best fit, as is further explained in the Results section.

For contrasting the fit of a simple multiple linear regression model with the other nonlinear models of varying complexity, Model 7 was included in the analysis. Model 7, a multiple linear regression equation, is a rather crude approach that does not account for the history of the development of yield prediction models and their underlying biological mechanisms; on the contrary, it assumes all main effects and their interactions are additive. Nonetheless Model 7 was included for comparison purposes: if Model 7 fit the data as well or nearly as well as the other complex nonlinear models, the level of complexity supported by the data would be questioned. It must be noted that the equation presented here as Model 7 was the best fitting model of a body of multiple linear regression equations that included cubic main effects, squared main effects, squared interactions, logarithms of main terms, and logarithms of interactions were explored. Thus, Model 7, the best-fitting multiple regression model found by step-wise regression analysis, was:

$$y = \beta_0 + \beta_1 W + \beta_2 \rho_w + \beta_3 \rho_c + \beta_4 R + \beta_5 N + \beta_6 \rho_w^2 + \beta_7 \rho_c^2 + \beta_8 N^2 + \beta_9 N:W + \beta_{10} R:W$$

MODEL 7 (2.10)

where all β 's are regression coefficients, and all variables have been defined above. All 5 main effects are included in Model 7. The hypothesized nonlinear effects of wheat density, wild oat density, and nitrogen rate on wheat yield are included via their squared terms. Interactions between water and nitrogen and water and herbicide are also included in Model 7.

The least squares method (LS), as opposed to Fisher's maximum likelihood method (ML), to determine goodness-of-fit was used because residuals were normally distributed. Exploring the normality of residuals was accomplished by investigating residual versus fit, response versus fit, and residual Normal Q-Q plots in S-PLUS. Residuals of the models fitted to the combined data set were shown to be normal after the square root transformation of the dependent variable was used in the model. The square root transformation has been previously used for wheat yield modeling (O'Donovan et al. 1985). Although these two methods do not yield identical squared standard error ($\hat{\sigma}^2$) values for linear and non-linear models since ML and LS estimators differ by a factor of $n/n-p+1$, the difference is slight given our large sample size of 1627 points (Burnham and Anderson 1998). Mean squared errors ($\hat{\sigma}$), R^2 values, and AIC and BIC statistics were used for comparing these non-nested models (Burnham and Anderson 1998). BIC was used in addition to AIC because it penalizes over-fitting (e.g. using more model parameters) more severely. Given the large number of observations, however,

conclusions made from AIC and BIC statistics were in agreement. AIC was used instead of AIC_c^2 because of our large sample size (Burnham and Anderson 1998).

An additional model selection statistic computed was “information complexity” (ICOMP). ICOMP was included in our analysis because it combines goodness-of-fit (i.e. minus twice the maximum log likelihood) with a measure of complexity that is different from AIC and BIC by penalizing for high correlations among parameter estimates (Bozdogan 2000). Low parameter redundancy and high parameter stability is desirable. Like AIC and AIC weights (i.e. $\Delta AIC_i = AIC_{\min} - AIC_i$), a model with minimum ICOMP is chosen as the best-fitting model among competing models (Bozdogan 2000). Because ICOMP values were in agreement with AIC and BIC values, only ΔAIC values are reported here.

Results

Scatter plot analysis of independent data sets

Once independent data sets were obtained and organized (see Table 2.1), all scatter plots were made and examined for consistent trends. Trends within and across data sets were sought. First, results of data analyses including herbicide treatments will be discussed. Secondly, we will discuss data that included nitrogen treatments, and conclude with results from experiments that only investigated the influence of wheat and weed densities (with no herbicide and nitrogen treatments) on yield.

² AIC_c has an additional biomass correction term; however, when the number of data points is large with respect to the number of model parameters, the difference between AIC_c and AIC is negligible.

Scatter plots of Van Wychen et al.'s (2002) data of yield versus wild oat density grouped by herbicide rate (Figure 2.5) revealed an expected pattern of increasing yield with decreasing wild oat density in response to increased herbicide rate. It was evident that the slopes and intercepts of yield versus wild oat density at various herbicide rate levels were different, indicating a possible interaction between wild oat density and herbicide rate influencing crop yield. The zero-herbicide rate showed a slightly negative slope and low intercept in yield response while the plot of the full label herbicide rate showed a shift in data toward lower wild oat densities and overall higher yields. Another experiment with herbicide rate treatments (Blackshaw and Molnar 2002) indicated that wheat yield decreased with increasing wild oat density, but the herbicide rate effect was not distinguishable (Figure 2.6).

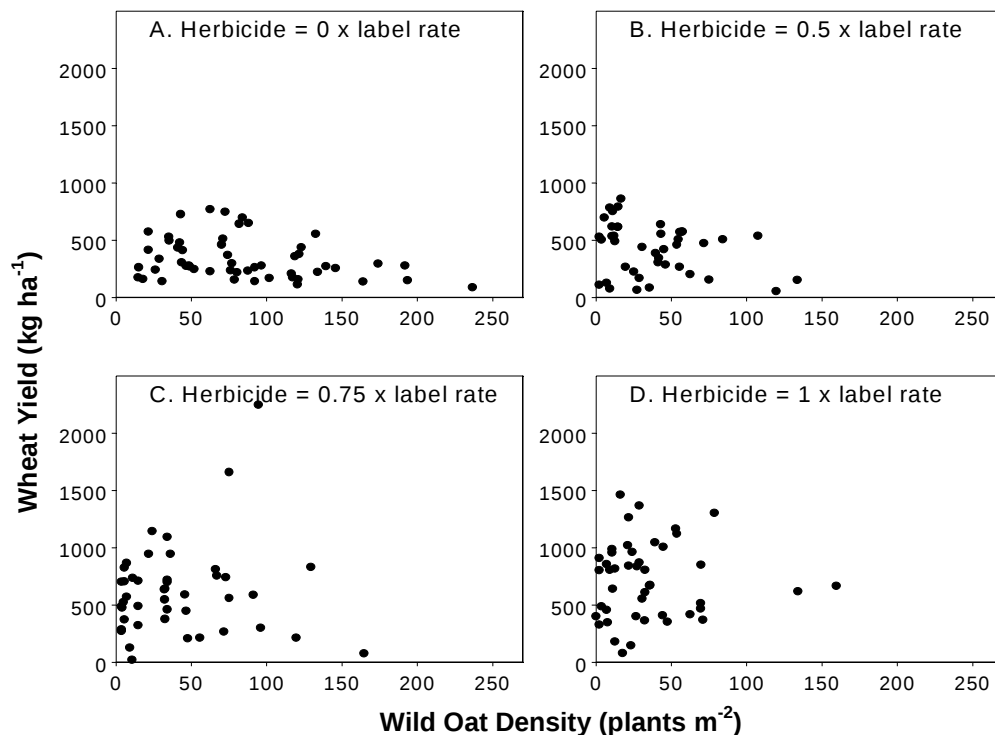


Figure 2.5. Wheat yield versus wild oat density, grouped by herbicide rate relative to the label rate (Van Wychen, 2002). The herbicide used in Figures 1A-D was imazamethabenz.

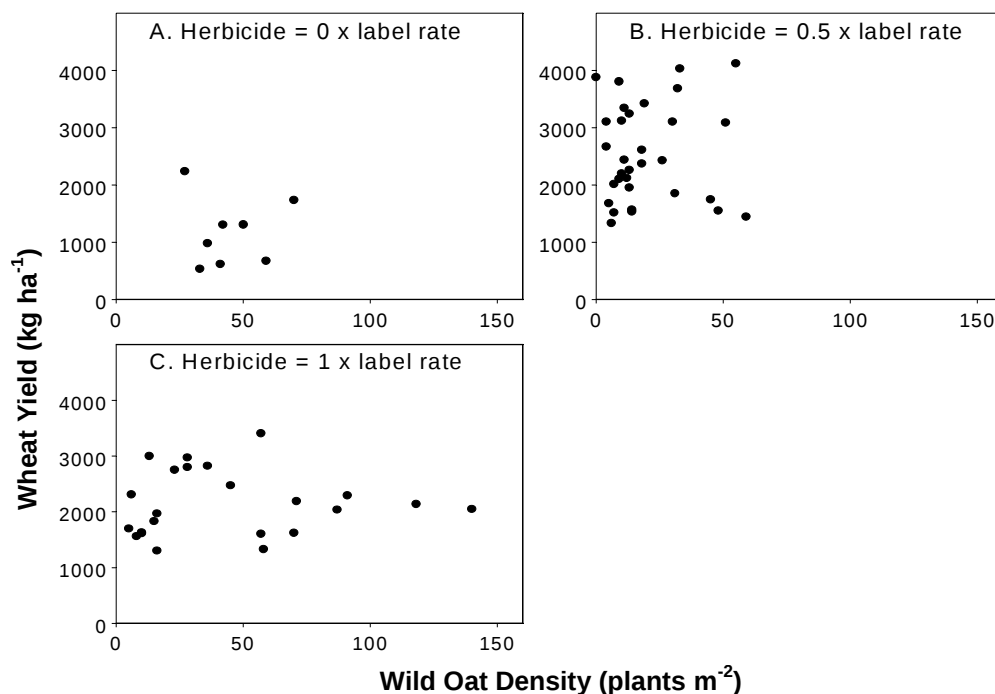


Figure 2.6. Wheat yield versus wild oat density, grouped by clodinafop-propargyl and thifensulfuron methyl+ tribenuron methyl herbicide rate relative to the label rate (Blackshaw and Molnar, 2002).

When nitrogen rate was varied within a wild oat infested field, the wheat yields showed large variability and no indication that nitrogen was a reliable input for increasing yield at this site during the period of data collection (Figure 2.7 and 2.8). Data in Figure 2.7 was taken from a field in a drought which may explain the lack of nitrogen influence on yield. Blackshaw and Molnar (2002) only included two N rates in their wheat-wild oat competition study and variability was high, therefore, it was difficult to decipher any trends due to nitrogen from the yield vs. wild oat density scatter plots (Figure 2.8). A quadratic response of wheat yield to wild oat density is suggested by the scatter of data (Figure 2.8).

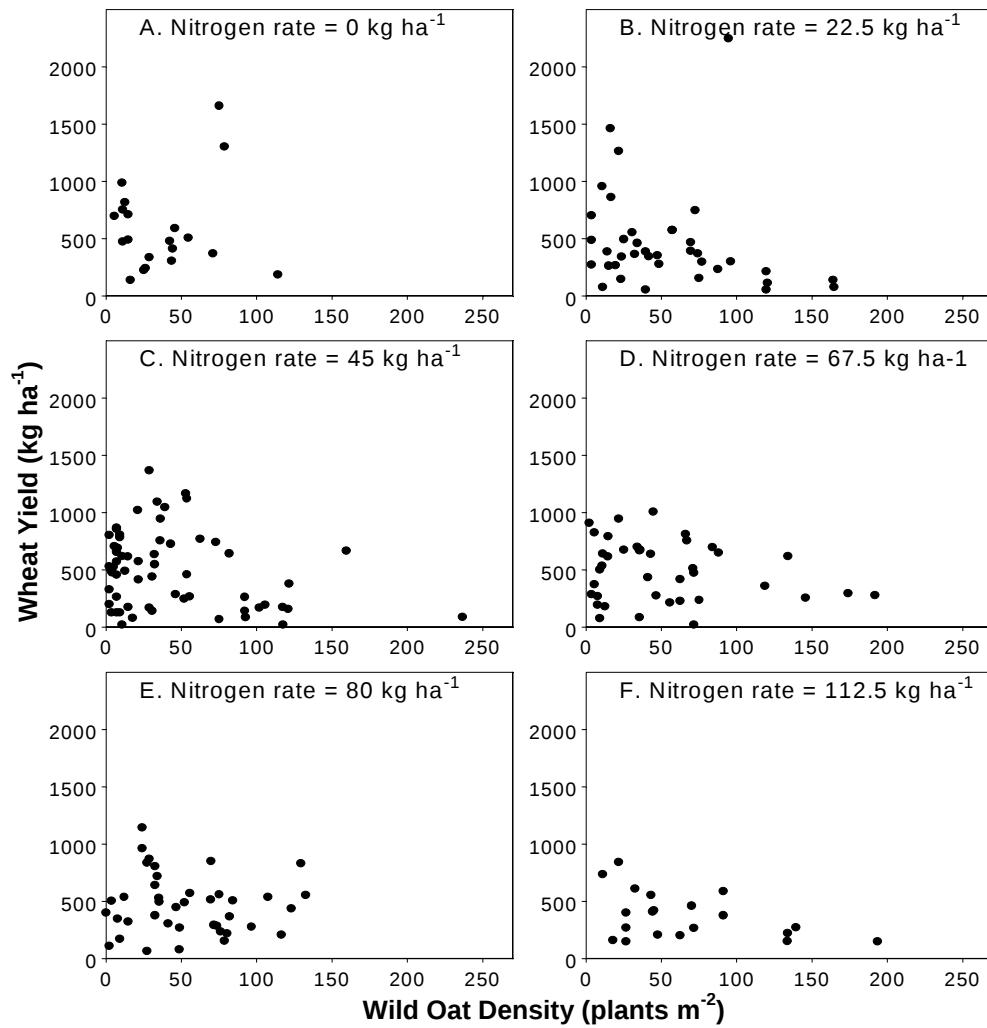


Figure 2.7. Wheat yield versus wheat density, grouped by nitrogen rate (Van Wychen, 2002).

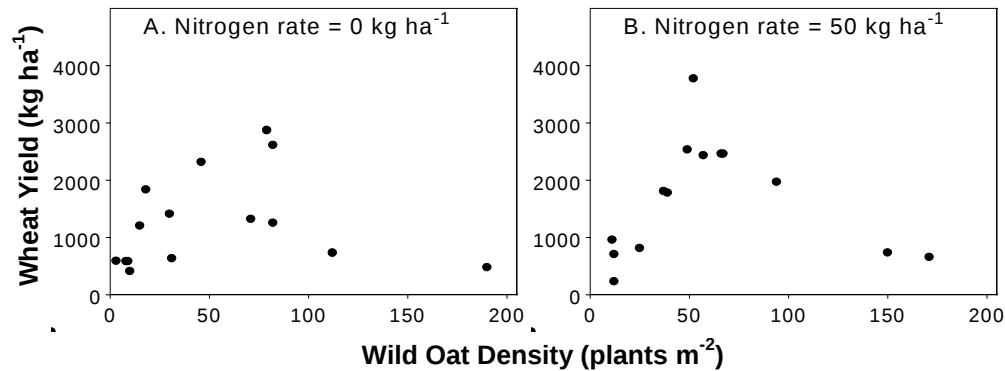


Figure 2.8. Wheat yield versus wheat density grouped by nitrogen rate (Blackshaw and Molnar, 2002).

The key finding of the scatter plot analysis was that a large amount of variability remained even when inputs such as herbicide and fertilizer were increased. In addition, the patterns in the scatter plots did not indicate that non-linear functions should be selected over linear equations to model input responses.

Most of the data sets gathered did not vary nitrogen and herbicide rate but measured only wheat yield as a function of wheat density and wild oat density. The most prominent result from the yield vs. wild oat density scatter plots was the large amount of variability that was revealed (Figures 2.9 – 2.12). While some of the scatter plots showed a faint non-linear trend of decreasing yield as wild oat density increased (Figures 2.9 and 2.12), some showed more linearity (Figures 2.10 and 2.11). Nonetheless, the large variability makes this determination difficult, and necessitates the exploration of further predictor variables. Wheat yield increased as crop density increased, yet wheat density may not have been at high enough densities in those studies to demonstrate the well documented hyperbolic yield response (Figures 2.13 – 2.14) (Jasieniuk et al. 2000). Again, much variance is evident, especially at higher wheat density levels. Yield vs.

wheat density and yield vs. wild oat density data points were grouped by GSP levels which indicated a slight trend of increased yield with increased GSP (Figures 2.9 – 2.14).

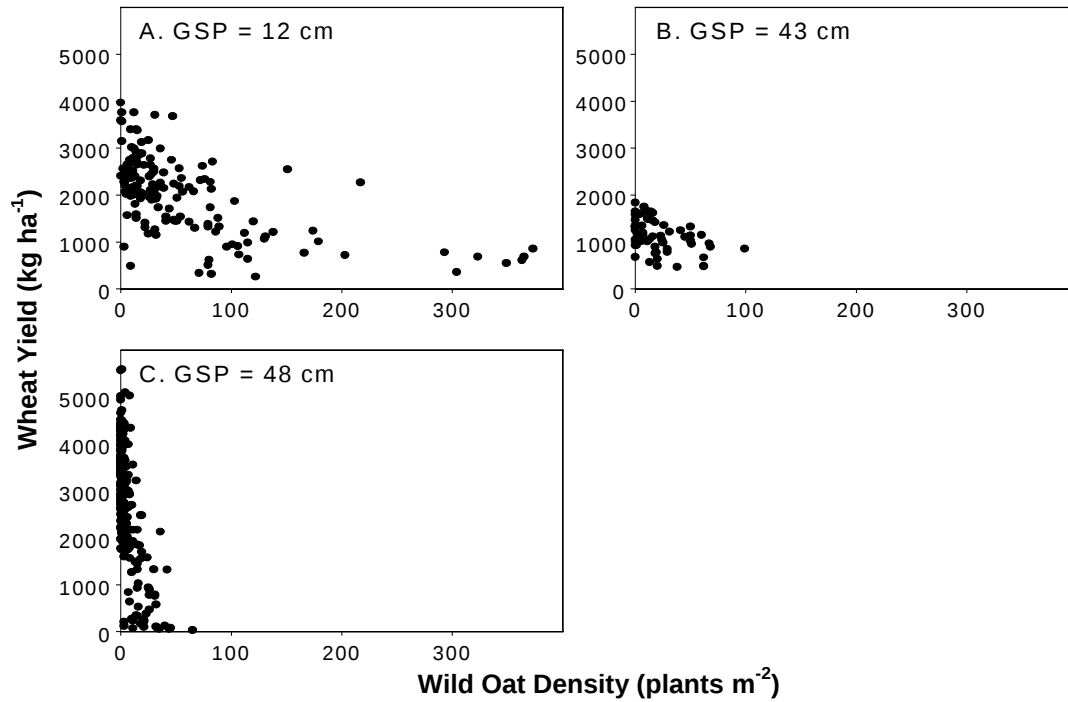


Figure 2.9. Wheat yield versus wild oat density over three years and grouped by GSP values (Martin 1987).

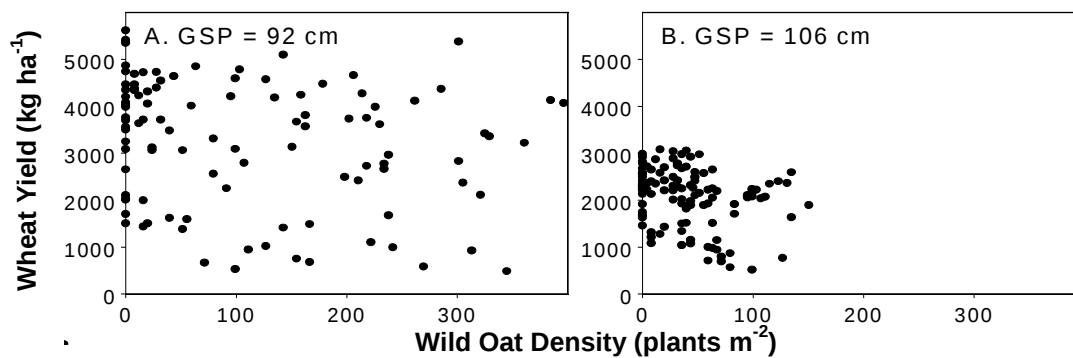


Figure 2.10. Wheat yield versus wild oat density over two years and grouped by GSP values (Murphy, unpublished data).

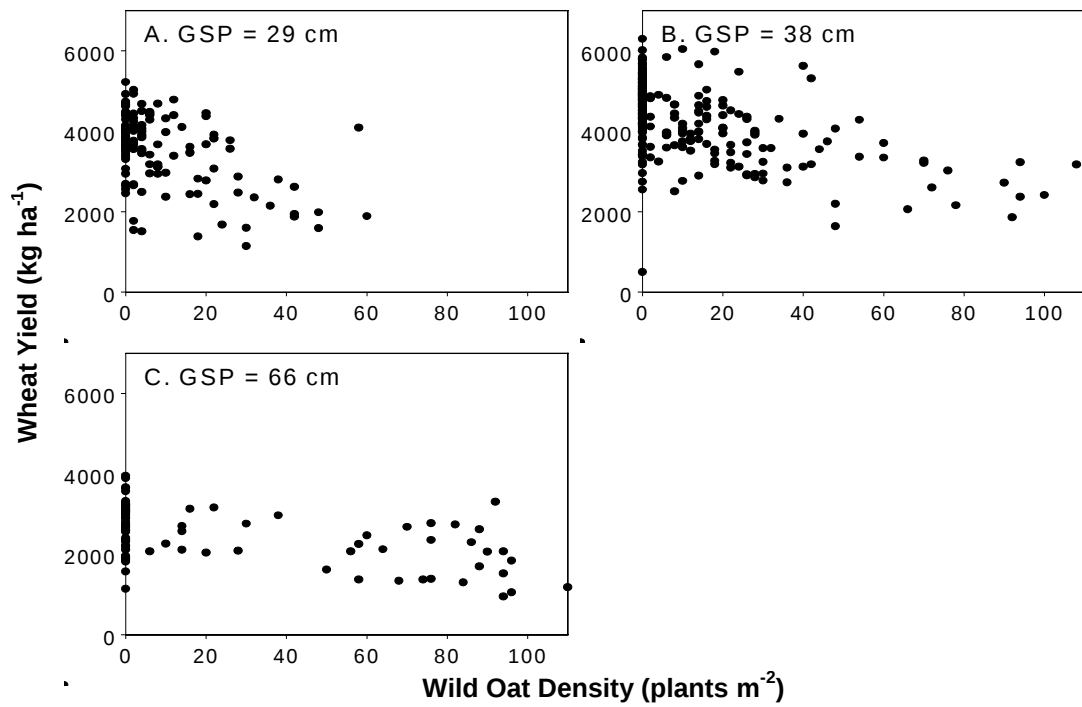


Figure 2.11. Wheat yield versus wild oat density over two years and grouped by GSP values (Rew, unpublished data).

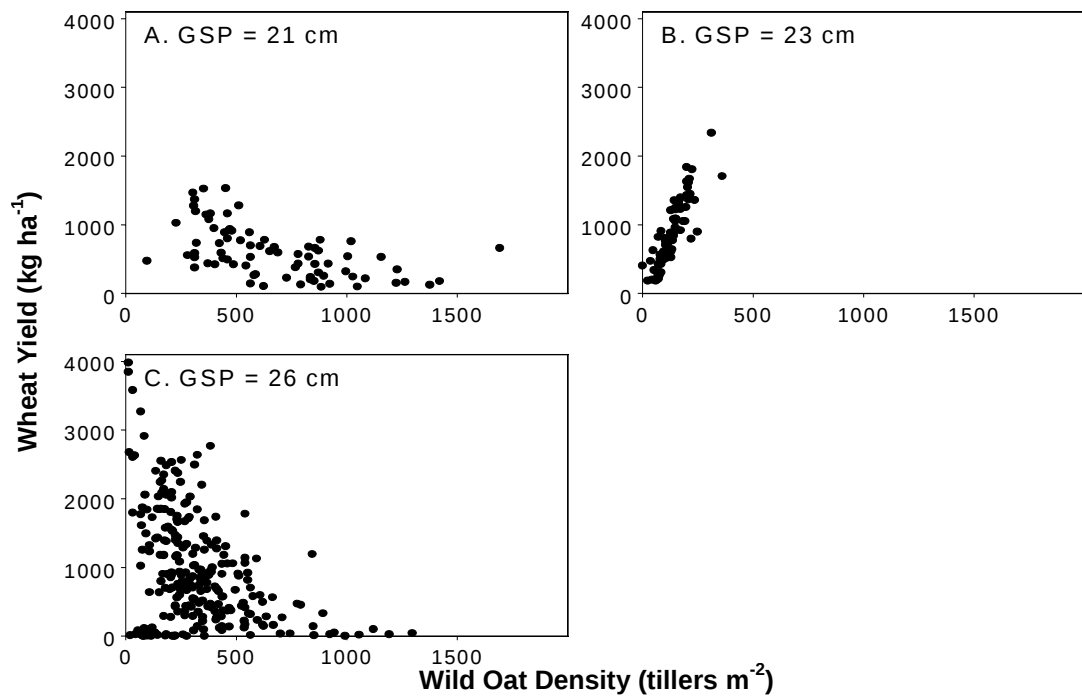


Figure 2.12. Wheat yield versus wild oat density over three years and grouped by GSP values (Maxwell, unpublished data).

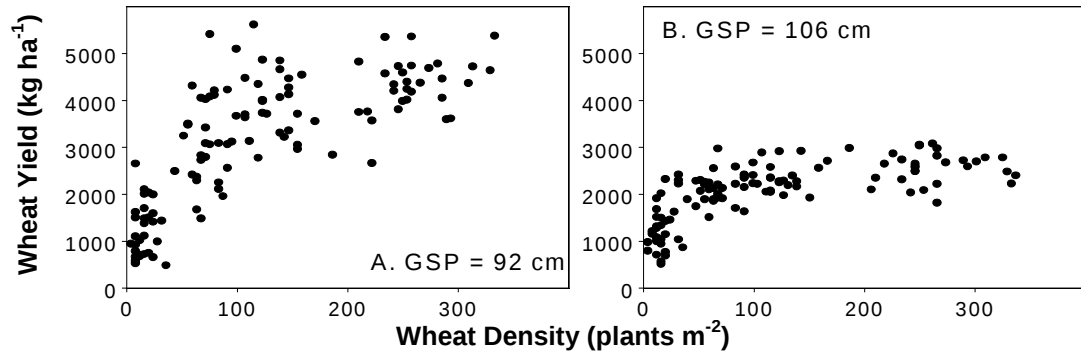


Figure 2.13. Wheat yield versus wheat density of two years and respective GSP values (Murphy, unpublished data).

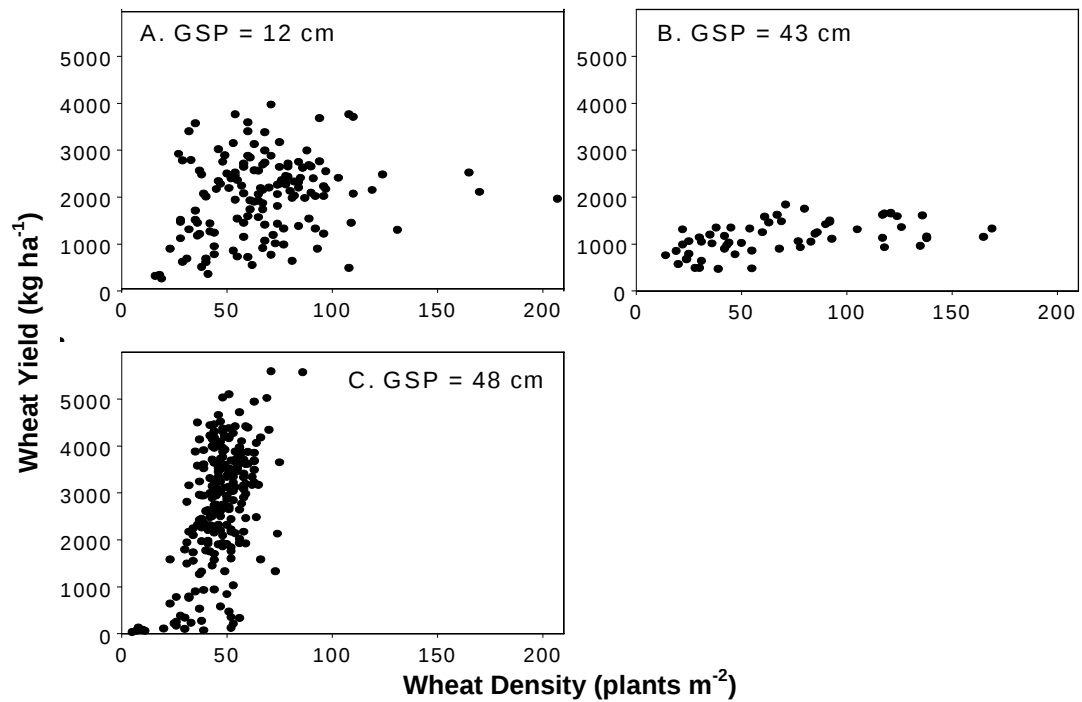


Figure 2.14. Wheat yield versus wheat density of three years and respective GSP values (Martin, 1987).

Regression analysis on independent data sets

Although scatter plots can provide a visualization of main effects and possible interactions, more quantitatively rigorous analysis was used to determine whether or not the trends were significant. Therefore, standardized linear regression analysis was conducted to determine significant main effects, interactions, and squared and cubed main effects (at the 90% level) (Table 2.2). The list of regression models corresponding to each data set demonstrates the lack of definite trends across all data sets. Specifically, each predictor variable shows little or no influence in some data sets while being the most influential predictor in other data sets. Wild oat density had the most (negative) influence on yield in 5 of 15 (33%) experiments that measured that variable, wheat density had the most influence in 2 of 15 (13%) data sets, nitrogen rate had the most influence in 2 of 10 (20%) data sets, herbicide rate had the most influence in 2 of 4 (50%) data sets, and GSP had the most influence in 4 of 18 (22%) data sets. In some data sets, such as 2 and 14 (Table 2.2), an increase in weeds correlated with an increase in yield as indicated by the significant wheat-wild oat interaction. GSP, because it had a negative coefficient in some regressions, and there was only one GSP value per year, reveals that it is likely to be a year effect rather than a predictor solely based on water availability.

Table 2.2. Regressions of individual data sets. “wht” is wheat density, “wo” is wild oat density, “nitro” is nitrogen rate, “herb” is herbicide rate relative to the recommended label rate, and “gsp” is growing season precipitation. “weed” in data sets 7-9 is a variable that measured total weed infestation, not only wild oat infestation. Bolded variables are significant in the regression equation at the 90% level; non-bolded variables are not.

Data set	Variables included in the regression analysis	Standardized regression equation including only coefficients significant at/above the 90% level	R ²	n
1	wht,wo,nitro,gsp	$y = 1367 + 299\text{gsp} + 710\text{wht}$	0.92	32
2	wht,wo,herb,gsp	$y = 2183 - 408\text{wo} - 326\text{gsp} + 274\text{wht} + 236\text{her} + 307\text{herb*wo}$	0.91	62
3	wht,wo,gsp	$y = 5450 - 839\text{wo} + 766\text{gsp} + 741\text{wht}$	0.94	94
5	nitro,gsp**	$y = 3246 + 969\text{nitro} - 215\text{nitro}^2 + 335\text{gsp} - 80\text{gsp}^2$	0.94	719
6	nitro,gsp	$y = 4054 + 784\text{nitro} + 354\text{gsp} - 308\text{gsp}^2$	0.93	72
7	wht, weed ,nitro,gsp	$y = 1680 - 89\text{weed}$	0.96	89
8	wht,weed,nitro, gsp	$y = 1645 + 78\text{gsp}$	0.94	134
9	wht, weed ,nitro, gsp	$y = 2348 + 155\text{gsp} - 98\text{weed}$	0.95	92
10	wht,weed ,nitro, gsp	$y = 1109 - 694\text{weed} + 305\text{gsp} - 147\text{wht}$	0.87	95
11	wht, wo , gsp	$y = 2361 - 499\text{wo}$	0.83	475
12	wht, wo**	$y = 246 - 17\text{wo} + 10\text{wht}$	0.99	25
13	wht, wo, gsp	$y = 877 + 516\text{wht} - 64\text{wo} + 41\text{gsp}$	0.85	413
14	wht, wo, gsp	$y = 2609 + 723\text{wht} + 669\text{gsp} - 338\text{wo} + 277\text{wht*gsp} + 83\text{wht*wo}$	0.95	236
16	wht, wo, gsp	$y = 3354 - 1330\text{wo} + 361\text{wht} - 258\text{gsp} + 599\text{wht*gsp}$	0.95	490
18	wht, wo ,nitro, herb,gsp	$y = 436 + 38\text{herb} + 118\text{gsp} - 33\text{wo}$	0.86	305
19	wht,wo,nitro, herb,gsp	$y = 484 + 154\text{herb} - 51\text{gsp}$	0.77	218
20	wht,wo,nitro,herb,gsp	$y = 430 - 111\text{gsp} + 87\text{herb} + 25 \text{wht}$	0.87	230

* gsp values include irrigation water

** data set 12 did not include gsp because there was only one growing season of data

The following list summarizes our findings from the scatter plot and regression analysis of individual data sets:

- 1) Most of the data sets showed a linear or saturation response where increased yield occurred with increasing crop density. Almost all showed a linear decrease of yield with increasing weed density.
- 2) Some of the data sets that included herbicide treatments showed a positive response to herbicide in the yield/weed density relationship. Specifically, herbicides changed slopes and/or vertically shifted the regression lines. The herbicide response was a within-season yield response, and was not consistent over years.
- 3) Regression analysis of experiments that included nitrogen treatments indicated that nitrogen had little or no effect, which was probably due to site-specific conditions including residual soil nitrogen and insufficient soil moisture to make nitrogen available to the crop. There was no detectable GSP threshold above which nitrogen rate affected yield response.
- 4) Nearly all data sets reported growing season precipitation as a predictor variable; however, it was impossible to separate this variable from generalized year and location effects.
- 5) The variability within data sets suggests the need for site-specific parameterization of yield response models and the need for more research to determine the interactions responsible for yield.

Yield prediction modeling using combined data

Given the lack of conclusive findings, objective 3, building a five-variable yield prediction model based on prior knowledge of crop-weed interactions was optimistic. It was clear that a limited amount of inference could be obtained from our collection of independent data sets that measured less than all five predictor variables. However, to obtain a more accurate sense of predictability from combining independently-produced disjoint data sets, we proceeded with creating two-way scatter plots of the combined data set and fitting the seven previously described models to the combined data.

Starting with a description of the two-way scatter plots grouped by a third variable, Figure 2.15 shows the trend of wheat yield versus wild oat density grouped by herbicide rate. Wild oat density decreased with increased herbicide rate; however, this was true for wheat yield as well. Yield decreased with increased herbicide rates (above the 0.5 label rate) may possibly be due to herbicide injury, especially when water was limited (Grundy et al. 1996). Another possible explanation for the lack of a distinct trend is that the less productive spaces in the field are intolerant to wild oat as well as wheat, causing lower wild oat and wheat densities and lower yields.

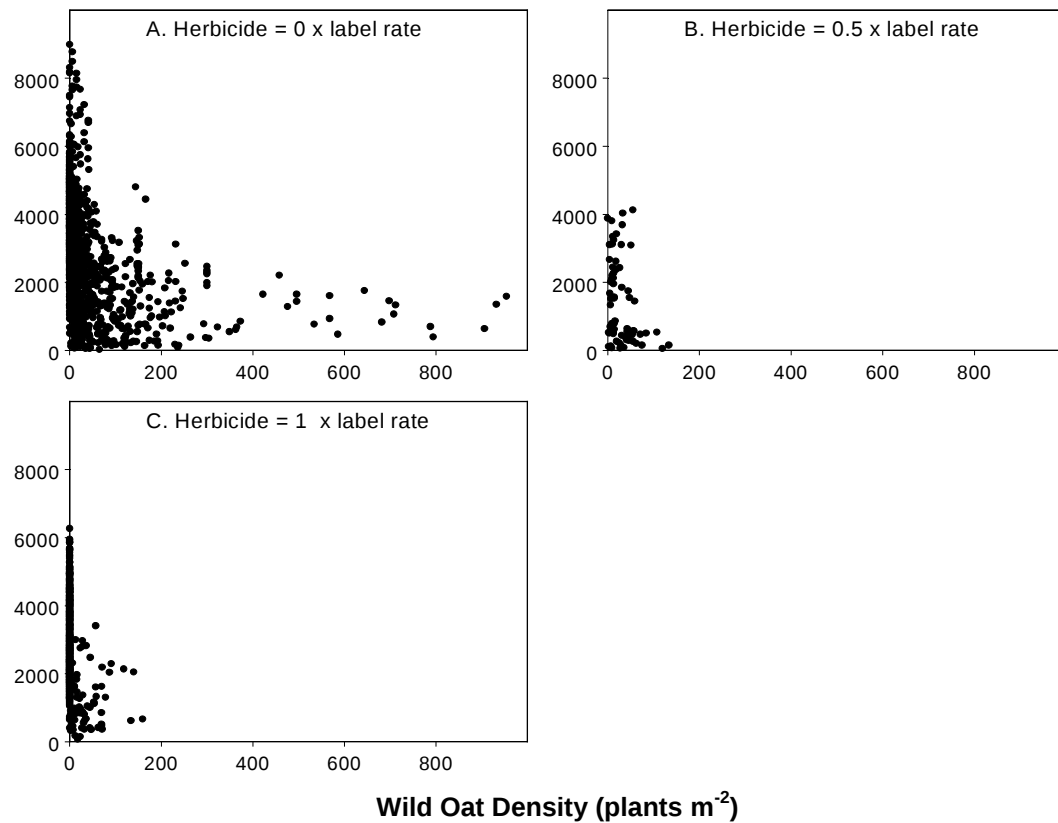


Figure 2.15. Wheat yield versus wild oat density grouped by herbicide rate using the combined data set.

Figures 2.16 and 2.17 were included to reveal the effects nitrogen have on wheat yield and wild oat density together, and on wheat yield alone (i.e. without considering the effects of weed density). As shown by Figure 2.16, increased nitrogen does not guarantee increased wheat yield, especially when wild oat density is high (see Figure 2.16D). Overall, Figure 2.17 shows that if wild oat density is not considered, nitrogen does increase yield, albeit with much variation though the highest yields were recorded at the medium fertilization rate (i.e. at the nitrogen rate of 85 kg ha^{-1}). It must be noted, however, that there were more data points at the nitrogen level of 75 kg ha^{-1} . Figure 2.16

indicates a nonlinear trend of yield versus wild oat density, however it is not clear if Figure 2.17 reveals linearity or non-linearity.

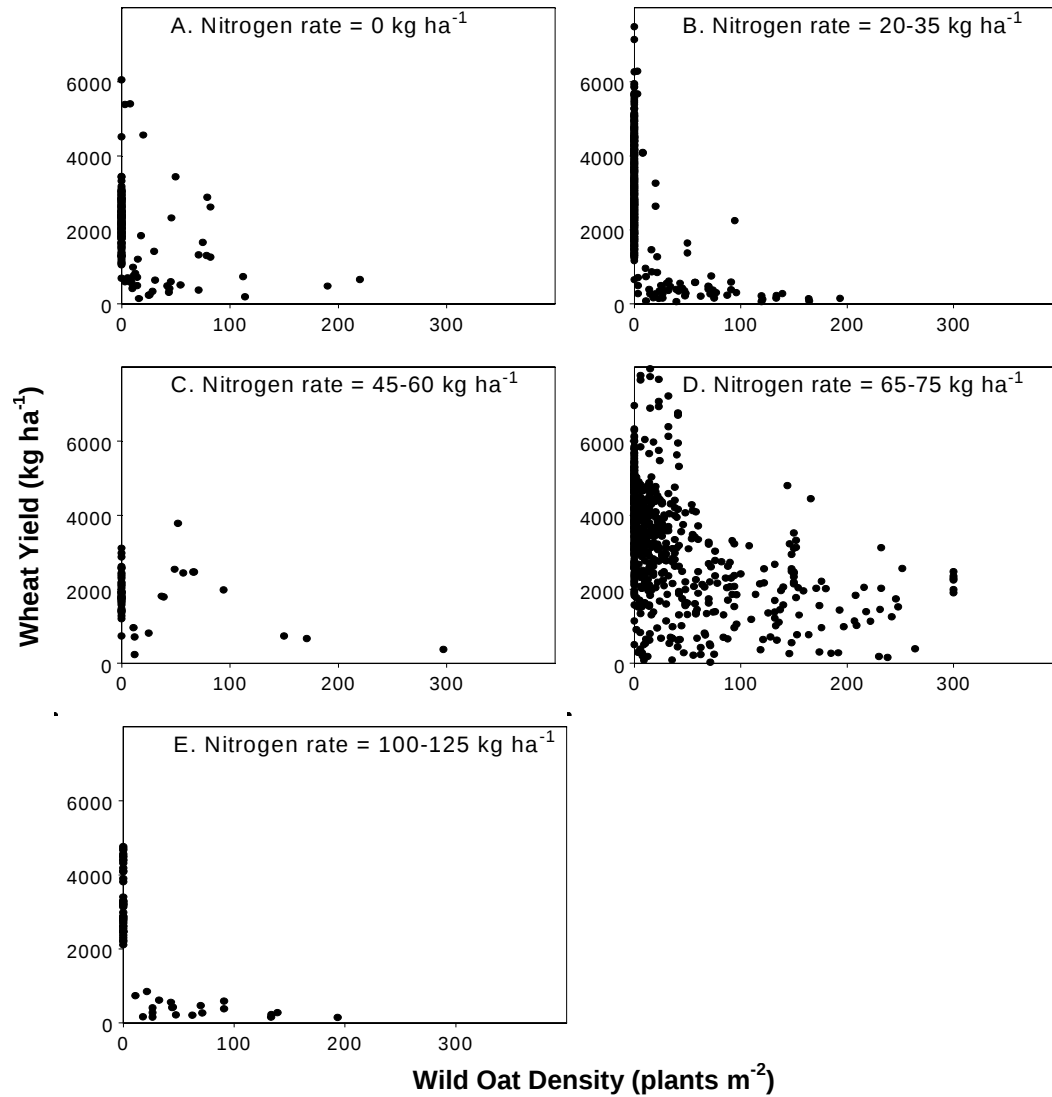


Figure 2.16. Wheat yield versus wild oat density grouped by nitrogen rate using the combined data set. There were more data points at the fertilizer rate of 75 kg N ha^{-1} .

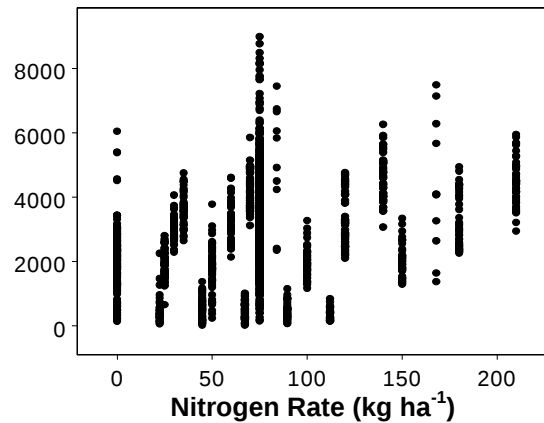


Figure 2.17. Scatter of wheat yield versus nitrogen rate using the combined data set.

Figure 2.18 reveals that nitrogen rate, along with increasing wheat density does not guarantee increased wheat yield, but a nonlinear trend, albeit large variance, shows that increasing wheat density does increase wheat yield; and, higher wheat yields are seen in those plots with the highest nitrogen rates (see Figure 2.18D). Also, when nitrogen rate is high, wheat density does not necessarily need to be high to increase yield. Perhaps the most prominent result is the large variance revealed at all nitrogen rates (Figures 2.16-2.18).

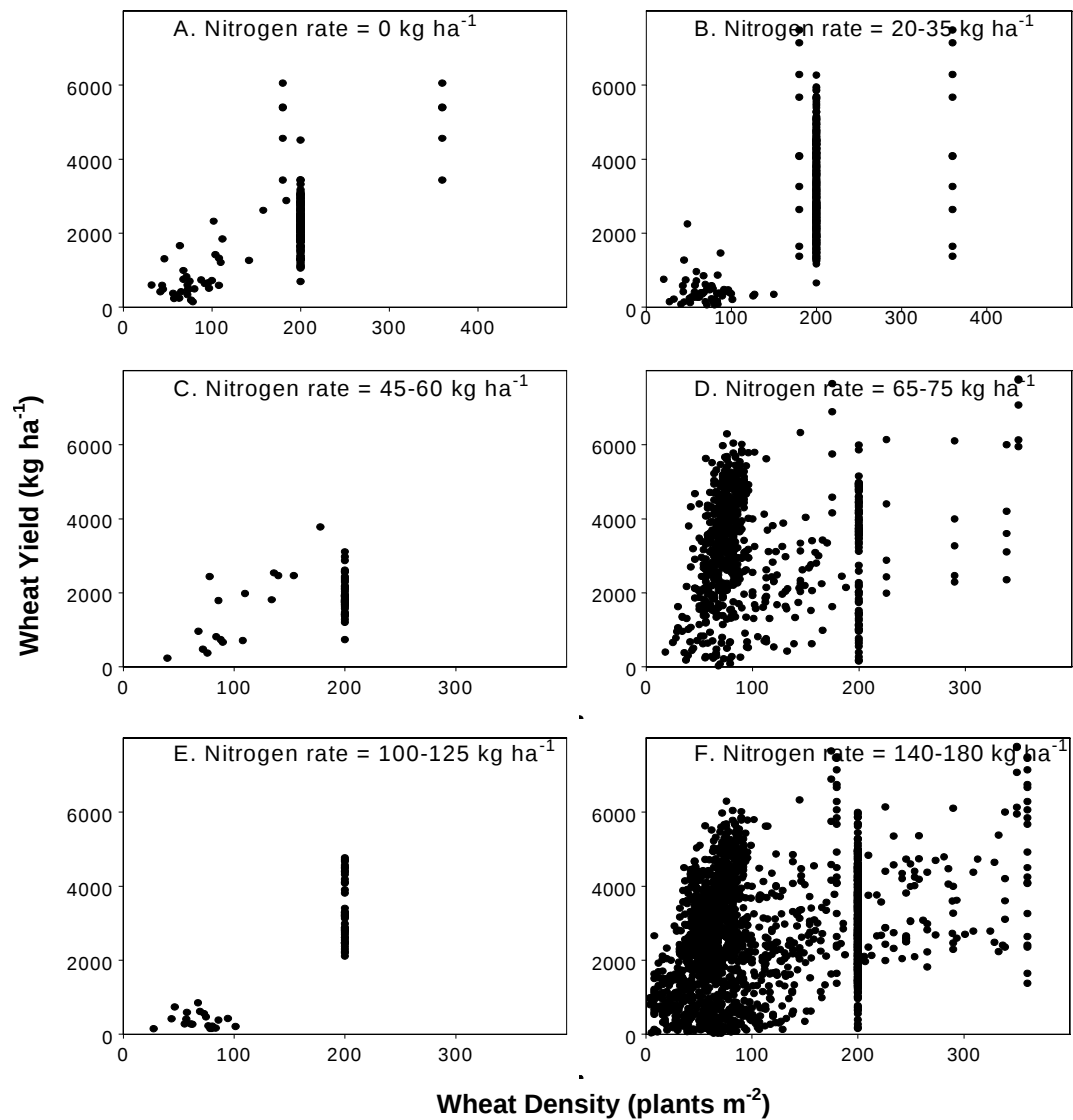


Figure 2.18. Wheat yield versus wheat density grouped by nitrogen rate using the combined data set.

Yield prediction modeling using combined data

Using the trends and lack of trends revealed from the scatter plots of the combined data set, we chose seven models, as previously described, for testing their predictability. Also inherently tested was the value of a combined data set, created from

disjoint data sets, for model fitting. The equations chosen for model-fitting reveal a range of complexity, as indicated in the range of numbers of estimable parameters in Table 2.3. Table 2.3 also shows each model in its reduced form, see Methods section for further explanation. Reduction of Model 5 and 6 was necessary for convergence of parameter estimates. In other words, a strong enough signal from the data did not warrant inclusion of certain parameters and hypothesized trends in these two models.

Table 2.3. Models fitted to the combined data set.

Model	#of estimable parameters
1 $y = y_{wf} \left(1 - \frac{\iota \rho_w}{1 + \iota \rho_w / \alpha} \right)$	3
2 $y = \frac{r \rho_c}{1 + b \rho_c + f \rho_w}$	3
3 $y = \frac{y_{wf}}{\frac{1 + \beta_{R_0} \rho_{w_0}}{1 + \left(\frac{R}{e^{R_{50}}} \right)^B}}$	3
4 $y = \left(\frac{\varphi \rho_c}{1 + \varphi \rho_c / y_{\max}} \right) \left(1 - \frac{\iota \rho_w}{1 + \iota \rho_w / \alpha} \right)$	4
5 $y = \left(\frac{\varphi \rho_c}{1 + \varphi \rho_c / (\beta_0 + \beta_1 W)} \right) \left(1 - \frac{\iota \rho_w}{1 + \iota \rho_w / \alpha} \right)$	5
6 $y = \frac{\varphi \rho_c}{1 + \left(\frac{\varphi \rho_c}{(\beta_0 + \beta_1 \sqrt{W} + \beta_2 \sqrt{N})} \right) + \left(\frac{\iota \rho_w}{1 + \iota \rho_w / (\beta_{00} + \beta_1' \sqrt{W} + \beta_3 \sqrt{H})} \right)}$	8
7 $y = \beta_0 + \beta_1 W + \beta_2 \rho_w + \beta_3 \rho_c + \beta_4 R + \beta_5 N + \beta_6 \rho_w^2 + \beta_7 \rho_c^2 + \beta_8 N^2 + \beta_9 W : R + \beta_{10} N : R$	11

Δ AIC values (Table 2.4) showed that the best fitting model was the multiple linear regression model, closely followed by a reduced version of Model 5 (i.e. reduced from its form in equation 5), as revealed by its lowest residual standard error. The ranges of Δ AIC values are quite large partly due to large sample size. To visually examine goodness-of-fit of each model, response (observed yield) values versus fitted (predicted yield) values were plotted (Figure 2.19). Models 5 and 7, closely followed by Model 6, provided far better yield predictability than the other 4 models (Figure 2.19).

Table 2.4. Summary of model-selection statistics (n=1627). “*” indicate parameters whose values were set at the indicated number to allow non-linear least squares convergence. Rank is the order of the best fitting (in bold) to poorest fitting model.

Model	Parameter Values			ΔAIC	R^2	MSE $\hat{\sigma}$	Rank
	Fitted Parameters	Estimates	p-values				
1	ι :	0.02	<.0001	1459	0.210	14.9	5
	y_{wf} :	56.2	<.0001				
	α :	0.50	<.0001				
2	r :	26.6	0.2402	1458	0.208	14.9	4
	b :	0.47	0.2475				
	f :	0.27	0.2474				
3	β_{R0} :	0.001	0.0021	2156	0.0	18.5	7
	B :	2.7	<.0001				
	y_{wf} :	40*					
4	y_{wf} :	58.6	<.0001	1508	0.096	15.1	6
	φ :	7.1	<.0001				
	ι :	0.01	<.0001				
	α :	1*					
5	ι :	0.003	<.0001	238	0.628	10.2	2
	φ :	0.002	<.0001				
	α :	0.45	<.0001				
	β_0 :	133.3	<.0001				
	β_1 :	1.38	<.0001				
6	ι :	0.174	<.0001	472	0.564	11.1	3
	φ :	1.73	<.0001				
	β_0 :	25.0	<.0001				
	β_1 :	5.75	<.0001				
	β_2 :	1.36	<.0001				
	β_{00} :	2.44	<.0001				
	β_1 :	-0.15	<.0001				
	β_3 :	2.72	0.0002				
7	$\beta_0(\text{incpt})$	10.42	<.0001	0	0.705	9.0	1
	$\beta_1(\text{gsp})$	-0.12	0.0021				
	$\beta_2(\text{wo})$	-0.10	<.0001				
	$\beta_3(\text{wheat})$	0.32	<.0001				
	$\beta_4(\text{nitro})$	-0.08	0.0121				
	$\beta_5(\text{herb})$	-25.4	<.0001				
	$\beta_6(\text{wo}^2)$	0.0001	<.0001				
	$\beta_7(\text{wheat}^2)$	-0.0003	<.0001				
	$\beta_8(\text{nitro}^2)$	-0.0003	<.0001				
	$\beta_9(\text{nitro:gsp})$	0.0039	<0.001				
	$\beta_{10}(\text{herb:gsp})$	0.55	<0.001				

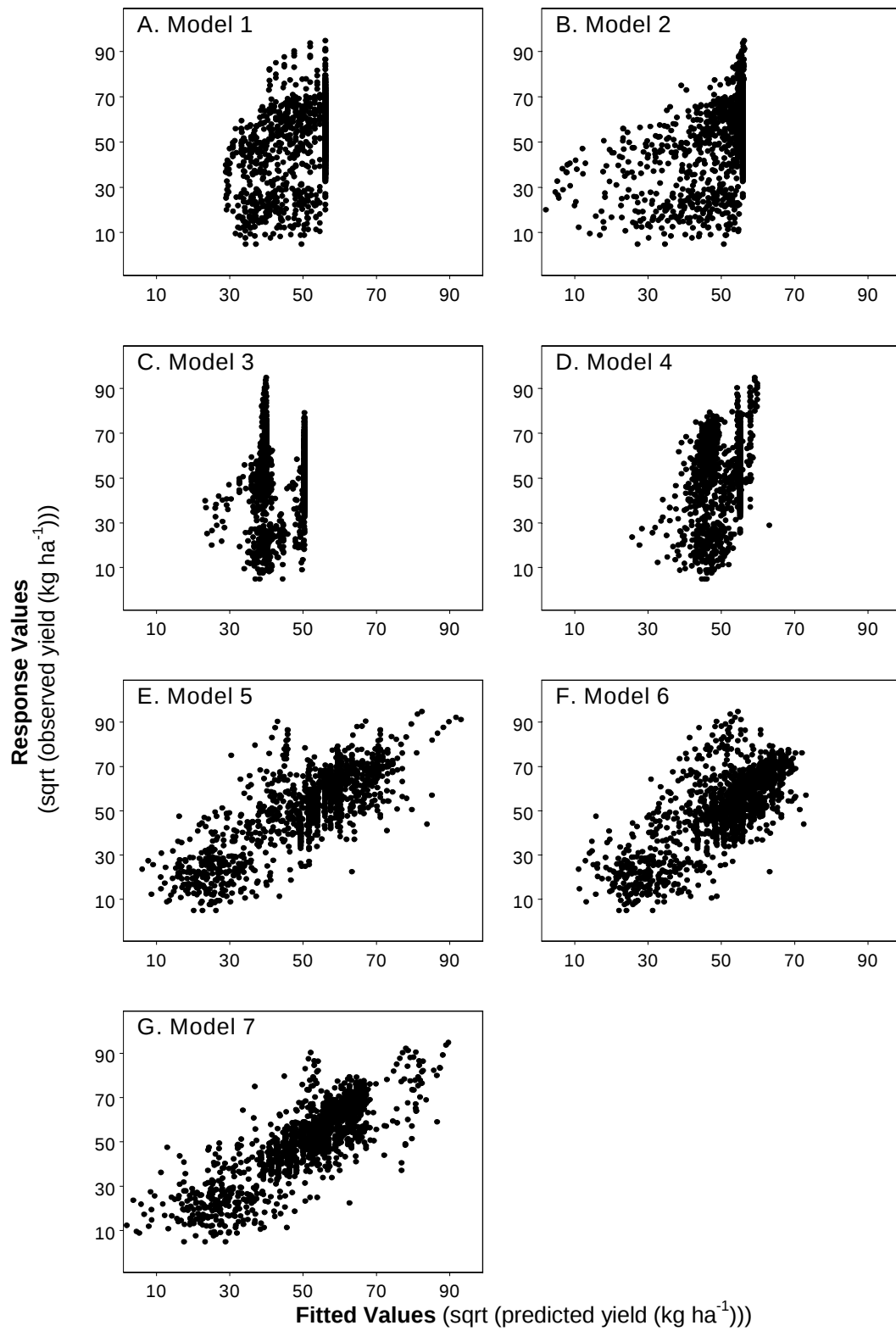


Figure 2.19. Scatter plots showing goodness-of-fit for each model.

Discussion

The approach of combining data sets for model building has proven useful since the best fitting models (e.g. Models 5 – 7) of the candidate set of models include input influences on wheat and wild oat competition. Including the influence of GSP, nitrogen and herbicide rate, as well as wild oat density on wheat yield is an improvement in empirical agronomic prediction modeling. The inference made with which to parameterize the models is based on several decades of agronomic experiments. Below is a discussion of model performance.

Goodness-of-fit of the *best* models—Models 5, 6, and 7

A high level of model complexity was supported by fitting the models to the combined data set even though the scatter plot analysis of individual data sets and the combined data set revealed much variability and a lack of increased yield trends as inputs were increased. Specifically, all five predictor variables in Models 6 and 7 were shown to be significantly influential on yield. Despite Model 7's assumption that all main effects, squared main effects, and interactions are additive, this model was able to capture previously found interactions—specifically between nitrogen and water (Henry et al. 1971, Campbell et al. 1993, Engel et al. 2001) and between herbicide and water (Grundy et al. 1996). Model 7, albeit a linear model, also supported the asymptotic behavior of wheat density and wild oat density on yield. Coefficients for GSP and nitrogen rate however were negative, implying their negative influence on wheat yield. Thus, caution must be exercised over the seemingly good fit produced by Model 7 to the data. An

overall major weakness of Model 7, whether it was fit to this combined data set or any future measurements, was that it did not draw upon decades of agronomic research that have established first principle nonlinear responses of wheat yield to many of the variables studied here (Bowden and Friesen 1967, Bell and Nalewaja 1968, Wilson and Peters 1982, O'Donovan et al. 1985, Martin et al. 1987).

On the contrary, Model 5, the second best-fitting model, does include underlying nonlinear yield responses with parameters that are of the correct sign, such as an estimate of the initial rate of yield increase as crop density increases from zero, an estimate of the initial rate of yield loss as weed density increases from zero, and the asymptote for maximum proportional yield loss as weed density increases. Additionally, Model 5 supports a greater level of complexity than previously developed nonlinear plant competition models by including growing season precipitation as a predictor variable.

Model 6, while not producing as low of an AIC value as Model 5 nor as high of a coefficient of determination, has converged with the inclusion of nitrogen and herbicide rate as well as GSP. The predicted versus observed yield plots show remarkable goodness-of-fit to the combined data as compared with previously developed agronomic models (Figure 2.18). While the modeling results show substantial advancement in the area of yield prediction, the sizable variability in the data, as revealed by the scatter plot and standardized regression analysis, is cause for further inquiry.

Possible theories of why nitrogen and herbicide rate were not significant in Model 5 and the influence of GSP and nitrogen on wheat yield were negative in Model 7 are: 1) inherent variability in agroecosystems, 2) poor predictor metrics, 3) limited data, and 4) duplicity of input influence, i.e. the inputs that have positive influence on wheat yield

also have positive influence on wild oat growth (e.g. water and nitrogen), and what decreases weed infestation (e.g. lack of water and herbicide) can also decrease yield. Concerning variability in agroecosystems, several studies have reported the variability of nitrogen's effect on yield (Carlson and Hill 1985b, Moore and Tyndale-Biscoe 1999), the variability of weed response to herbicide rates and/or poor performance of herbicide (Wilson 1979, Davies et al. 1989, Martin and Felton 1993). Possible reasons for poor input performance were: weather conditions had much greater influence than spatially applied fertilizer (Moore and Tyndale-Biscoe 1999), low available water at planting (Fawcett 1967, Martin and Felton 1993), corresponding time of emergence of the crop and weed (Peters and Wilson 1983, Spitters and Aerts 1983, O'Donovan et al. 1985, Bubar 1991), soil type (Jensen 1985), and crop nutrition (Colwell and Esdaile 1966). Nonetheless several studies show yield and net return benefits from reduced or variable-rate herbicide applications (Gerowitt et al. 1984, Erviö et al. 1991, Fykse 1991, Grundy et al. 1996, Walker et al. 2002).

Despite the inherent variability in ecosystems, confidence can be placed in the following trends; first, fertilizer can increase wheat yield to a threshold level. Beyond this level yield has been shown to decline, possibly because wild oat was better able to utilize nitrogen fertilizer and thus gain a competitive advantage over wheat (Sexsmith and Russell 1963, Bell and Nalewaja 1968, Bowden and Friesen 1968, Carlson and Hill 1985b, Campbell et al. 1993). Secondly, herbicide can decrease wild oat infestation levels and subsequently decrease wheat yield, but at a threshold level, herbicide can cause crop injury especially in drought-stressed crops or when there is a lack of weed competition (Grundy et al. 1996).

A deeper look at variability surrounding nitrogen rate and GSP concerns the appropriateness of the metrics used for prediction variables. For example, Campbell et al. (1993) and Engel et al. (2001) concluded that the response to nitrogen could decrease over time, presumably due to available nitrogen in soil that improves under no tillage and annual adequate fertilization. It was likely that some of the variability surrounding nitrogen rate would be explained if stored soil nitrogen as well as applied nitrogen fertilizer were measured. Additional explanatory metrics of may be fertilizer placement (Campbell et al. 1993) and timing of fertilizer application (Scursoni and Arnold 2002). Unfortunately but not surprisingly, the metrics residual soil nitrogen, soil moisture, and time of relative wheat and wild oat emergence were not measured in the data sets that were assembled.

The development and performance of the seven chosen models relied on the amount of inference that can be drawn from collected data. Inferences were limited since none of the data sets measured all five predictor variables at more than one level. Thus assumptions were necessary and sources of variation were overlooked. For example, soil type was not considered in the models. Rather, soil type was essentially treated as uniform across the field (i.e. not contributing to wheat yield) even though none of the field experiments included soil type measurements. Additionally, relative time of emergence, which was not included in the vast majority of data sets, was assumed the same for wheat and wild oat for our model development purpose. A more thorough understanding of the underlying biology of wheat-wild oat competition with varying combinatorial levels of nitrogen, fertilizer, and water will be necessary to reveal the *best* first principle characterization of the influence of wheat density, wild oat density,

nitrogen rate, herbicide rate, and growing season precipitation on wheat yield, as well as more accurate parameter estimates.

Our collection of worldwide data sets represents the combined efforts of an entire discipline over the last several decades, which forms the basis for the best-fitting three and five-variable models presented in this paper. While the fit of Models 5 and 6 in particular is a remarkable step in yield prediction modeling, we make the case for future data collection to further investigate the variability in wheat-wild oat system, thus allowing further 5-variable model development. While investigating the patterns within and between data sets was extremely useful, there remain unanswered questions:

- How do wheat and wild oat plants compete with varying water, nitrogen, and herbicide treatments in combination?
- Do the interactions of nitrogen and water and herbicide and water play a large enough role to be included in a nonlinear prediction model?
- Does crop injury due to herbicide at high rates have a large enough influence on yield such that it should be included in the model?
- Why is nitrogen's influence on wild oat density in the nonlinear prediction models (Models 5 and 6) not supported by the data although this effect has been presented in the literature?
- Could adequate support for including the nonlinear influences of nitrogen, water, and herbicide in the wheat-wild oat model exist given a 5-variable experiment with sufficient treatment levels and replication?

- Will net returns be improved using site-specific recommendations from Models 5 – 7 using the parameter estimates calculated from the combined data set?

A method by which to answer these questions and to reveal ecological first principles of wheat and wild oat competition with varying levels of inputs is the execution of a 5-variable experiment in a controlled environment (e.g. a greenhouse). In a controlled environment setting soil type can be held constant and moisture level throughout the growing period can be more accurately controlled as a treatment. Furthermore, variability attributed to different soil types with differing soil moisture capacities, the effects of varying times of emergence, and the effects of residual soil nitrogen can be omitted from the system. Besides controlling the complexity of factors that a field experiment cannot, controlled environment experiments, such as those conducted in a greenhouse, can allow for relatively quick replication compared to field experiments and can allow for the generation of hypotheses that can be further tested in the field (Freckleton and Watkinson 2001). Such a controlled environment experiment would be a first step toward elucidating ecological first principles by producing one-of-a-kind five-variable experimental results from which hypotheses could be produced and the proposed prediction models could be updated, outlining guidelines for future field experimentation for site-specific management.

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References Cited

- Barton, D.L., D.C. Thill, and B. Shafii. 1992. Integrated wild oat management affects spring barley yield and economics. *Weed Technology* 6:129-135.
- Bauder, J., P. Brown, J. Jacobsen, and H. Ferguson. 1987. Estimating small grains yield potential from stored rainfall probabilities. *Montguide* MT 8325.
- Beck, M.W. 1997. Inference and generality in ecology: current problems and experimental solutions. *Oikos* 78:265-273.
- Beckie, H.J., A.P. Moulin, C.A. Campbell, and S.A. Brandt. 1995. Testing the effectiveness of four simulation models for estimating nitrates and water in two soils. *Canadian Journal of Soil Science* 75:135-143.
- Berti, A. and G. Zanin. 1994. Density equivalent: a method for forecasting yield loss caused by mixed weed populations. *Weed Research* 34: 327-332.
- Bell, A.R., and J.D. Nalewaja. 1968. Competition of wild oat in wheat and barley. *Weed Science* 16:505-508.
- Blackshaw, R. E., J. R. Moyer and K. N. Harker. 2002. Integration of cultural practices for sustainable weed management in direct seeding systems. Edmonton, AB: Alberta Agricultural Research Institute Final Report. 62 pp.
- Blackshaw, R. E., L. J. Molnar and H. H. Janzen. (*in review*). Nitrogen fertilizer timing and application method affects weed competition and spring wheat yield. *Weed Science* (*submitted*).
- Bleasdale, J.K.A., and J.A. Nelder. 1960. Plant competition and crop yield. *Nature* 188:342.
- Bowden, B.A., and G. Friesen. 1967. Competition of wild oats (*Avena fatua* L.) in wheat and flax. *Weed Research* 7:349-359.
- Bozdogan, H. 2000. Akaike's Information Criteria and recent developments in Information Complexity. *Journal of Mathematical Psychology* 44:62-91.
- Brain, P., B.J. Wilson, K.J. Wright, G.P. Seavers, and J.C. Caseley. 1999. Modeling the effect of crop and weed on herbicide efficacy in wheat. *Weed Research* 39:21-35.
- Brooks, R.J., M.A. Semenov, and P.D. Jamieson. 2001. Simplifying Sirius: sensitivity analysis and development of a meta-model for wheat yield production. *European Journal of Agronomy* 14:43-60.

- Brown, D., and P. Rothery. 1993. *Models in Biology: mathematics, statistics and computing* John Willey and Sons, Chichester.
- Brown, P.L., and G.R. Carlson. 1990. Grain yields related to stored soil water and growing season rainfall. *Agricultural Experiment Station* 35.
- Bubar, C.J. 1991. Competition between *Avena fatua* L. and *Triticum aestivum* L. with varying time of emergence. Ph.D. Thesis. University of Saskatchewan.
- Campbell, C.A., F. Selles, R.P. Zentner, and B.G. McConkey. 1993. Available water and nitrogen effects on yield components and gran nitrogen of zero-till spring wheat. *Agronomy Journal* 85:114-120.
- Carlson, H., J. Hill, and K. Baghott. 1982. Wild oat competition in spring wheat. *Proceedings of the 33rd Annual Californian Weed Conference*. pp. 13-24
- Carlson, H.L., and J.E. Hill. 1985a. Wild oats (*Avena fatua*) competition with spring wheat: plant density effects. *Weed Science* 33:176-181.
- Carlson, H.L., and J.E. Hill. 1985b. Wild oat (*Avena fatua*) competition with spring wheat: effects of nitrogen fertilization. *Weed Science* 34:29-33.
- Chancellor, R.J., and N.C.B. Peters. 1974. The time of the onset of competition between wild oats (*Avena fatua* L.) and spring cereals. *Weed Research* 14:197-202.
- Chipanshi, A.C., E.A. Ripley, and R.G. Lawford. 1997. Early prediction of spring wheat yields in Saskatchewan from current and historical weather data using CERES-Wheat model. *Agricultural and Forest Meteorology* 84:223-232.
- Christensen, S., E. Nordbo, T. Heisel, and A.M. Walter. 1998. Overview of developments in precision weed management, issues of interest and future directions being considered in Europe, p. 3-13, *In* R. W. Medd and J. E. Pratley, eds. *Precision Weed Management of Crops and Pastures*. CRC for weed management systems, Adelaide, Australia.
- Coble, H.D. and D.A. Mortensen. 1992. The threshold concept and its application to weed science. *Weed Technology* 6: 191-195.
- Colwell, J. D. and R. J. Esdaile. 1966. The application of production function analysis for the estimation of fertilizer requirements of wheat in northern New South Wales. *Australian Journal of Experimental Agriculture and Animal Husbandry* 6: 418-424.
- Cousens, R. 1985a. An empirical model relating crop yield to weed and crop density and a statistical comparison with other models. *Journal of Agricultural Science*

105:513-521.

- Cousens, R. 1985b. A simple model relating yield loss to weed density. *Annals of Applied Biology* 107:239-252.
- Cousens, R. 1986. The use of population models in the study of the economics of weed control. EWRS Symposium, Economic Weed Control, Long Ashton Research Station, Bristol, Avon, UK. pp. 269-277.
- Cousens, R., P. Brain, J.T. O'Donovan, and P.A. O'Sullivan. 1987. The use of biologically realistic equations to describe the effects of weed density and relative time of emergence on crop yield. *Weed Science* 35:720-725.
- Davies D. H. K., A. J. Whiting, G. M. Whytock. 1989. Yield responses to herbicide use and weed levels in winter wheat and spring barley in Scottish trials and consequences for economic models. *Proceedings from Brighton Crop Protection Conference--Weeds*. pp.955-960
- DeJong, E., and D.A. Rennie. 1967. Physical soil factors influencing the growth of wheat *Can. Cent. Wheat Symp. Pub. Western Co-op Fertilizers Ltd., Calgary, Canada.*
- Dieleman, J.A., D.A. Mortensen, D.D. Buhler, C.A. Cambardella, and T.B. Moorman. 2000a. Identifying associations among site properties and weed species abundance. I. Multivariate analysis. *Weed Science* 48:567-575.
- Dieleman, J.A., D.A. Mortensen, D.D. Buhler, and R.B. Ferguson. 2000b. Identifying associations among site properties and weed species abundance. II. Hypothesis generation. *Weed Science* 48:576-587.
- Dille, J.A. 2002. Predicting weed species occurrence based on site properties and previous year's weed presence. *Precision Agriculture* 3:193-207.
- Engel, R. 1993. Winter wheat response to available nitrogen and water Fertilizer Facts, Montana State University Extension Service. vol 1, no. 4.
- Engel, R., D. Long, and G. Carlson. 2001. Nitrogen Requirement and Yield Potential of Spring Wheat as Affected by Water. MSU Extension Service Agricultural Experiment Station.
- Farazdaghi, H., and P.M. Harris. 1968. Plant competition and crop yield. *Nature* 217:289-290.
- Fawcett, R.G. 1967. Factors influencing the development and grain yield of spring wheat grown on the North-West plains of New South Wales, with special reference to soil-water-plant relationships. Ph.D. Thesis, University of East Anglia.

- Fernandez, R., and R.J. Laird. 1959. Yield and protein content of wheat in central Mexico as affected by available soil moisture and nitrogen fertilization. *Agronomy Journal* 51:33-36.
- Firbank, L.G., A.M. Mortimer, and P.D. Putwain. 1985. *Bromus sterilis* in winter wheat: a test of a predictive model. *Aspects of Applied Biology* 9:59-66.
- Firbank, L.G., and A.R. Watkinson. 1990. On the effects of competition from monocultures to mixtures, p. 165-193 *Perspectives on Plant Competition*.
- Freckleton, R.P., and A.R. Watkinson. 2001. Nonmanipulative determination of plant community dynamics. *TRENDS in Ecology and Evolution* 16:301-307.
- Godwin, D., J.T. Ritchie, U. Singh, and L. Hunt. 1990. User's Guide to CERES Wheat-V2.10 International Development Center, Muscle Shoals, AL.
- Gonzalez-Andujar, J.L., and J.N. Perry. 1995. Models for the herbicidal control of the seed bank of *Avena sterilis*: the effects of spatial and temporal heterogeneity and of dispersal. *Journal of Applied Ecology* 32:578-587.
- Grundy, A.C., N.D. Boatman, and R.J. Foud-Williams. 1996. Effects of herbicide and nitrogen fertilizer application on grain yield and quality of wheat and barley. *Journal of Agricultural Science* 126:379-385.
- Haun, J.R. 1974. Prediction of spring wheat yields from temperature and precipitation data. *Agronomy Journal* 66:405-409.
- Henry, J.L. 1971. The effect of soil zone, available soil nitrogen level and nitrogen fertilization on the yield and quality of stubble seeded cereal grain. Soil Fertility Workshop, Ext. Div., University of Saskatchewan. 22pp.
- Henry, J.L., J.B. Boole, and R.C. McKenzie. 1986. Effect of nitrogen water interactions on yield and quality of wheat in Western Canada, *In* A. E. Slinkard and D. B. Fowler, eds. *Wheat Production in Canada: a Review*. University of Saskatchewan, Saskatoon.
- Henson, J.F., and L.S. Jordan. 1982. Wild oat (*Avena fatua*) competition with wheat (*Triticum aestivum* and *T. turgidum durum*) for nitrate. *Weed Science* 30:297-300.
- Holliday, R. 1960. Plant population and crop yield: Part I and Part II. *Field Crop Abstract* 13.
- Hunter, A.S., C.J. Gerard, H.M. Waddoups, W.E. Hall, H.E. Cushman, and L.A. Alban. 1958. The effect of nitrogen fertilizers on the relationships between increases in

- yields and protein content of pastry type wheats. *Agronomy Journal* 50:311-314.
- Jasieniuk, M., B.D. Maxwell, R.L. Anderson, J.O. Evans, D.J. Lyon, S.D. Miller, D.W. Morishita, A.G. Ogg, S. Seefeldt, P.W. Stahlman, F.E. Northam, P. Westra, Z. Kebede, and G.A. Wicks. 1999. Site-to-site and year-to-year variation in *Triticum aestivum*--*Aegilops cylindrica* interference relationships. *Weed Science* 47:529-537.
- Jasieniuk, M., B.D. Maxwell, R.L. Anderson, J.O. Evans, D.J. Lyon, S.D. Miller, D.W. Morishita, A.G. Ogg, and S.S. Seefeldt. 2000. Evaluation of models predicting winter *Triticum aestivum* yield as a function of *Triticum aestivum* and *Aegilops cylindrical* densities. *Weed Science* 49:48-60.
- Jensen, P.K. 1985 Review of yield responses to weed control in one thousand spring barley experiments. *Proceedings from British Crop Protection Conference—Weeds* pp.687-692
- Johnson, G.A., D.A. Mortensen, and A.R. Martin. 1995. A simulation of herbicide use based on weed spatial distribution. *Weed Research* 35:197-205.
- Kim, D.S., P. Brain, E.J.P. Marshall, and J.C. Caseley. 2002. Modelling herbicide dose and weed density effects on crop:weed competition. *Weed Research* 42:1-13.
- Kropff, M.J., and C.J.T. Spitters. 1991. A simple model of crop loss by weed competition from early observation on relative leaf area of the weeds. *Weed Research* 31:97-105.
- Lehane, J.J., and W.J. Staple. 1965. Influence of soil texture, depth of soil moisture storage and rainfall distribution on wheat yields in southwestern Saskatchewan. *Canadian Journal of Soil Science* 45:207-219.
- Li, M., and R.S. Yost. 2000. Management-oriented modeling: optimizing nitrogen management with artificial intelligence. *Agricultural Systems* 65:1-27.
- Lindquist, J.L. and M.J. Kropff. 1996. Applications of an ecophysiological model for irrigated rice (*Oryza sativa*)-*Echinochloa* competition. *Weed Science* 44: 52-56.
- Long, D.S., R.E. Engel, G.A. Nielson, A.J. Bussan, G.R. Carlson, M.P. Henry, B.J. Kozar, and B.E. Maxwell. In review. Precision nitrogen management in wheat: lessons learned from multidisciplinary research.
- Martin, R.J., B.R. Cullis, and D.W. McNamara. 1987. Prediction of wheat yield loss due to competition by wild oats. *Journal of Agricultural Research* 38:487-499.
- Martin, R.J., and W.L. Felton. 1993. Effect of crop rotation, tillage practice, and herbicides on the population dynamics of wild oats in wheat. *Australian Journal*

of Experimental Agriculture 33:159-165.

- Moore, G.A., and J.P. Tyndale-Busoe. 1999. Estimation of the importance of spatially variable nitrogen application and soil moisture holding capacity to wheat production. *Precision Agriculture* 1:27-338.
- Mortensen, D.A., G.A. Johnson, and L.J. Young. 1993. Weed distribution in agricultural fields, p. 113-124, *In* P. C. Robert and R. H. Rust, eds. *Soil Specific Crop Management*. ASA-CSSA-SSSA, Madison, WI.
- Mortimer, A.M. 1987. Contributions of plant population dynamics to understanding early succession, p. 57-80 *Colonization, Succession, and Stability*. Blackwell Scientific Publications, Oxford.
- Neidig, R.E., and R.S. Snyder. 1924. The relation of moisture and available nitrogen to the yield and protein content of wheat. *Soil Science* 18:173-179.
- Neter, J., M.H. Kutner, C.J. Nachtsheim, and W. Wasserman. 1996. *Applied Linear Statistical Models*. 4th Ed. ed. McGraw-Hill, Boston.
- Norris, R.F. 1992. Case history for weed competition/population ecology: Barnyardgrass (*Echinochloa crus-galli*) in sugarbeets (*Beta vulgaris*). *Weed Technology* 6:220-227.
- O'Donovan, J.T., E.A. Remy, P.A.O. Sullivan, D.A. Dew, and A.K. Sharma. 1985. Influence of the relative time of emergence of wild oat (*Avena fatua* L.) on yield loss of barley (*Hordeum vulgare*) and wheat (*Triticum aestivum*). *Weed Science* 33:498-503.
- Peters, N.C.B. and B.J. Wilson, 1983. Some studies on the competition between *Avena fatua* L. and spring barley. II. Variation of *Avena fatua* emergence and development and its influence on crop yield. *Weed Research* 23:305-311.
- Racz, G.J. 1974. Effect of nitrogen supply, water supply and temperature on the yield and protein content of cereal grains. 18th Man. Soil Sci. Soc. Meetings, Dec. 1974, Winnipeg. pp.219-228
- Radford, B.J., B.J. Wilson, O. Carthedge, and F.B. Watkins. 1980. Effect of wheat seeding rate on wild oat competition. *Aust. Journal of Experimental Agriculture and Animal Husbandry* 20:77-81.
- Ritchie, J.T., and S. Otter. 1985. Description and performance of CERES-Wheat: a user-oriented wheat yield model, *In* ARS Wheat Yield Project, Vol. ARS-38. W. O. Willis, ed. Agricultural Research Service, US Department of Agriculture, Temple,

TX.

- Salonen, J. 1992. Yield responses of spring cereals to reduced herbicide doses. *Weed Research* 32:439-499.
- Sattin, M., G. Zanin, and A. Berti. 1992. Case history for weed competition/population ecology: velvetleaf (*Abutilon theophrasti*) in corn (*Zea mays*). *Weed Technology* 6:213-219.
- Scursoni, J.A., and R.B. Arnold. 2002. Effect of nitrogen fertilization timing on the demographic processes of wild oat (*Avena fatua*) in barley (*Hordeum vulgare*). *Weed Science* 50:616-621.
- Sexsmith, J.J., and G.C. Russell. 1963. Effect of nitrogen and phosphorus fertilization on wild oat and spring wheat. *Canadian Journal of Plant Science* 43:64-70.
- Shatar, T.M., and A.B. McBratney. 2000. Empirical modeling of relationships between sorghum yield and soil properties. *Precision Agriculture* 1:249-276.
- Shinozaki, K., and T. Kira. 1956. Intraspecific competition among higher plants VII. Logistic theory of the C-D effect. *Journal of Institute of Polytechnics, Osaka City Univ* D7:35-72.
- Spandl, E., B.R. Durgan, and D.W. Miller. 1997. Wild oat (*Avena fatua*) control in spring wheat (*Triticum aestivum*) and barley (*Hordeum vulgare*) with reduced rates of postemergence herbicides. *Weed Technology* 11:591-597.
- Spitters, C.J.T. and R. Aerts 1983. Simulation of competition for light and water in crop-weed associations. *Aspects of Biology*. 4: 467-483.
- Stollen, E.W., S.K. Harrison, L.M. Wax, E.E. Regnier, and E.D. Nafziger. 1987. Weed interference in soybeans (*Glycine max*). *Review Weed Science* 3: 155-181.
- Swanton, C.J., S. Weaver, P. Cowan, R. Van Acker, W. Deen, and A. Shreshta. 1999. Weed thresholds: theory and applicability. *In: Expanding the Context of Weed Management*. D.D. Buhler, ed. p.9-29.
- Thurston, J.M. 1962. The effect of competition from cereal crops on the germination and growth of *Avena fatua* L. in a naturally infested field. *Weed Research* 2:192-207.
- Streibig, J.C. 1980. Models for curve-fitting herbicide dose response data. *Acta Agriculturae Scandinavica*. 30:59-64.

- Streibig, J. C., M. Rudemo, J. E. Jensen. 1993. Dose-response curves and statistical models. *In* Herbicide Bioassays. J.C. Streibig and P. Kudsk (eds). CRC Press, Boca Raton.
- Tollenaar, H. 1992. Reinterpretation and evaluation of some simple descriptive models for weed-crop interference in terms of one-sided and two-sided competition. *Oikos* 65:256-264.
- VanWychen, L.R. 2002. Field-scale spatial distribution, water use, and habitat of wild oat in the semiarid Northern Great Plains. Ph.D Thesis, Montana State University, Bozeman, Montana.
- Walker, S.R., R.W. Medd, G.R. Robinson, and C. B. R. 2002. Improved management of *Avena ledoviciana* and *Phalaris paradoxa* with more densely sown wheat and less herbicide. *Weed Research* 42:257-270.
- Warder, F.G., J.J. Lehane, W.C. Hinman, and W.J. Staple. 1963. The effect of fertilizer growth, nutrient uptake and moisture use of wheat on two soils in southwestern Saskatchewan. *Canadian Journal of Soil Science* 43:107-116.
- Weaver, S.E. 1991. Size-dependent economic threshold for three broadleaf weed species in soybeans. *Weed Technology* 5:674-679.
- Willey, R.W., and S.B. Heath. 1969. The quantitative relationships between plant population and crop yield. *Advances in Agronomy* 21:281-321.
- Williams, G.D.V. 1973. Estimates of prairie provincial wheat yields based on precipitation and potential evapotranspiration. *Canadian Journal of Plant Science* 53:17-30.
- Wilson, B.J. 1979. Post-emergence control of wild oats in Queensland with difenzoquat, flamprop-methyl, dichlofop methyl and barban. *Australian Journal of Experimental Animal Husbandry* 19:108-117.
- Wilson, B.J., and N.C.B. Peters. 1982. Some studies of competition between *Avena fatua* L. and spring barley 1. The influence of *A. fatua* on yield of barley. *Weed Research* 22:143-148.
- Wilson, B.J., R. Cousens, and G.W. Cussans, 1984. Exercises in modeling population of *Avena fatua* to aid strategic planning for the long-term control of this weed in cereals. *Proceedings of the 7th International Symposium on Weed Biology, Ecology and Systematics*, pp. 287-294.

- Wilson, B.J., R. Cousens, and K.J. Wright. 1990. The response of spring barley and winter wheat to *Avena fatua* population density. *Annals of Applied Biology* 116:601-609.
- Wilson, B.J., and K.J. Wright. 1990. Predicting the growth and competitive effects of annual weeds in wheat. *Weed Research* 30: 201-211.

CHAPTER 3

WHEAT YIELD PREDICTION MODELING FOR SITE-SPECIFIC FERTILIZER
AND HERBICIDE MANAGEMENT BASED ON A FIVE-VARIABLE
GREENHOUSE EXPERIMENTAbstract

With an improved understanding of the variables influencing wheat yield, herbicide and fertilizer applications can be made more cost effective through site-specific and variable rate management. Our research has attempted to increase the understanding of the variance in dryland spring wheat yield caused by the interaction of managed inputs and natural factors for the optimization of agricultural inputs using precision agriculture technology. Previously we have investigated the development of an empirical five-variable wheat yield model by obtaining independently collected on-farm and experiment station data sets from dryland spring wheat growing regions in the USA, Canada and Australia. We had chosen these data sets because wheat yield was a function of at least two of the five predictor variables: wheat and wild oat density, nitrogen and herbicide rate, and available water. The best-fit nonlinear yield model to the combined data set included crop and wild oat density, and growing season precipitation; nitrogen and herbicide rates were not significant factors in the model. These results illustrate the large amount of unexplored variation in wheat yield, and the lack of ecological first principles upon which farmers base input management decisions, especially when weed infestation causes competition for limited nitrogen and water. To take an initial step towards elucidating the biological mechanisms of wheat-wild oat competition with varying

combinatorial levels of resources, we conducted a five-variable full-factorial greenhouse experiment where wheat yield (i.e. dry wheat biomass) was the dependent variable and independent predictor variables were wheat and wild oat density, herbicide and nitrogen rate, and available water. The best-fitting yield model to the greenhouse data set was a nonlinear equation including all five variables and was shown to fit the data considerably better than four previously developed agronomic models. The long-term goal of our research is to build a decision support system for site-specific and variable-rate management of herbicide, fertilizer, and crop seeding rate considering varying levels of available water and weed infestation. This initial exploration has provided considerable support for future on-farm experiments and yield prediction modeling. In addition, it established a first principle model to be parameterized for use in different dryland spring wheat growing regions.

Introduction

Our research has attempted to increase the understanding of the variables influencing yield and their interactions, so that precision agriculture technologies can be employed to apply farm inputs in the most efficient manner. We have focused on 5 highly influential and easily measured variables of wheat yield: wheat density, wild oat density, nitrogen rate, herbicide rate, and available water. Specifically, Chapter 2 of this thesis has attempted to increase the understanding of the variables influencing wheat yield through the development of a yield prediction model. The motivation for developing a yield prediction model is the core of a decision support system through which site-

specific management strategies of nitrogen, fertilizer, and crop seeding rate could be recommended. A wheat yield model, based on the first principle mechanisms of plant competition for limited resources in a variable environment, has been previously undeveloped.

For the purpose of model building, we have attempted to utilize existing on-farm and experiment station data sets to their fullest to investigate wheat-wild oat competition at different combinatorial resource levels. Our investigation of the worldwide collection of data sets was requisite, revealing trends found in previous studies, such as a saturation yield response with increasing crop density and a negative hyperbolic decrease in yield with increasing weed density. More surprising results included the lack of consistent trends as herbicide and fertilizer were increased, making the building of a yield prediction model very difficult.

Despite the large amount of variation in yield that was revealed with increased inputs, the independent data sets were combined into one and fit to seven models of varying complexity. The best fitting model, perhaps due to the relative ease of convergence, was a multiple linear regression equation that included all five predictors but did not reflect the history of agronomic modeling. The second best fitting-model was a revised version of the double-hyperbolic model (Jasieniuk et al. 2000) that included growing season precipitation, as well as wheat and wild oat density. Although the combined data, with 1627 observations, supported an advance in nonlinear yield modeling via the three-predictor double-hyperbolic model, the large amount of variation in wheat yield did not support the addition of nitrogen and herbicide to this model. The absence of herbicide and nitrogen rate from wheat-wild oat competition models illustrates

the lack of concrete knowledge upon which farmers base their input management decisions.

Sufficient data rarely exists to parameterize ecological models. Model selection is constrained by data sets without a full complement of factors and not enough replication over time. Although our worldwide collection of independent data sets represent the combined efforts of many agronomic scientists over the last several decades, this investigation affirmed the necessity for more data collection to further elucidate the underlying biological mechanisms of plant competition with varying combinatorial levels of inputs. To increase the level of understanding of the factors influencing wheat yield, and to develop a five-predictor variable yield model, a large five-variable factorial experiment replicated several times was critical. However, before conducting an expensive field experiment we designed a greenhouse experiment where conditions and variables could be more controlled, thus aiming to remove extreme variability found in field data (see Chapter 2).

The greenhouse experiment held soil type constant and systematically varied fertilizer rate, herbicide rate, water level, weed and crop density. In addition, there was no confounding history of management (i.e. residual from previous years' applied fertilizer and herbicide, and stored soil water). Besides controlling the complexity of factors that a field experiment cannot control, greenhouse experiments can allow for relatively quick replication compared to field experiments and can allow for the generation of hypotheses that can be further tested in the field (Freckleton and Watkinson 2001). We were not able to select a first principle model for our variables of interest

using a large compilation of field data sets. Therefore, we were compelled to conduct the controlled greenhouse experiment to identify the first principle spring wheat yield model.

Thus, the specific objectives of this study were to 1) conduct a five-variable factorial experiment where spring wheat (*Triticum aestivum* L.) yield was the dependent variable, 2) investigate the mechanisms of competition between spring wheat and wild oat (*Avena fatua* L.) with varying combinations of nitrogen, herbicide, and water levels, and 3) develop and parameterize a yield prediction model based on the 5 mentioned variables. The overall future goal of this research is to use the best-fitting predictive yield model in a decision support system which farmers and crop consultants can at least in part, parameterize and use to optimize inputs (crop seeding, herbicide, and nitrogen rates).

A rigorous assessment of methods for elucidating the underlying biological mechanisms and identifying the best-fitting first principle yield prediction model was conducted. While the methods used to analyze the data appear tedious, the complexity of the wheat-wild oat agroecosystem requires meticulous investigation.

Materials and Methods

To explore competition of spring wheat (cv. 'McNeal') and wild oat with varying levels of inputs, a greenhouse experiment was conducted from May-September 2003 at the Plant Growth Center at Montana State University in Bozeman, Montana. The experiment consisted of three levels of wheat density (1, 2, and 3 plants per pot corresponding to 170, 340, and 510 plants m⁻²), three levels of wild oat density (0, 2, and

4 plants per pot corresponding to 0, 340, and 680 plants m^{-2}), four fertilizer rates (0, 22.5, 45, and 90 kg N ha^{-1}), four herbicide rates (0, 0.5 $\times$, 0.75 $\times$, and 1 $\times$ the label rate of imazamethabenz) and three water levels (low, medium, and high corresponding to 27.5%, 19.7%, and 17.0% mass water content of the soil). Due to concerns that the wetting and drying cycles in the greenhouse could be further complicated by the size of the pots in which plants were grown (J. Wraith, personal communication), a 17.8-cm diameter “standard azalea” pot size was used. The pot size was assumed to mimic field conditions such that water was assumed to reach the entire root zone with every watering. Due to the large number of pots (e.g. 432), replications were performed consecutively rather than simultaneously.

The soil used in all replications consisted of two parts silt loam and one part washed concrete sand. To determine water treatments, a soil water retention relationship was determined by drying soil samples over two weeks to estimate hydraulic conductivity. Resulting measured gravimetric soil water contents were fitted to van Genuchten’s (1980) parametric equation to determine soil matric potentials (Wraith et al. 1995). The estimated mass water content of the soil was 27.5%, 19.7%, and 17.0% corresponding to soil matric potentials of -0.1, -4, and -12 MPa. Each pot was filled with 1800g of dry soil, sown with the corresponding densities of wheat and wild oat, and watered to field capacity for full germination. After which pots were allowed to dry to the desired matric potential. Pots were weighed every two to three days and watered to the desired percent water content (i.e. 27.5% for the high water treatment, 19.7% for the medium, and 17.0% for the low) and were allowed to dry until the next watering. When wheat reached the boot stage, approximately 32 to 35 days after sowing, wheat and wild

oat plants were clipped at the soil surface and dried in a 50°C oven for 48 hours. Dried wheat and wild oat plants from each pot were weighed. Competition between wheat and wild oat plants was observed only until the boot stage to reduce the effect of the plants growing in pots. Wheat and wild oat were planted in nine density and spatial arrangements (Figure 3.1).

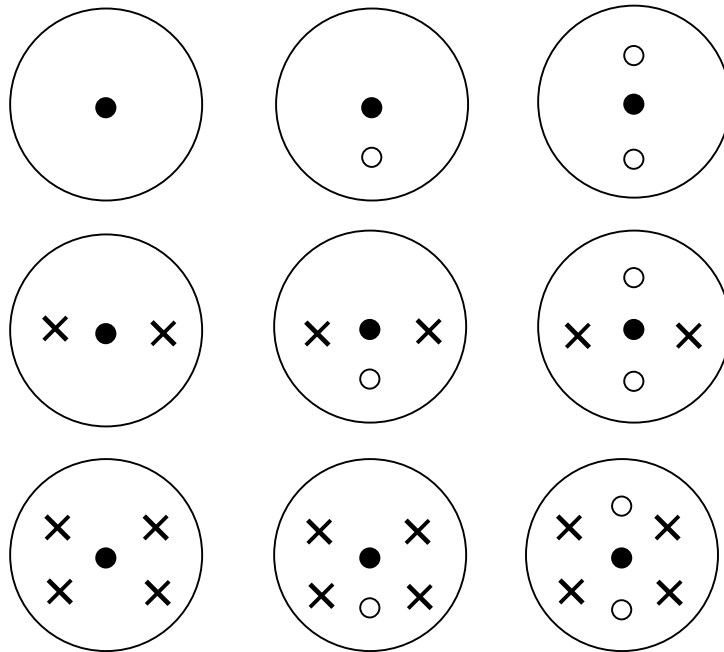


Figure 3.1. The nine spatial combinations of wheat and wild oat seeding are illustrated. O's represent wheat plants and X's represent wild oat plants. Darkened circles represent the central wheat plants that were analyzed in the third replication for neighborhood intra-specific as well as inter-specific competition.

When one wheat plant was sown it was always placed at the center of the pot with any competing wild oats surrounding it. When two and three wheat plants were sown they were done so in a line, to mimic the competition a wheat plant would experience within a row of a field, with individual wheat plants to the front and back of the center

plant. The three levels of wild oat density were used to replicate a situation with no weed pressure, medium infestation, and high weed infestation. All non-center wheat and wild oat plants were sown 2.5 cm from the center wheat plant using cardboard templates. For each of the nine combinations of plant densities, each level of nitrogen, herbicide, and water was applied in combination for a total of 432 pots per replication. Ammonium nitrate fertilizer was applied to the plants ten days after planting.

Regression techniques have been recently applied to the study of plant population dynamics, specifically such that intra- and interspecific components of interactions and the intensity and importance of competition can be evaluated (Freckleton and Watkinson 2001). Thus, standardized regression was performed to further understand the underlying mechanisms of wheat and wild oat competition in the presence of varying levels and combinations of inputs. All variables were standardized such that the size of their coefficients indicated their individual influences on wheat biomass and each variable's influence could be compared. Standardizing was accomplished by the following calculation:

$$X_{i,s} = \frac{X_i - \bar{X}}{\sqrt{\frac{\sum (X_i - \bar{X})^2}{n-1}}} \quad (\text{Brown and Rothery 1993}) \quad (3.1)$$

Plant biomass was assumed to have a linear relationship to yield (Cousens and Mortimer 1995), therefore wheat biomass (i.e. yield) was regressed on all five variables— wheat and wild oat density (or biomass), nitrogen and herbicide rate, and total water applied. All variables were standardized such that the size of their coefficients indicated their

individual influences on wheat biomass and each variable's influence could be compared. For the purpose of exploring the largest influences on wild oat growth, “standardized” regression (see Equation 3.1) was also performed with wild oat biomass being the dependent variable and wheat density, wheat biomass, wild oat density, nitrogen rate, herbicide rate, and total water applied as the independent variables. Main effects, squared and cubed main effects, inverses of main effects, and all interactions were explored using backward stepwise regression. A third regression analysis was performed where the center wheat plant's biomass was treated as the dependent variable and regressed on non-center wheat plant biomass, wild oat density, wild oat biomass, nitrogen rate, herbicide rate, and water level to determine the effects of intra-specific as well as inter-specific competition. A final method of analysis included three-way scatter plots to visualize trends in the data, including those of linearity and non-linearity, main effects, and interactions. The best-fit regression models were determined using AIC values using the backward stepwise regression procedure in S-PLUS.

As an additional exploratory method of the mechanisms of competition between spring wheat and wild oat with varying combinatorial levels of inputs, scatter plots were created to visually reveal the influence each variable had on wheat biomass, as well as main effect-interactions, and linear and nonlinear trends.

The third objective of our research was to assess the current state of yield prediction by model fitting techniques used to find the first principle model of our greenhouse data set, and to attempt to include the agricultural inputs, nitrogen, herbicide, and water, into the yield prediction model. The greenhouse data set was fit to the seven models, as described in Chapter 2, to determine the level of complexity the data would

support (Table 3.2). Model 5 is represented in two forms: one form included Streibig et al.'s (1993) herbicide dose response (Model 5A), and the other included herbicide effects on wild oat in the form of a linear regression equation nested within the larger model (Model 5B) (Table 3.1).

Table 3.1. Candidate set of models.

Model	
1	$y = y_{wf} \left(1 - \frac{\iota \rho_w}{1 + \iota \rho_w / \alpha} \right)$ (Cousens 1985b)
2	$y = \frac{r \rho_c}{1 + b \rho_c + f \rho_w}$ (Baeumer and deWit 1968, Wright 1981, Weiner 1982, Jolliffe et al. 1984)
3	$y = \frac{y_{wf}}{1 + \beta_{R_0} \rho_{w_0}} \left(1 + \left(\frac{R}{e^{R_{50}}} \right)^B \right)$ (Kim et al. 2002)
4	$y = \left(\frac{\varphi \rho_c}{1 + \varphi \rho_c / y_{\max}} \right) \left(1 - \frac{\iota \rho_w}{1 + \iota \rho_w / \alpha} \right)$ (Jasieniuk et al. 2000)
5A	$y = \left(\frac{\varphi \rho_c}{1 + \varphi \rho_c / (\beta_0 + \beta_1 f(W) + \beta_2 f(N) + \beta_{12} (W * N))} \right) \left(1 - \frac{\iota \rho_w}{1 + \iota \rho_w / \left(\alpha_{\min} + \frac{\alpha_{\max} - \alpha_{\min}}{1 + e^{B(R - R_{50})}} \right)} \right)$
5B	$y = \left(\frac{\varphi \rho_c}{1 + \varphi \rho_c / (\beta_0 + \beta_1 f(W) + \beta_2 f(N) + \beta_{12} f(W * N))} \right) \left(1 - \frac{\iota \rho_w}{1 + \iota \rho_w / (\beta_{00} + \beta_1' f(W) + \beta_2' f(H) + \beta_{13} f(W * H))} \right)$
6	$y = \frac{\varphi \rho_c}{1 + \left(\frac{\varphi \rho_c}{(\beta_0 + \beta_1 f(W) + \beta_2 f(N) + \beta_3 f(H))} \right) + \left(\frac{\iota \rho_w}{1 + \iota \rho_w / (\beta_{00} + \beta_1' f(W) + \beta_2' f(W) + \beta_3' f(H))} \right)}$
7	$y = \beta_0 + \beta_1 W + \beta_2 \rho_w + \beta_3 \rho_c + \beta_4 N + \beta_5 R + \beta_6 \rho_c^2 + \beta_7 \rho_w^2 + \beta_8 N^2 + \beta_9 W : R + \beta_{10} N : W + \beta_{11} \rho_w : W$

Residuals of the models fitted to the greenhouse data set were shown to be normal after square root transformation of the dependent variable, thus the least squares method (LS) to determine goodness-of-fit, as opposed to Fisher's maximum likelihood method (ML), was used. Residual standard errors ($\hat{\sigma}$), as well as the AIC and BIC statistics were used for comparing these non-nested models (Burnham and Anderson 1998). BIC for each model were calculated in addition to AIC because it penalizes over-fitting (e.g. using more model parameters) more severely. Given the large number of observations, however, conclusions made from AIC and BIC statistics were in agreement. AIC was used instead of AIC_c because of our large sample size (Burnham and Anderson 1998).

Information complexity (ICOMP) was included in our analysis because it combines goodness-of-fit (i.e. minus twice the maximum log likelihood) with a measure of complexity that is different from AIC and BIC by penalizing for high correlations among parameter estimates (Bozdogan 2000). Thus, model selection was based on low parameter redundancy and high stability. Like AIC and AIC weights (i.e. $\Delta AIC_i = AIC_{\min} - AIC_i$), a model with minimum ICOMP is chosen as the best-fitting model among competing models (Bozdogan 2000). Only ΔAIC values are reported here because ICOMP values and BIC values were in agreement with AIC values.

Results

Standardized regression analysis

Water level was consistently the most influential variable across all standardized regressions, whether the dependent variable was wheat biomass, wild oat biomass, or

individual center wheat plant biomass, was that. Model A (Table 3.2) shows the resulting best-fit regression equations when data from all three replicates were combined.

Table 3.2. Two best-fit standardized regression models with different dependent variables.

Regression model A		Regression model B	
Dependent variable	Independent variables	Dependent variable	Independent variables
<i>total wheat biomass</i>	$= 0.78$ $+ 0.29 \text{ water}$ $- 0.18 \text{ oat density}$ $+ 0.17 \text{ wheat density}$ $+ 0.001 \text{ herbicide}^*$ $+ 0.0009 \text{ nitrogen}^*$ $+ 0.04 \text{ oat density}^2$ $- 0.04 \text{ wheat density}^2$ $- 0.03 \text{ nitrogen}^2$ $+ 0.03 \text{ water:herbicide}$ $- 0.02 \text{ water:nitrogen}$ $n = 1244$ $AIC=98$ $R^2 = 0.64$	<i>center wheat biomass</i>	$= 0.50$ $+ 0.22 \text{ water}$ $- 0.16 \text{ oat biomass}$ $- 0.11 \text{ non-ctr wheat biomass}$ $+ 0.02 \text{ nitrogen}$ $+ 0.01 \text{ herbicide}^*$ $+ 0.04 \text{ water}^2$ $+ 0.02 \text{ oat biomass}^2$ $- 0.02 \text{ nitrogen}^2$ $- 0.03 \text{ water:oat biomass}$ $- 0.02 \text{ water:non-ctr wheat biomass}$ $- 0.02 \text{ herb: non-ctr wheat biomass}$ $n = 431$ $AIC=14$ $R^2 = 0.52$

* The dependent variable of regression model A was total wheat biomass (per pot) while the dependent variable of model 2 was the biomass of the target wheat plant (per pot). Variables were ordered according to their influence on the dependent variable. Model A used the independent variables wheat and wild oat density, while regression model B used wheat and wild oat biomass. “Water” refers to total water applied throughout the growing period; “nitrogen” and “herbicide” refers to their respective rates. “Non-ctr wheat biomass” in model B was the biomass of the wheat plants in the pot that are not the target wheat plants. All variables were significant at the 0.05 level unless denoted with an *. Main effects denoted with * were included because their interactions and/or squared terms were significant. The number of observations (n) used in model B is only 431 because target wheat biomass was only measured in replication 3.

A second result of the standardized regression analysis was that wild oat density in model A and wild oat biomass in regression model B (Table 3.2) was the second-most influential variable on wheat biomass (i.e. yield). Wheat density/biomass closely followed wild oat density/biomass as the third most influential variable on wheat

biomass. Thus, influences of the crop and weed densities/biomass illustrate the importance of crop seeding rate, crop density, and weed infestation level on yield. Surprisingly, herbicide and nitrogen were much less influential on wheat biomass in this experiment, as given by the small size of their coefficients in comparison to the size of the coefficients associated with the three most influential variables. As nitrogen and water both increased the growth of the crop and weed, the positive affects of nitrogen and water on wheat biomass, the dependent variable, may be negated by increasing wild oat biomass on the right hand side of the equation. Similarly as herbicide level increased, herbicide injury to the crop increased, which could decrease the magnitude of herbicide rate's positive coefficient on the right hand side of the equation.

Wheat density has a strong positive influence on wheat biomass, the dependent variable, as shown by regression model A. Similarly, Radford et al. (1980), Martin et al. (1987), and Barton et al. (1992) concluded that wheat seeding rate influenced wheat's competitive ability against wild oat. Furthermore, increased net returns and increased wild oat control can be obtained by increasing the crop-seeding rate (Radford et al. 1980, Barton et al. 1992). With the target wheat plant biomass as the dependent variable, regression model B revealed intra-specific competition between wheat plants given the negative sign of the coefficient for the biomass of the neighbor wheat plants.

While increased wheat density increased yield to an asymptotic level, regression models A and B both reveal that wild oat biomass/density was slightly more influential on total wheat biomass than wheat density. This result is in agreement with studies by Martin and Field (1988) who concluded that when wheat and wild oat are sown simultaneously, wild oat was more competitive due to its greater root competitive ability.

Likewise Pavlychenko and Harrington (1935) reported that wild oat eventually grew a root area four times greater than wheat.

When squared and cubed main effects were added to the regression model there was evidence of saturation at high wheat density (model A, Table 3.2), high wild oat biomass (models A and B, Table 3.2), and high nitrogen rates (models A and B, Table 3.2). Non-linearity of biomass response in wheat–wild oat competition experiments, were also found by Bell and Nalewaja (1968), Carlson et al. (1982), Wilson and Peters (1982), and O'Donovan et al. (1985). Cubed main effects and inverses of main effects were explored for thoroughness, but unsurprisingly, were not significant in the models.

Regression model A agreed with previous studies that have found significant interaction between water and nitrogen. Low available soil water and excess nitrogen will result in low wheat yields, albeit high protein concentration in grain (Neidig and Snyder 1924, Campbell et al. 1993, Engel et al. 2001). Henry et al. (1971) explained that under drought conditions nitrogen fertilization usually has little effect on yield. The relative importance of nitrogen, as compared to the interaction of water and nitrogen, regression model A also agrees with the following statement: “the relative importance of the water factor and the nitrogen factor will vary from study to study, depending on the degree of stress imposed by the individual factors. However, when these two factors are varied over any appreciable range, the contribution of the interaction factor is as large or larger than the effects on the individual variables” (Henry et al. 1971). Regression model A showed the positive interaction between herbicide and water on wheat biomass, which supported the finding that herbicide efficacy depends on soil moisture. Furthermore, low

soil water conditions can result in ineffective herbicide applications and in some cases injury of the crop (Grundy et al. 1996).

We separately investigated regression models for those data points in the high-water treatment level given the knowledge that herbicides and fertilizers perform more efficiently with sufficient water (Neidig and Snyder 1924, Campbell et al. 1993, Henry et al. 1971, Grundy et al. 1996, Engel et al. 2001). The high-water treatment regression models looked very similar to models A and B of Table 3.2 with water level, wheat density, and wild oat biomass highly influential on wheat yield (see Appendix B).

Scatter plot analysis

While standardized regression analysis was important to reveal the magnitude of influence each variable had on wheat biomass, scatter plot analysis visually revealed trends. Overall, a large amount of variance was revealed in the scatter plots than was expected from the data obtained in controlled environment experiments. Figure 3.2 shows two-way plots of wheat biomass vs. wild oat biomass; each nitrogen rate was graphed separately so that trends were more clearly visible. While the scatter of yield versus wild oat biomass points look similar when nitrogen was increased from 0 kg ha⁻¹ to 22.5 and 45 kg ha⁻¹¹, there was an evident decrease in wheat biomass points and an increase in higher wild oat biomass points (see points beyond 300 g m⁻²)² as nitrogen was increased to 90 kg ha⁻¹.

¹ These nitrogen rates were scaled to the surface area of our pot.

² Wheat biomass was measured in g pot⁻¹ but was converted to g m⁻².

The scatter plots of wheat biomass versus wild oat biomass grouped by herbicide rate show little difference at the 0x, 0.5x, and 0.75x rate (Figure 3.3 A-C). At the 0x, 0.5x, and 0.75x rates, wheat biomass reaches or nearly reaches 500 g m^{-2} . At the full herbicide rate (i.e. 1x the label rate) the wild oat biomass points were more concentrated in the lower left corner of the graph with the highest wheat biomass value not reaching 400 g m^{-2} ; thus, a more definite decrease in wild oat biomass is shown with some injury to the crop (Figure 3.3D). Figure 3.3 may show a slight advantage for reduced herbicide rates, where more wild oat biomass points were concentrated in the lower left corner of the 0.75x rate graph as compared to the graph of the 0.5x label rate.

The effects of varying nitrogen and herbicide rates on wheat biomass in combination with the three levels of water were investigated (Figures 3.4 and 3.5). Nitrogen rate increased wheat biomass at the highest water level, albeit with large variance (Figure 3.4). There was not much difference of wheat biomass across nitrogen rates as water was increased from low to medium levels (Figures 3.4A and B). Herbicide was most effective at increasing wheat yield at the highest water level (Figure 3.5). Again, much variance is shown.

While water was shown to have the most influence on wheat biomass, (Table 3.2), water has a large positive influence on wild oat biomass (Figure 2.6). Furthermore, water increased rather than decreased variance when added to the system. Another way of examining data scatter was plotting wheat biomass versus amount of water applied, grouped by level of wild oat infestation (Figure 3.7). At low and medium levels of wild oat infestation, water increased wheat biomass in a similar way (Figure 3.7A and B). At the highest level of wild oat infestation (Figure 3.7C), the slope of the scatter decreased

in steepness, revealing that at this density the effects of increased water on wheat yield was weak.

Overall higher levels of water did not necessarily decrease variance in the system, but rather, increased it as occurred with increased levels of fertilizer. It could be argued that the effects of herbicide were different from the effects of water and nitrogen as inputs. For example, the variance of data points seemed to decrease when herbicide level was increased. Perhaps this was due to the fact that herbicide was the one variable of the three inputs that harms wild oat plants, while water and fertilizer help yield as well as increasing the biomass of wild oat plants. This complexity illustrates why site-specific management of inputs and their interactions remains a challenge to develop. What was good for the crop was also good for the weed (e.g. nitrogen and water to a point), and what harmed the weed also harmed the crop (e.g. herbicide at high rates).

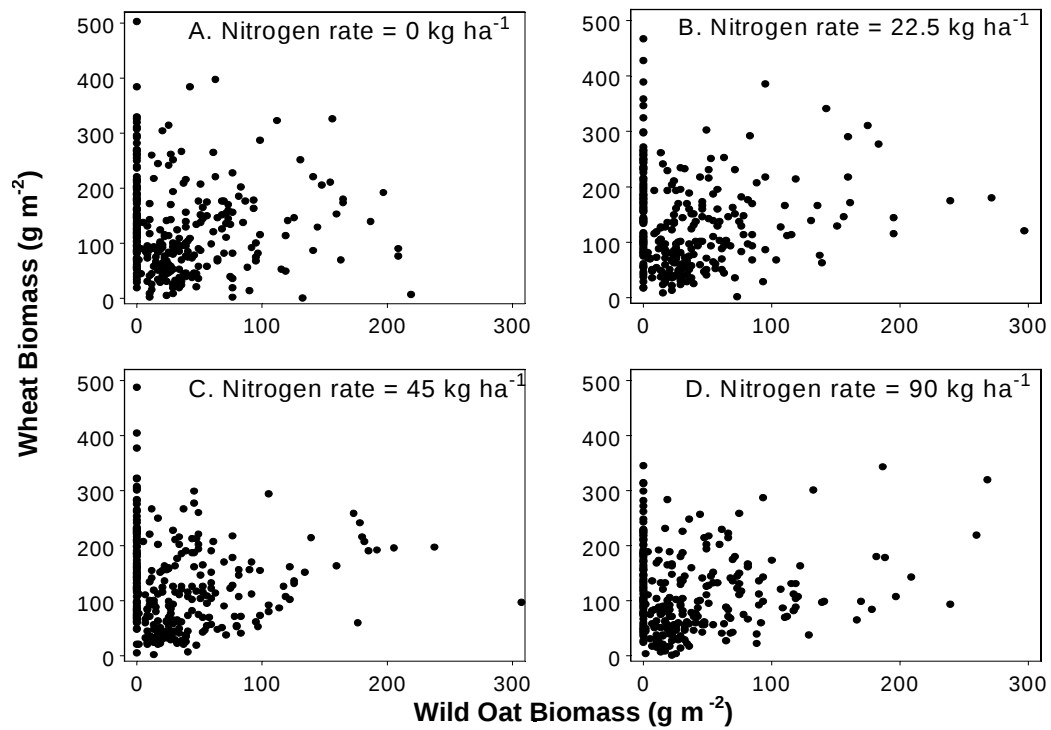


Figure 3.2. Wheat biomass versus wild oat biomass at one of the four levels of nitrogen rates applied—0, 22.5, 45, and 90 kg N ha⁻¹.

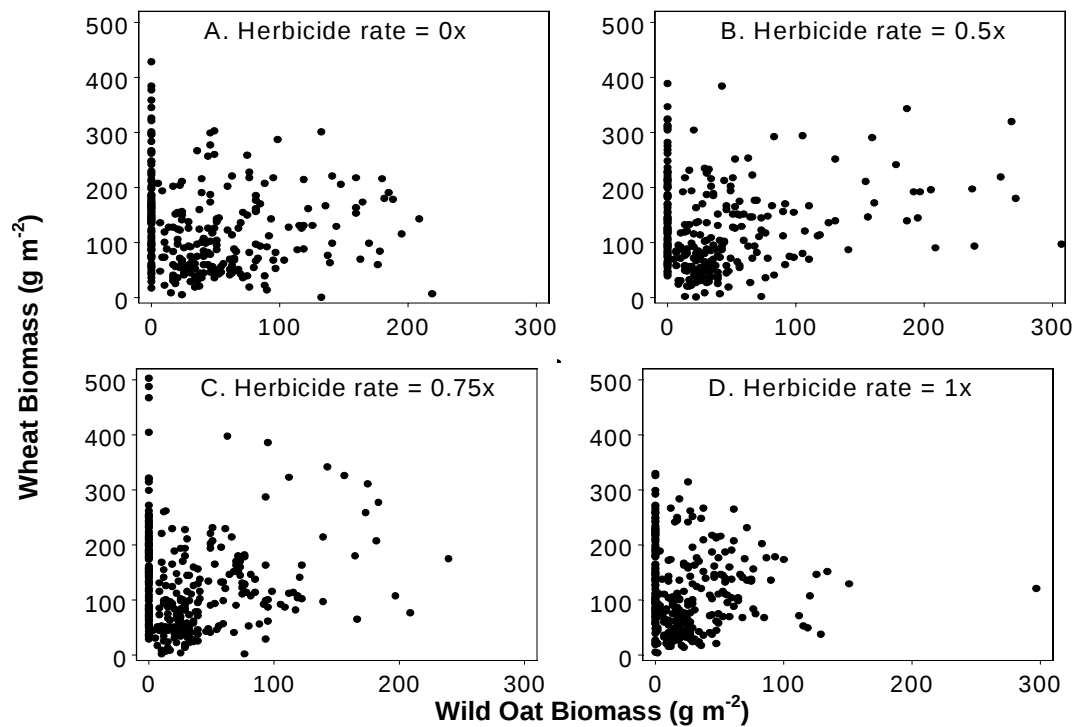


Figure 3.3. Wheat biomass versus wild oat biomass at one of the four levels of herbicide rates applied—0×, 0.5×, 0.75×, and 1× the label rate of imazamethabenz.

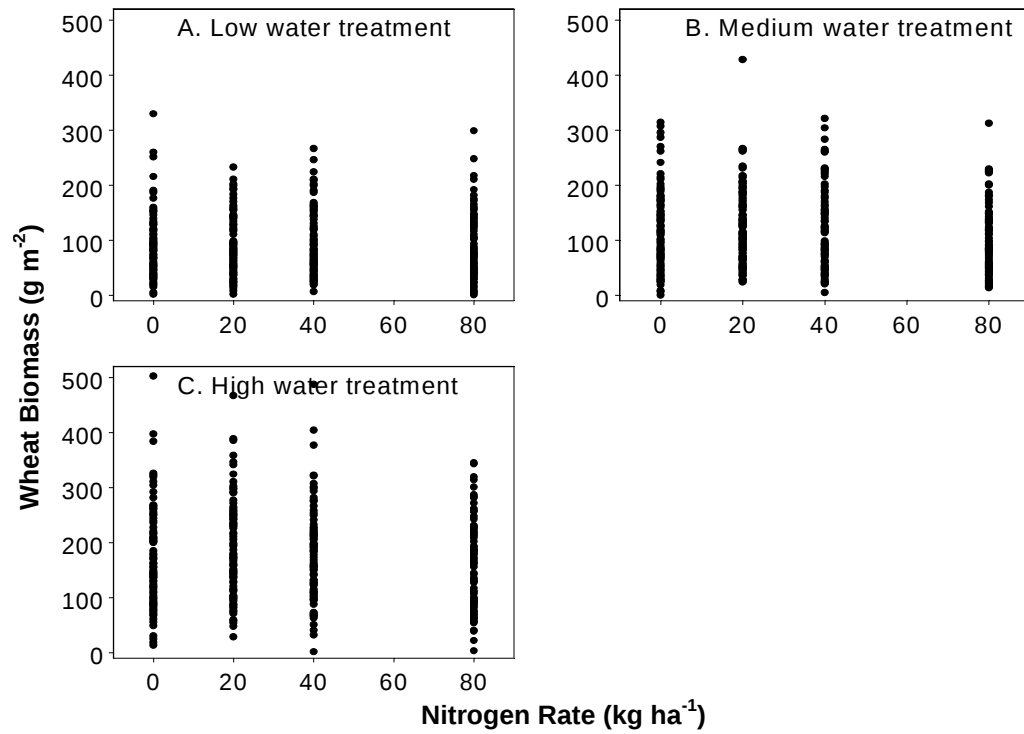


Figure 3.4. Wheat biomass versus nitrogen rate at each water level applied during the growing period.

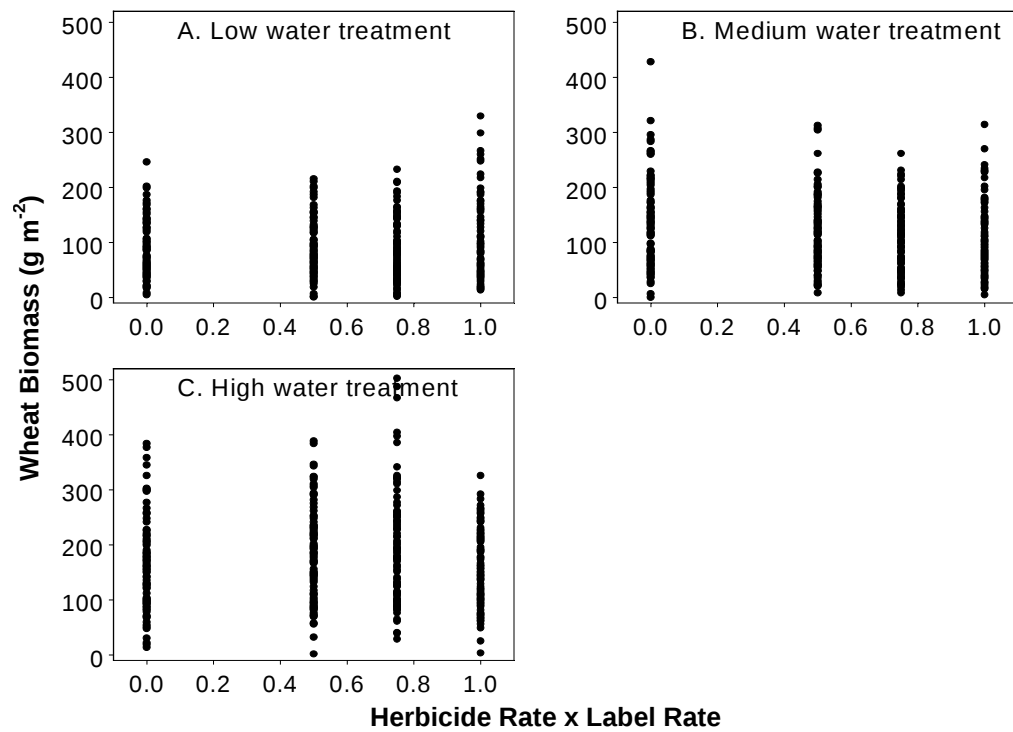


Figure 3.5. Wheat biomass versus herbicide rate at each water level applied during the growing period.

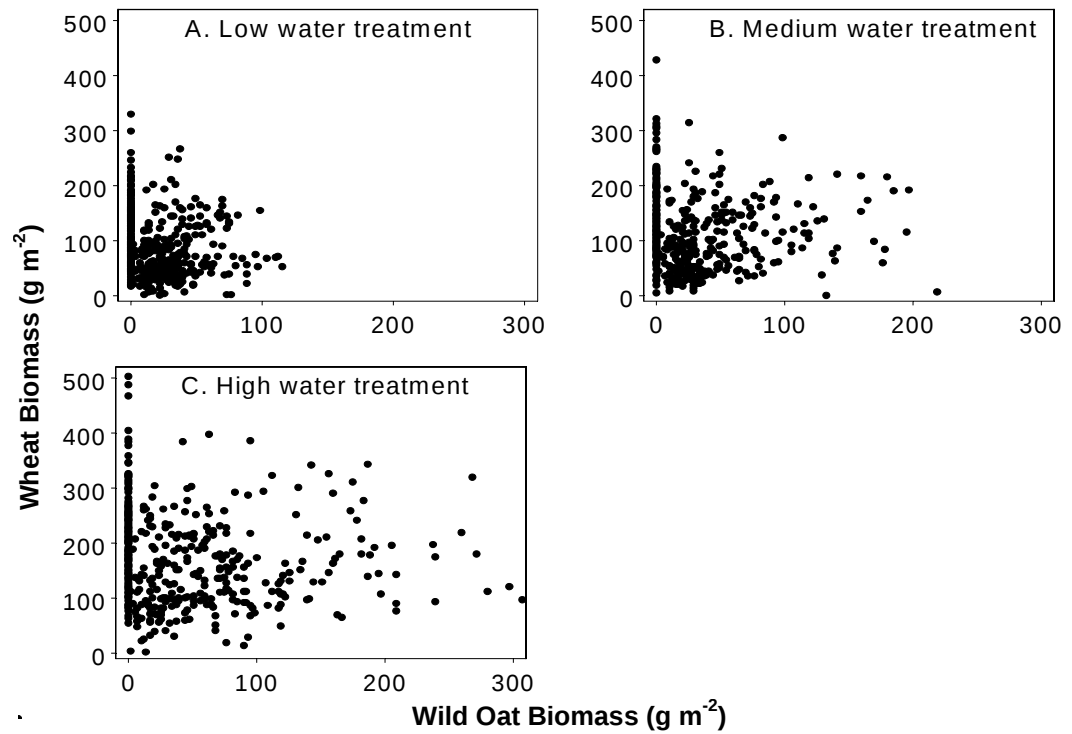


Figure 3.6. Each plot shows wheat biomass versus wild oat biomass at one of the three water levels applied during the growing period.

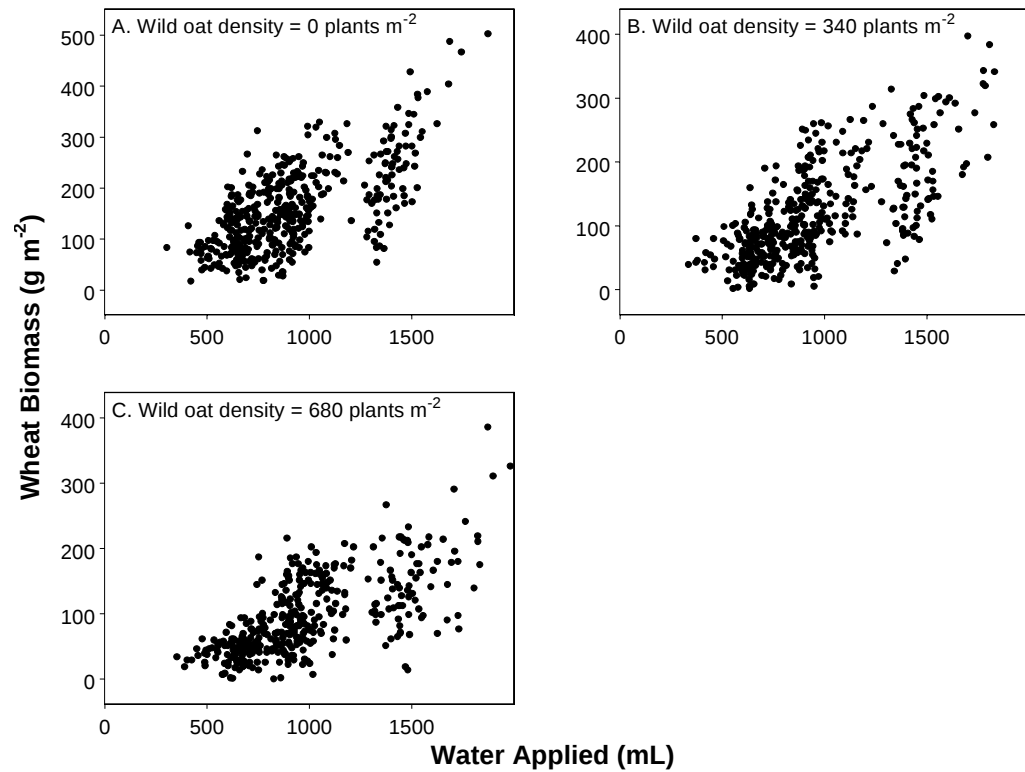


Figure 3.7. Wheat biomass versus water applied during the growing period at each level of weed infestation.

Model selection

Regression and scatter plot analysis were conducted on data from the 5-variable greenhouse experiment to elucidate the underlying biological mechanisms of wheat-wild oat competition with varying combinatorial levels of resources. We chose four previously developed models yield for biomass prediction (Table 3.3) based on their goodness-of-fit to our greenhouse data. All three replications of the greenhouse experiment were combined into a single data set to which the 7 models were fit³.

Model 5a did not reach convergence when herbicide was added to the model via the herbicide dose response equation. Therefore, $\alpha_{\min} + \frac{\alpha_{\max} - \alpha_{\min}}{1 + e^{B(R - R_{50})}}$ was reduced to α for convergence, and the total number of estimable parameters became 7. Models 5a, 5b, and 6 (Table 3.3) include the transformations for water, nitrogen, and herbicide (e.g. $\sqrt{W}$, $\sqrt{N}$, and $\sqrt{H}$) found to provide the best-fit and biological reality. The nitrogen:water and herbicide:water interaction terms in Model 5a, 5b, and 6 are left without being square-root transformed because such a transformation provided a worse fit (i.e. higher AIC, BIC, and ICOMP values and lower R^2 values).

³ After investigating each replication individually, no unusual patterns between replications were revealed (see Appendix A). Additionally, standardized regressions of yield on the other five variables for each replication revealed very similar results. Thus, all three replications were combined into one data set

Table 3.3. Models fitted to the combined data set. Models 5a, 5b, and 6 have been revised to include the transformations for water and nitrogen (e.g. $\sqrt{W}$ and $\sqrt{N}$) found to provide the best fit. The herbicide-dose function within Model 5a has been reduced to the parameter α for convergence.

Model	no. of estimable parameters
1 $y = y_{wf} \left(1 - \frac{\iota \rho_w}{1 + \iota \rho_w / \alpha} \right)$	3
2 $y = \frac{r \rho_c}{1 + b \rho_c + f \rho_w}$	3
3 $y = \frac{y_{wf}}{\frac{1 + \beta_{R_0} \rho_{w_0}}{1 + \left(\frac{R}{e^{R_{50}}} \right)^B}}$	3
4 $y = \left(\frac{\varphi \rho_c}{1 + \varphi \rho_c / y_{\max}} \right) \left(1 - \frac{\iota \rho_w}{1 + \iota \rho_w / \alpha} \right)$	4
5a $y = \left(\frac{\varphi \rho_c}{1 + \varphi \rho_c / (\beta_0 + \beta_1 \sqrt{W} + \beta_2 \sqrt{N} + \beta_{12} W * N)} \right) \left(1 - \frac{\iota \rho_w}{1 + \iota \rho_w / \alpha} \right)$	7
5b $y = \left(\frac{\varphi \rho_c}{1 + \varphi \rho_c / (\beta_0 + \beta_1 \sqrt{W} + \beta_2 \sqrt{N} + \beta_{12} W * N)} \right) \left(1 - \frac{\iota \rho_w}{1 + \iota \rho_w / (\beta_{00} + \beta_1' \sqrt{W} + \beta_3' \sqrt{H} + \beta_{13}' W * H)} \right)$	10
6 $y = \frac{\varphi \rho_c}{1 + \left(\frac{\varphi \rho_c}{(\beta_0 + \beta_1 \sqrt{W} + \beta_2 \sqrt{N} + \beta_3 \sqrt{H})} \right) + \left(\frac{\iota \rho_w}{1 + \iota \rho_w / (\beta_{00} + \beta_1' \sqrt{W} + \beta_2' \sqrt{N} + \beta_3' \sqrt{H})} \right)}$	9
7 $y = \beta_0 + \beta_1 W + \beta_2 \rho_w + \beta_3 \rho_c + \beta_4 N + \beta_5 R + \beta_6 \rho_c^2 + \beta_7 \rho_w^2 + \beta_8 N^2 + \beta_9 N : W + \beta_{10} W : R + \beta_{11} \rho_w : W$	12

Table 3.4. Summary of model-selection statistics (n=1244). “*” indicate parameters whose estimates were set at the indicated value to allow convergence. MSE is mean squared error (i.e. residual standard error).

Model	Parameter Values			ΔAIC	R^2	MSE ($\hat{\sigma}$)
	Fitted parameters	Estimates	p- values			
1	τ :	0.0007	0.0009	1161	0.117	0.256
	α :	0.48	0.0032			
	y_{wf} :	0.94	<.0001			
2	r :	0.013	<.0001	871	0.306	0.227
	b :	0.011	<.0001			
	f :	0.002	<.0001			
3	β_{R0} :	0.0005	<.0001	1513	0.0	0.295
	y_{wf} :	0.65	<.0001			
	B :	0.9*				
4	τ :	0.006	<.0001	876	0.305	0.228
	φ :	0.010	<.0001			
	α :	0.52	0.0035			
	y_{wf} :	1.35	<.0001			
5a	τ :	0.001	0.0153	14	0.651	0.161
	φ :	0.009	<.0001			
	β_0 :	-0.37	<.0001			
	β_1 :	0.06	<.0001			
	β_2 :	0.015	0.0041			
	β_{12} :	-0.0000	0.0014			
	α :	0.68	0.0020			
5b	τ :	0.001	0.0106	15	0.652	0.161
	φ :	0.009	<.0001			
	β_0 :	-0.24	0.5834			
	β_1 :	0.05	<.0001			
	β_2 :	0.0008	0.8555			
	β_{12} :	-0.0002	0.0035			
	β_{00} :	0.96	0.0007			
	$\beta_{1'}$:	-0.013	0.0231			
	$\beta_{3'}$:	-0.053	0.1835			
	$\beta_{13'}$:	0.0004	0.0150			

Table 3.4 continued...

Table 3.4. (continued)

Model	Parameter Values			ΔAIC	R²	MSE ($\hat{\sigma}$)
	Fitted parameters	Estimates	p- values			
6	ι :	0.005	<.0001	0	0.656	0.160
	ϕ :	1.07	<.0001			
	β_0 :	-29.3	<.0001			
	β_1 :	3.26	<.0001			
	β_2 :	0.096	0.5419			
	β_3 :	-2.67	0.0754			
	β_{00} :	12.2	0.0191			
	β_1' :	-0.182	0.0322			
	β_2' :	0.147	0.1021			
	β_3' :	-4.02	0.1034			
7	β_0	0.056	0.2365	57	0.651	0.168
	$\beta_1(\text{water})$	0.0005	<.0001			
	$\beta_2(\text{oat})$	-0.0005	<.0001			
	$\beta_3(\text{wht})$	0.002	<.0001			
	$\beta_4(\text{nitro})$	0.002	0.0005			
	$\beta_5(\text{herb})$	-0.100	0.0241			
	$\beta_6(\text{wht}^2)$	-0.0000	<.0001			
	$\beta_7(\text{oat}^2)$	0.0000	0.0001			
	$\beta_8(\text{nitro}^2)$	-0.0000	0.0033			
	$\beta_9(\text{nitro:water})$	0.0002	0.0003			
	$\beta_{10}(\text{herb:water})$	-0.001	0.0053			
	$\beta_{11}(\text{oat:water})$	-0.0000	0.0100			

As revealed by its lowest Δ AIC and mean squared error ($\hat{\sigma}$) values, and highest R² value, the best-fitting model is Model 6 (Table 3.4). Model 6 includes available water and nitrogen effects on wheat biomass, and water and herbicide effects on wild oat biomass. Models 5a, 5b, and 7 provide reasonable fits according to their Δ AIC, MSE, and R² values. Model 5a and 5b have the second lowest Δ AIC and MSE values. Models 5 - 7 fit the data similarly well, and are strikingly better fits of the data than Models 1 – 4 (Figure 3.8). A relatively low amount of variance is shown in the predicted versus fitted yield scatter plots of Models 5-7 (Figure 3.8 E-H).

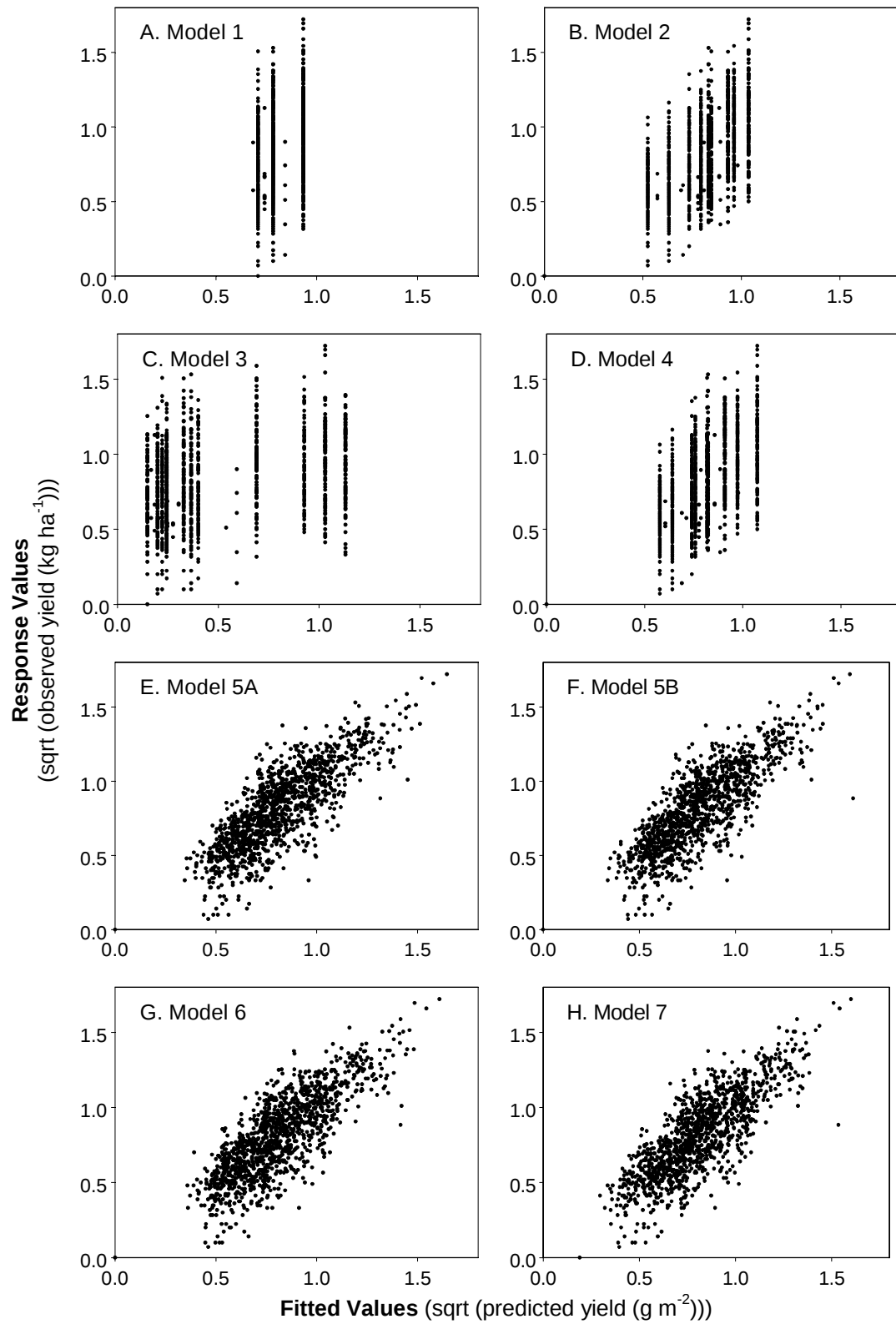


Figure 3.8. Scatter plots showing goodness-of-fit for each model.

Discussion

The main contribution of this work was to identify a first principles model that includes the agronomic variables that can be controlled with management (crop seeding rate, nitrogen rate, herbicide rate) and a set of variables that naturally cause variation (weed density, water level) in crop yield. Identification of such a model is crucial in the development of a decision support system for optimizing major inputs for wheat production. The predicted versus observed yield values scatter plots reveal a major advance in the accuracy of yield prediction modeling through the use of five-variable empirical model (Figure 3.8E – H) over historically used empirical models (Figure 3.8A – D). As illustrated in Figure 3.8, three models performed considerably better than the other four and elucidated underlying biological mechanisms. Specifically, the two best fitting models, Models 5b and 6:

- estimate the initial rate of yield increase as crop density increased from 0 (by the parameter ϕ)
- estimate the initial rate of yield loss as weed density increases from 0 (by the parameter ι)
- imply asymptotic behavior of yield versus wheat density and yield versus wild oat density
- show that water, nitrogen, and herbicide significantly affect crop density (Model 5b only shows water and nitrogen to significantly affect wheat density)
- show that water, nitrogen, and herbicide affect weed density (Model 5b only shows water and nitrogen to significantly affect wild oat density)

- show interactions between nitrogen and water and herbicide and water (Models 5a and 5b only)
- indicate nitrogen, herbicide, and water have nonlinear effects on wheat yield by their square root transformations.

Furthermore, this greenhouse experiment has allowed the questions asked in Chapter 2 to be addressed. Following are the questions and responses based on the greenhouse experiment results and subsequent model fitting.

- How do wheat and wild oat plants compete with varying water, nitrogen, and herbicide treatments in combination?

According to the parameter estimates derived from the fit of Model 6 to the greenhouse experiment, wheat appears to out-compete wild oat for water. Alternative possible explanations are that wild oat is more susceptible to drought than wheat, or wheat's growth is more positively influenced by water than wild oat growth. Nitrogen has a positive effect on wheat and wild oat density, but has a slightly large positive effect on the wild oat plants, indicating that wild oat out-competes wheat for nitrogen across water and herbicide treatments. Herbicide has a negative effect on both wild oat and wheat across all nitrogen and water levels, but its negative effect on wild oat is nearly two times as great in magnitude.

- Do the two-way interactions of nitrogen and water and herbicide and water play a large enough role to be included in a nonlinear prediction model?

While the literature supports such interactions, specifically between nitrogen and water (Henry et al. 1971, Campbell et al. 1993, Engel et al. 2001) and herbicide and water (Grundy et al. 1996), they are not supported by Model 6's fit the greenhouse data. Model

5b's fit to the greenhouse data does support the inclusion of these interactions.

Observably, further investigation is warranted to decipher this disagreement in results.

- Does crop injury due to herbicide at high rates have a large enough influence on yield that it should be included in the model?

Crop injury has been shown to have a significant influence on yield prediction by fitting Models 6 and 7 to the greenhouse data. This result indicates additional inference from the greenhouse data set over the independently collected field data.

- Why is nitrogen's influence on wild oat density in the nonlinear prediction models (Models 5 and 6) not supported by the combined field data although this effect has been presented in the literature?

While the independently combined field data does not show nitrogen's influence on wild oat density to be significant, fitting Models 5 –7 to the greenhouse data reveals that nitrogen does have significant influence on wild oat density. Thus, the greenhouse data results support past literature results and reveals additional inference over the combined field data. Additionally, this result reveals the value in further experimentation in the greenhouse where all five variables can be measured in combination. None of the field data sets include all five variables measured at least three levels in combination, thus limiting inference.

- Could adequate support for including the nonlinear influences of nitrogen, water, and herbicide in the wheat-wild oat model exist given a five-variable experiment with sufficient treatment levels and replication?

Through the two regression components of Model 6 (e.g. $(\beta_0 + \beta_1\sqrt{W} + \beta_2\sqrt{N} + \beta_3\sqrt{H})$ and $(\beta_{00} + \beta_1'\sqrt{W} + \beta_2'\sqrt{N} + \beta_3'\sqrt{H})$) fit to the greenhouse data, there is evidence of improved fit using square root transformations. The square root transformation implies nonlinearity of the effects these three predictor variables have on yield. Model 5a implies that the nonlinear effects of herbicide on wild oat density via the herbicide dose curve (Streibig et al.1993) was not shown to be significant. Given that only four herbicide rates were included our experiment, however, the sigmoidal dose-response curve would be reasonably difficult to fit. For such a curve to be fit, at least 6 rates would be needed. α , however, was fit and we propose the effects of herbicide lie within this parameter estimate.

- Will net returns be improved using site-specific recommendations from the best fitting model using the parameter estimates calculated from the combined data set?

To determine possible improvement of net return using site-specific recommendations as output by the best-fitting model, we propose that Model 6, the best fitting model of the candidate set of models, be used for optimization of localized nitrogen and herbicide rates. Optimization of inputs throughout a field is possible using early season wheat and wild oat seedling densities and localized soil moisture values as input values to explore how well the model and parameter estimates output localized variable rate management strategies. Such a demonstration would reveal the direction for further research in this area, specifically involving the execution of on-farm and on-agricultural experiment station studies.

In summary, the goodness-of-fits illustrated in Models 5 – 7 reveal sizeable potential for the advancement of localized variable rate input management using precision agriculture technologies via a decision support system. The goodness-of-fits also demonstrate, despite their large expense, the value in large-variable number factorial experiments. We propose that Model 6, the best fitting model of the candidate set of models, be used for optimization of localized nitrogen and herbicide rates using parameter estimates obtained from the greenhouse study and the independently collected field data. Such a demonstration would reveal the value in using Model 6 for yield prediction and the development of site-specific management strategies.

Additionally, future research should include the investigation into other possible predictor variables. For example, early season measurements of residual soil nitrogen and soil moisture are critical to the influences of nitrogen, herbicide, and growing season precipitation on yield, and should be investigated for inclusion into the nitrogen and water variables. In addition, the execution of a field experiment, in the form of on-farm experimentation, is necessary as a follow-up to the greenhouse experiments. Future large-scale plot and/or on-farm measurements will be useful for assessment of parameter stability, parameter probability distributions, and site-specific constraints of parameter estimations in the quest for optimization of agronomic inputs.

References Cited

- Baeumer, K., and C.T. DeWit. 1968. Competitive interference of plant species in monocultures and mixed stands. *Netherlands Journal of Agricultural Science* 16:103-122.
- Barton, D.L., D.C. Thill, and B. Shafii. 1992. Integrated wild oat management affects spring barley yield and economics. *Weed Technology* 6:129-135.
- Bell, A.R., and J.D. Nalewaja. 1968. Competition of wild oat in wheat and barley. *Weed Science* 16:505-508.
- Bozdogan, H. 2000. Akaike's Information Criteria and recent developments in Information Complexity. *Journal of Mathematical Psychology* 44:62-91.
- Brown, D., and P. Rothery. 1993. *Models in Biology: mathematics, statistics and computing* John Willey and Sons, Chichester.
- Burnham, K.P., and D.R. Anderson. 1998. *Model Selection and Inference: a practical information-theoretic approach* Springer-Verlag New York Inc., New York.
- Campbell, C.A., R.P. Zentner, F. Selles, B.G. McConkey, and F.B. Dyck. 1993. Nitrogen management for spring wheat grown annually on zero-tillage: yields and nitrogen use efficiency. *Agronomy Journal* 85:107-114.
- Carlson, H., J. Hill, K. Baghott. 1982. Wild oat competition in spring wheat. 33rd Annual Californian Weed Conference.
- Cousens, R. 1985b. A simple model relating yield loss to weed density. *Annals of Applied Biology* 107:239-252.
- Cousens, R., and M. Mortimer. 1995. *Dynamics of Weed Populations* Cambridge University Press, Cambridge.
- Engel, R., D. Long, and G. Carlson. 2001. Nitrogen requirement and yield potential of spring wheat as affected by water. MSU Extension Service Agricultural Experiment Station.
- Freckleton, R.P., and A.R. Watkinson. 2001. Nonmanipulative determination of plant community dynamics. *TRENDS in Ecology and Evolution* 16:301-307.
- Grundy, A.C., N.D. Boatman, and R.J. Foud-Williams. 1996. Effects of herbicide and nitrogen fertilizer application on grain yield and quality of wheat and barley. *Journal of Agricultural Science* 126:379-385.

- Henry, J. L. 1971. The effect of soil zone, available soil nitrogen level and nitrogen fertilization on the yield and quality of stubble seeded cereal grains. Soil Fertility Workshop, Ext. Div., University of Saskatchewan.
- Jasieniuk, M., B.D. Maxwell, R.L. Anderson, J.O. Evans, D.J. Lyon, S.D. Miller, D.W. Morishita, A.G. Ogg, and S.S. Seefeldt. 2000. Evaluation of models predicting winter *Triticum aestivum* yield as a function of *Triticum aestivum* and *Aegilops* cylindrical densities. *Weed Science* 49:48-60.
- Jolliffe, P.A., A.N. Minjas, and V.C. Runeckles. 1984. A reinterpretation of yield relationships in replacement series experiments. *Journal of Applied Ecology* 21:227-243.
- Kim, D.S., P. Brain, E.J.P. Marshall, and J.C. Caseley. 2002. Modelling herbicide dose and weed density effects on crop:weed competition. *Weed Research* 42:1-13.
- Martin, R.J., B.R. Cullis, and D.W. McNamara. 1987. Prediction of wheat yield loss due to competition by wild oats. *Journal of Agricultural Research* 38:487-499.
- Martin, M.P.L.D., and R.J. Field. 1988. Influence of time of emergence of wild oat on competition with wheat. *Weed Research* 28:111-116.
- Neidig, R.E., and R.S. Snyder. 1924. The relation of moisture and available nitrogen to the yield and protein content of wheat. *Soil Science* 18:173-179.
- O'Donovan, J.T., E.A.d.S. Remy, P.A.O. Sullivan, D.A. Dew, and A.K. Sharma. 1985. Influence of the relative time of emergence of wild oat (*Avena fatua* L.) on yield loss of barley (*Hordeum vulgare*) and wheat (*Triticum aestivum*). *Weed Science* 33:498-503.
- Pavlychenko, T.K., and J.B. Harrington. 1935. Root development of weeds and crops in competition under dry farming. *Scientific Agric.* 16:151-160.
- Radford, B.J., B.J. Wilson, O. Carthedge, and F.B. Watkins. 1980. Effect of wheat seeding rate on wild oat competition. *Aust. Journal of Experimental Agriculture and Animal Husbandry* 20:77-81.
- Streibig, J.C., M. Rudemo, and J.E. Jensen. 1993. Dose-response curves and statistical models, *In* J. C. Streibig and P. Kudsk, eds. *Herbicide Bioassays*. CRC Press, Boca Raton.
- van Genuchten, M.T. 1980. A closed-form equation for predicting the hydraulic conductivity of unsaturated soils. *Soil Science American Journal* 44:892-898.
- Weiner, J. 1982. A neighborhood model of annual-plant interference. *Ecology* 63:1237-

1241.

- Wilson, B.J., and N.C.B. Peters. 1982. Some studies of competition between *Avena fatua* and spring barley. I. The influence of *Avena fatua* on yield of barley. *Weed Research* 22:143-148.
- Wraith, J.M., J.M. Baker, and T.K. Blake. 1995. Water uptake resumption following soil drought: a comparison among four barley genotypes. *Journal of Experimental Botany* 46:873-880.
- Wright, A.J. 1981. The analysis of yield-density relationships in binary mixtures using inverse polynomials. *Journal of Agricultural Science* 96:561-567.

CHAPTER 4

INCREASING NET RETURN USING A FIVE-VARIABLE WHEAT YIELD
PREDICTION MODEL FOR SITE-SPECIFIC MANAGEMENT OF FERTILIZER
AND HERBICIDE IN A VIRTUAL FIELDAbstract

Site-specific farming technologies enable the application of variable rates of inputs to specific areas within a field according to their localized fertilizer and herbicide requirements based on variability in crop response to these inputs across fields. The long-term goal of site-specific management is to increase net returns and environmental health by more efficient input management. We demonstrate the use of a first-principle five-variable empirical yield prediction model in a decision support framework for site-specific management (SSM). The variables included in our model are wheat density, wild oat density, nitrogen rate, herbicide rate, and early season soil moisture. Current year economic returns from variable rate, low input, and high input management scenarios were compared for economic efficiency in the decision support system. Monte Carlo simulation was used to produce net return prediction probabilities for site-specific variable-rate management, low level input management, and high level input management of nitrogen and herbicide based on two sources of parameter estimates. Using parameter estimates derived from greenhouse data, the variable rate scenario resulted in a 57% and 66% probability of larger net return values over the low and high input management scenarios, respectively. Using parameter estimates derived from disjoint field data, the variable rate scenario resulted in a 48% and 57% probability of

larger net return values over the low and high input management scenarios, respectively. Average whole field net return values were \$348, \$125, and \$94 per hectare for the variable rate, low input, and high input scenarios respectively for yield optimization using the greenhouse-derived data. Average whole field net return values were \$3115, \$636, and \$548 per hectare for the variable rate, low input, and high input scenarios respectively for yield optimization using the field-derived data.

Introduction

Since at least the 1920's agronomists have recognized the inherent variability in agricultural fields (Gotway-Crawford et al. 1997). The recognition of within field variability and the ability to map such variability exposes a large potential for agricultural input optimization (Gotway-Crawford et al. 1997). Specifically, increased expense of herbicides and fertilizers, environmental concerns, development of weed resistance to herbicides, and relatively low crop prices have led to research aspirations for more efficient use of herbicides and fertilizers (O'Donovan 1996).

Site-specific agriculture technologies may allow considerable economic and environmental benefits from variable rate application of herbicide and nitrogen fertilizer. However, while the machinery for variable rate application exists and is continually improving, an ecologically based blueprint for farming according to localized conditions remains to be developed in the USA. Inherent in the development of a ecological first-principle model for site-specific farming is discovering why different areas of a field do not have the same productivity or crop response to broadcast input levels (Gotway-

Crawford et al. 1997). Chapters 2 and 3 of this thesis have attempted to elucidate these ecological first principles, specifically addressing how wheat and wild oat compete for water and nitrogen, and how varying herbicide rates affect each plant's competitiveness in the presence of varying levels of water and fertilizer.

In the last decade many papers have described experiments undertaken to develop independent site-specific management strategies for nitrogen fertilizer or herbicide (Gerowitt and Heitefuss 1990, Schueller 1992, Nordbo et al. 1994, Brown and Steckler, 1995, Johnson et al. 1995, Christensen et al. 1996, Long et al. 1996, Snyder et al. 1996, Heisel et al. 1997, Williams et al. 1998, Gerhards et al. 1999, Heisel et al. 1999, Moore and Tyndale-Biscoe 1999, Peters et al. 1999, Schmerler et al. 1999). While the techniques of site-specific management have been tested at the whole farm level, most studies have focused on only a single process, such as soil or yield mapping, fertilizer application, herbicide application, or sowing rate as an influence on crop yield (Schmerler et al. 1999).

To determine site-specific and variable-rate applications of herbicide alone, several studies evaluated weed seedling populations before spraying (Heisel et al. 1997, Williams et al. 1998, Gerhards et al. 1999, Heisel et al. 1999). Specifically, by targeting a threshold of moderate to high weed infestation levels, several studies reported 30-70% reduction of herbicide use (Nordbo et al. 1994, Brown and Steckler 1995, Johnson et al. 1995, Christensen et al. 1996, Gerhards et al. 1999, Heisel et al. 1999) and increased profitability over prophylactic full-field herbicide application (Gerowitt and Heitefuss 1990). Heisel et al. (1999) took field experimentation a step further by determining variable rate herbicide management strategies using linear regression models within a

Decision Algorithm for Patch Spraying (DAPS). Input values into the algorithm included weed seedling densities at every measured point and expected mean yield of the field; herbicide rate was accordingly optimized (Heisel et al. 1999). Heisel et al. (1999) recommended that their DAPS could be improved by the inclusion of a parameter for crop competitiveness.

Studies to determine fertilizer application rates have been based on creating management zones and appropriate application rates based on soil properties, specifically based on soil grid sampling and/or aerial photographs indicating various levels of productivity for the development of site-specific variable-rate management of fertilizer (Long et al. 1996, Snyder et al. 1996, Fleming et al. 1999, Moore and Tyndale-Biscoe 1999). Another method was to estimate yield potential from historic yield data and wheat tiller density maps developed from airborne photographs taken immediately prior to nitrogen application (Welsh et al. 1999). Results from this method indicated that the greatest response to nitrogen occurred at the historically high yielding sections of the field. In addition, they found that less nitrogen should be applied to areas with lower crop tiller density and more nitrogen to areas with high tiller density (Welsh et al. 1999). Economic analyses of variable-rate nitrogen strategies were favorable, indicating a gross benefit of £2.58 to £31.75 ha⁻¹ (Peters et al. 1999).

A major weakness of the previously described models is that they have focused on a single process and did not include many of the factors known to cause yield variability nor the factors that farmers must consider when making crop and weed management decisions (Wilkerson et al. 2002). In contrast to the previously described studies and models, Schmerler et al. (1999) investigated site-specific nitrogen

application, sowing rate of winter wheat, and herbicide application in field trials in Germany. They reported that the value of SSM for fertilizer application and crop seeding rate to be in the range of 30 – 100 DM ha⁻¹, whereas the cost of SSM was approximately 49 DM ha⁻¹ (Schmerler et al. 1999). SSM of herbicide application revealed savings of 25 DM ha⁻¹ when weed mapping was relatively inexpensive. It was concluded that the cost/benefit ratios do not justify the investment in SSM (Schmerler et al. 1999). While Schmerler et al. had the same goal as is presented in our study—to site-specifically apply inputs—their method of making localized input decisions was significantly different from the method presented in this paper. Specifically, Schmerler et al. determined nitrogen and seeding rates based on tissue and soil analyses throughout their fields and aerial maps of soil texture. Unlike the model we have presented, it is unclear how Schmerler et al.'s management decisions have integrated the influences of crop seeding, nitrogen and herbicide rates on yield.

Like Schmerler et al. (1999), Moore and Tyndale-Biscoe (1999) used the CERES model to investigate the performance of a wheat crop over a range of weather types, nitrogen rates, and soil types. They found that the benefits of spatially managed nitrogen, when applied at the beginning of the season, was modest on average and the range of weather conditions had a much greater impact than nitrogen. These results agree with Schmerler et al. (1999), but contrast with improved net returns of \$25 - \$95 ha⁻¹ previously reported by Schueller (1992). In addition, they reported that a large portion of yield variability could be explained by differing soil moisture holding capacities of the different soil types.

Several site-specific variable-rate strategies and yield prediction models have been developed as referenced above; however, there are few cases where crop models within decision support systems have been used in site-specific variable-rate management of inputs on farms (Sadler and Russell 1997, Wilkerson et al. 2002). Sadler and Russell (1997) noted that limited application of such models/decision support systems was due to the lack of data on within-field variability in crop response. In addition, many models have not included the complex interactions between soil, weather, and inputs in determining crop growth for *accurate* site-specific variable-rate management prescriptions, let alone competition between the crop and weeds for resources. Another weakness of current models is that they are largely deterministic, i.e. they produce an average predicted yield value based on specific input values for the whole field (Sadler and Russell 1997). The development of stochastic models, however, will increasingly develop as input parameter values can be characterized and continually updated by parameter distributions based on long-term agricultural experiments.

While some studies have indicated considerable economic and environmental benefits from site-specific management (Schueller 1992, Nordbo et al. 1994, Brown and Steckler 1995, Johnson et al. 1995, Christensen et al. 1996, Gerhards et al. 1999, Heisel et al. 1999, Peters et al. 1999), others were more cautious (Moore and Tyndale-Biscoe 1999, Schmerler et al. 1999). These differences reveal the difficulty in assessing the true value of site-specific variable rate models/decision support systems until they can more *accurately* describe yield potential probabilities based on a complex array of variables and their interactions, including crop density, weed density, available water, predicted growing season moisture, soil properties, herbicide efficacy, fertilizer efficacy, and the

competition between crops and weeds for inputs. Producing such a model is the overall objective of this project.

Despite the lack of field data from a single experiment describing the variability of wheat yield based on all five variables (i.e. wheat and wild oat competition in the presence of varying levels of fertilizer, herbicide, and water), we demonstrate how an empirical five-variable crop yield model can be used in a decision support system. The future objective is that the model will be parameterized locally using site-specific technology-based experiments. It is the only empirical wheat prediction model known to the authors that can provide experimentally based suggestions for herbicide and fertilizer rates in the presence of wild oat competition.

An empirical modeling approach, incorporating statistical and experiential components, has been employed rather than a mechanistic (“scientific”) model for several reasons: 1) farmers need to make decisions at a specific time, e.g. within days of planting the crop, 2) empirical models are more practical for farmers to parameterize than process models, and 3) mechanistic models, as of present, have been shown to be weak predictors of wheat yield (Barnett et al. 1997). While mechanistic, or “process models”, are extremely valuable for investigating physiological and phenological processes, they generally are not as suitable for agricultural management purposes because they require many more parameters that require highly technical approaches to quantify. More parameter values require more data from which to derive them, and the increased number of parameters in a model typically adds bias and variability. For example, the well-studied mechanistic model CERES-wheat (Ritchie and Otter 1985), which includes plant and soil processes to understand wheat yield, consists of at least 25 parameters to be

estimated. INTERCOM, another well-known crop growth mechanistic model requires 19 parameter estimates (Lindquist 2000). Some of the parameters included in these models, for example, are leaf area index, accumulation of thermal units, absorption of photosynthetic photon flux, total solar radiation, number of tillers, crop nitrogen content, soil temperature, and mass per m² of soil area for leaves, stems, grains and roots, to name a few. How can a farmer or even a crop consultant possibly (and *accurately*) estimate all these parameters? What matters to a farmer needing to make annual decisions about fertilizer and herbicide rate is early season information such as crop seedling stand, weed seedling density, and soil water availability. What happens environmentally across the entire field after the inputs have been applied – a drought or a period of low thermal units, for example—does little to help a farmer make those once-a-year spring time decisions. While we could incorporate forecasted values such as growing season precipitation, average solar radiation, and expected temperatures into our model, the model would still remain empirical, describing overall pattern. In addition, a farmer would gradually build a temporal distribution of parameter values steadily increasing his/her ability to quantify the probability of any given response.

Thus, the objectives of our research were 1) to demonstrate how an empirical five-variable yield prediction model outputs optimal site-specific variable-rate strategies for spring-applied fertilizer and herbicide by maximizing net return which is based on the input values of early season wheat seedling density, wild oat density, and water availability, 2) to compare the current year economic returns from variable-rate, low-input, and high-input management scenarios, and 3) to use Monte Carlo simulation to produce net return probabilities for three scenarios: localized variable-rate management,

low level input management, and high level input management of nitrogen and herbicide.

Materials and Methods

The first step in producing site-specific management suggestions was the development of the yield prediction equation. The five-variable wheat yield prediction model was developed for use within a decision support framework and based on experiments measuring at least two of the five predictor variables: wheat density, wild oat density, nitrogen rate, herbicide rate, and available water. The functional form of the model includes the asymptotic increase of yield loss as wild oat density increases, the asymptotic increase of yield as crop density increases, the positive influence of water and nitrogen on maximum wheat yield, the positive effects of water and nitrogen on wild oat density, the negative influence of herbicide on wild oat density, and the potential for crop injury due to herbicide. The nonlinear model selected for demonstration produced the best fit to greenhouse data (Chapter 3) and nearly the best fit to the field data (Chapter 2) over a candidate set of models. Specifically, the mathematical form of the model was:

$$y = \frac{\phi \rho_c}{1 + \left(\frac{\phi \rho_c}{(\beta_0 + \beta_1 \sqrt{W} + \beta_2 \sqrt{N} + \beta_3 \sqrt{H})} \right)} + \left(\frac{\iota \rho_w}{1 + \iota \rho_w / (\beta_0 + \beta_1 \sqrt{W} + \beta_2 \sqrt{N} + \beta_3 \sqrt{H})} \right) \quad (4.1)$$

where ρ_c was crop density, ρ_w was weed density, ϕ estimates the initial rate of yield increase as crop density increases from zero, and ι estimates the initial rate of yield loss as weed density increases from zero. The β coefficients described water, fertilizer, and

herbicide effects on wheat and wild oat growth. β_0 and β_{00} were the intercept terms in the linear regression components within the larger model.

The effects of available water, nitrogen rate, and herbicide rate on crop growth were described through the parameters β_0 , β_1 , β_2 , and β_3 . Water and nitrogen were previously shown to have nonlinear effects on wheat growth (DeJong and Rennie 1967, Engel et al. 2001). While nonlinear effects of each of these variables on wheat biomass has been observed, the model assumes linear effects of these variables on yield through the water-nitrogen-herbicide regression equation i.e. $(\beta_0 + \beta_1\sqrt{W} + \beta_2\sqrt{N} + \beta_3\sqrt{H})$ within the larger model. Nonlinear terms were shown to be insignificant in the model fit to the data sets collected from a range of spring wheat producing areas of the world. Thus, parameter estimates for nonlinear terms were unavailable. Water, nitrogen, and herbicide influence was added to the hyperbolic empirical model by assuming that these inputs contribute to the maximum yield value in a field where there is little to no competition from weeds.

The second water-nitrogen-herbicide component

i.e. $(\beta_{00} + \beta_1'\sqrt{W} + \beta_2'\sqrt{N} + \beta_3'\sqrt{H})$ assumes that water, nitrogen, and herbicide affect weed growth additively through the parameters β_{00} , β_1' , β_2' , and β_3' . Nitrogen has been shown to increase wild oat growth (and competitiveness) slightly more rapidly than crop growth (DiTomaso 1985), and herbicide injures wild oat greatly more than wheat. Therefore, the parameters β_i' parallel the parameters β_i , such that β_1' described water's influence on wild oat whereas β_1 describes water's influence on wheat, where $i = 1, 2, 3$.

The nonlinear square root transformations of water, fertilizer, and herbicide on wild oat density were included in equation 4.1 due to the models fit to the collected field and greenhouse data sets (Chapters 2 and 3).

The second step in the development of a method for site-specific input recommendation was the estimation of all nine model parameters. Parameter values in this demonstration were used from two sources: independently collected field data and from greenhouse collected data. All nine model parameters were determined from model fitting to the greenhouse data set. When the model was fit to the independently collected field data sets, seven parameters were fit, while β_2' and β_3 were not fit due to lack of convergence. Therefore, values for these two parameters were obtained from the model fit to the greenhouse data. For determining the probability of yield and net return values using variable rate management, low input management, and high input management, normal distributions have been assumed for all parameters. Table 4.1 shows the parameter means and standard deviations from the two data sources.

Table 4.1. Normal distribution parameter estimates for the nine model parameters. Parameters labeled with “na” were not estimated due to lack of convergence when they were included in the model.

parameter	Field Data		Greenhouse Data	
	mean	SD	mean	SD
ι	0.174	0.250	0.004	0.005
φ	1.730	0.740	1.067	0.532
β_0	25.040	18.900	-29.300	23.890
β_1	5.755	4.027	3.250	0.859
β_2	1.357	0.755	0.096	0.960
β_3	na	na	-2.670	9.128
β_{00}	2.443	2.471	12.170	31.560
β_1'	-0.146	0.161	-0.182	0.517
β_2'	na	na	0.147	0.547
β_3'	3.714	4.433	-4.016	14.990

The third step of our analysis included obtaining site-specific input values for early season wheat and wild oat densities and soil moisture level. The input values used were from a data set where 35 quadrats were established in a spring wheat field. In each of these quadrats early season wheat density and wild oat density were counted in plants m^{-2} , and water was measured using a neutron probe just prior to planting and then calibrated into cm of available water in the top 120 cm of soil (Van Wychen, unpublished data). While the actual 35 quadrats in Van Wychen’s experiment were assigned at random spatially throughout the field, a hypothesized simulated field was developed based on these 35 quadrats. It was assumed that each quadrat represents a management zone within the virtual field. The debate over the most efficient size of management zones was avoided by assuming wheat density, wild oat density, nitrogen rate, herbicide rate, and water level throughout were constant across each individual management zone.

All nine parameters were sampled from their assumed normal distributions and input into the model. Then, nitrogen and herbicide rates were optimized for the highest yield value for each of the 35 management zones in the field (Mathematica©, 2000), which were based on the 35 quadrat measurements by Van Wychen (unpublished data). A Monte Carlo program written in Mathematica⁶ produced net return prediction probabilities for each of the three scenarios, e.g. variable rate, low input, and high input cases, based on 100 random samples from each parameter distribution.

The low and high input scenarios included specified input values for fertilizer and herbicide rate (Table 4.2). Fertilizer and herbicide were optimized in the variable rate scenario based on the highest calculated net return given a range of input values (Table 4.2). The optimal values for herbicide and nitrogen, corresponding to the highest calculated net return in each of the management zones, were found using an optimization program written in Mathematica. Yield values throughout an individual management zone were assumed to be constant. This method avoids selection of weed density thresholds by optimizing net return based on a range of herbicide and nitrogen rates.

Table 4.2. Input values for each of the three scenarios.

	Parameter values		
	Low input	High input	Variable-rate input
Fertilizer rate (kg N ha ⁻¹)	45	158	0, 20, 40, 80, 100, 120, 140, 150
Herbicide rate (x label rate)	0.25	1	0, 0.25, 0.5, 0.75, 1

⁶ The Mathematica program is available from the authors

Revenue generated for the wheat yield and total costs for herbicide and nitrogen throughout the field, i.e. for every management zone, were calculated for each scenario. The price received for wheat yield was \$0.132 kg⁻¹ assuming 27 kg bu⁻¹, the average across 2003 for Montana (Montana Agricultural Statistics Service, 2003), cost of nitrogen fertilizer was \$0.113 kg⁻¹ (NASS, 2003) and herbicide was US\$25.15 unit-ha⁻¹ (Government of Alberta, 2003). Net return for the low and high input scenarios was calculated by the following equation:

$$\text{Net Return (\$ ha}^{-1}\text{)} = (Y * P) - N - H \quad (4.2)$$

where Y was yield (kg ha⁻¹), P was the price for wheat (\$ kg⁻¹), N was the cost of fertilizer (\$ ha⁻¹) and H was the cost of herbicide (\$ ha⁻¹). Labor, machinery, seed, and other husbandry costs were not included because they were assumed to be equivalent for each scenario. For the variable rate scenario the net return equation was slightly modified to include the additional technology application cost:

$$\text{Net Return (\$ ha}^{-1}\text{)} = (Y * P) - N - H - T \quad (4.3)$$

where P, N, and H hold the same values as in equation 4.2, but T has been added as the cost of required early season wheat and wild oat density and soil water samples and SSM technology costs. T has been estimated as \$12.36 ha⁻¹ based on Luschei's (2001) estimation of site-specific technology cost.

Results

The virtual field had considerable variability of soil moisture, wheat density, and wild oat density (Figure 4.1). Maps of the optimized input levels for fertilizer rate, herbicide rate, and the predicted yield values were produced by the optimization program using parameters derived from the combined field data (Figure 4.2) and greenhouse data. Average net returns were calculated for each management zone for each scenario (Figure 4.3). Each predicted yield value in each management zone (Figure 4.3) represents the average yield value over 100 simulations where parameter values were sampled from their distributions.

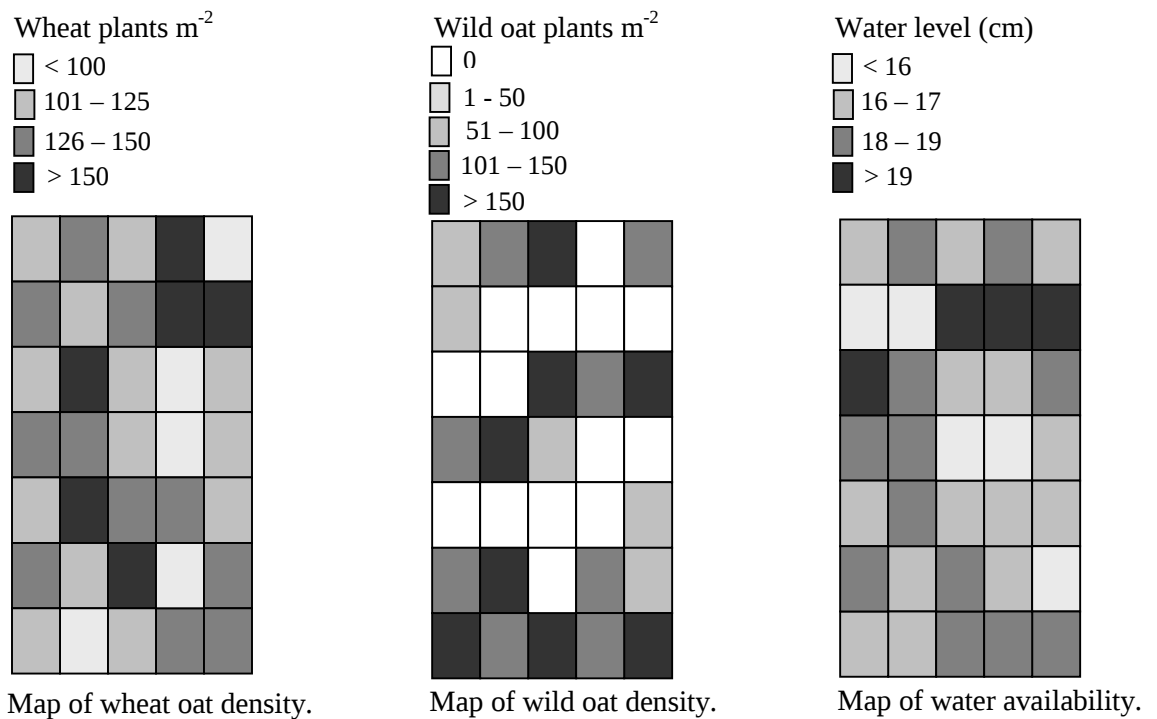


Figure 4.1. Localized input values for all three scenarios based on an experiment by Van Wychen (unpublished data). Each block within the field represents a management zone.

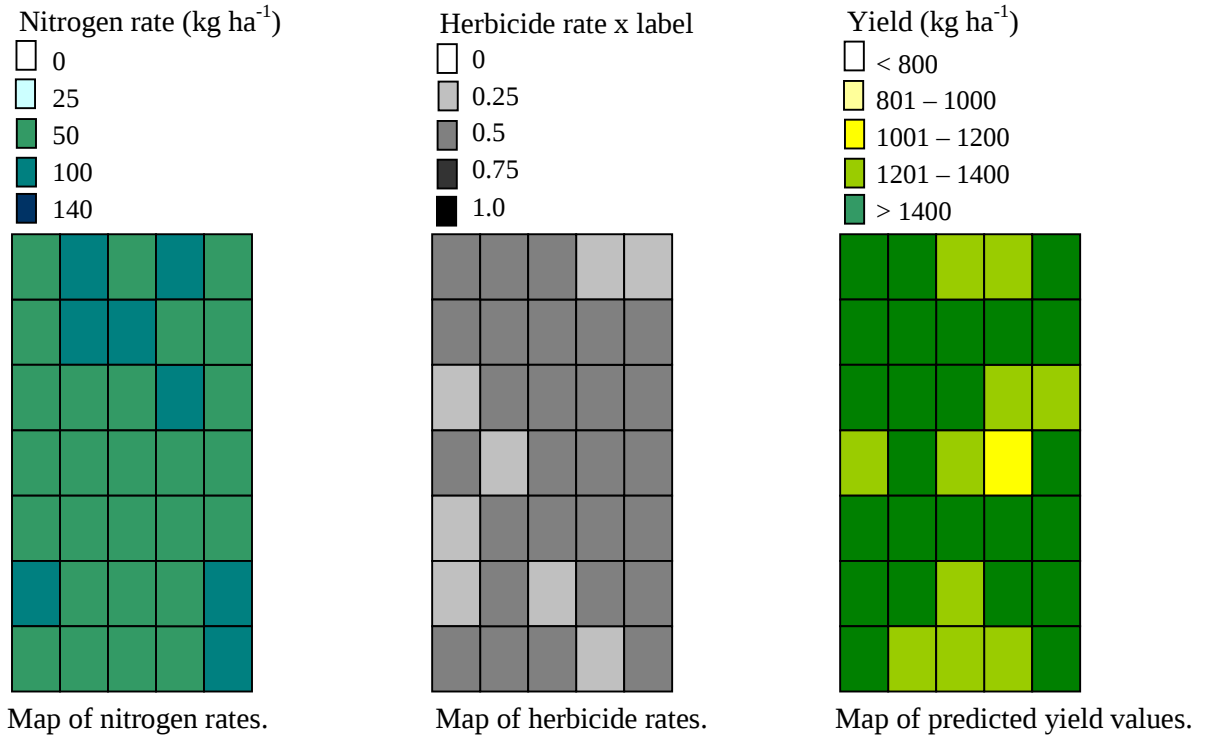


Figure 4.2. Localized optimum values for the variable rate scenario using field data-derived parameters. Each block within the simulated field represents a management zone.

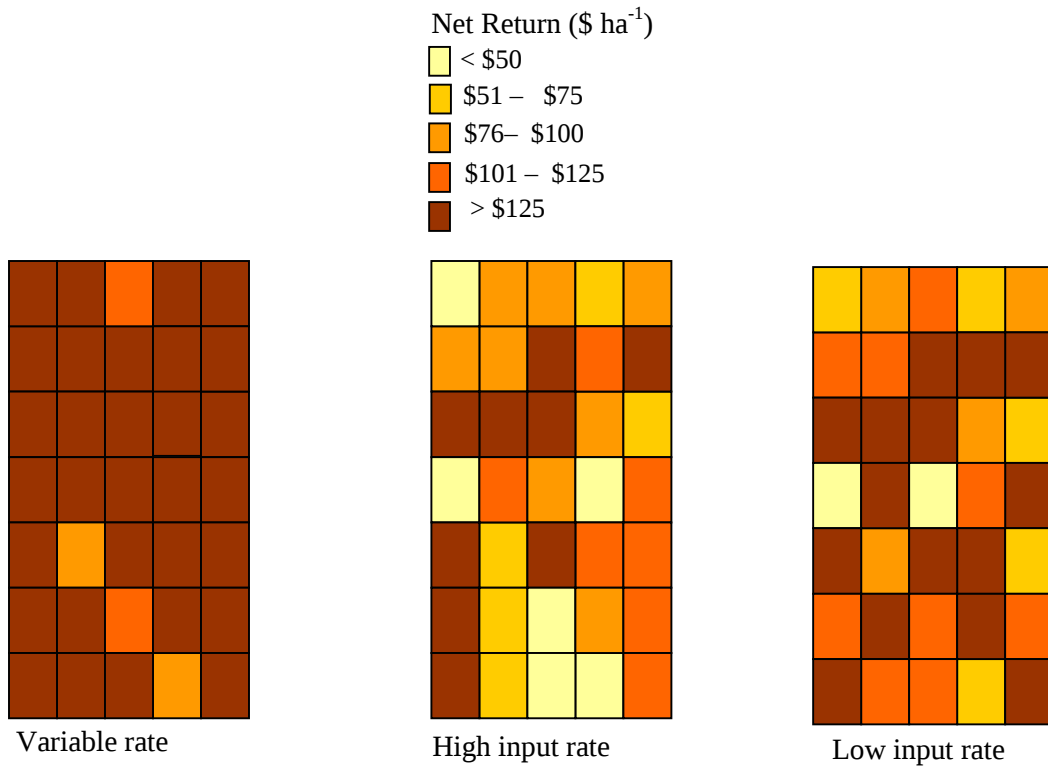


Figure 4.3. Net Return maps for the variable rate, high input, and low input scenarios.

At the start of each simulation parameter values were sampled at random from their distributions. Maps representing levels of net return within each management zone were made by averaging net return over 100 simulations. The number of occurrences throughout the simulation whereby the variable rate scenario produced a greater net return than the low and high input scenarios was calculated (Table 4.3).

Table 4.3. Percentages from 100 random samples drawn from each parameter's distribution that net return is greater for the variable rate scenario over the low input and high input scenarios. "var > low" and "var > high" refers to the percentage that net return is greater than the low input rate and high input rate, respectively. Net return and corresponding percentages were calculated for each management zone. "Average" is the mean percentage over the entire field.

management zone	combined data parameters		greenhouse data parameters	
	var > low	var > high	var > low	var > high
1	50%	70%	63%	74%
2	52%	67%	60%	68%
3	60%	80%	56%	60%
4	72%	84%	55%	72%
5	62%	66%	66%	62%
6	55%	62%	62%	66%
7	49%	68%	72%	70%
8	12%	16%	53%	65%
9	24%	22%	44%	62%
10	26%	19%	57%	60%
11	18%	21%	51%	58%
12	15%	18%	55%	56%
13	18%	17%	49%	65%
14	56%	71%	48%	66%
15	75%	84%	61%	76%
16	66%	86%	59%	83%
17	53%	61%	60%	73%
18	68%	85%	68%	72%
19	57%	81%	56%	76%
20	32%	28%	60%	57%
21	22%	25%	60%	58%
22	40%	42%	54%	59%
23	26%	22%	61%	66%
24	21%	16%	49%	64%
25	25%	23%	46%	64%
26	55%	68%	65%	66%
27	63%	81%	64%	64%
28	68%	80%	48%	64%
29	60%	68%	45%	60%
30	65%	67%	65%	62%
31	55%	70%	52%	52%
32	59%	76%	51%	70%
33	66%	87%	63%	77%
34	73%	84%	53%	80%
35	54%	68%	55%	60%
Average	48%	57%	57%	66%

Using the field data-derived parameters, the average probability that variable rate input management produced a higher net return than the low input scenario across the virtual field was 48%. The probability that variable rate input management produced a higher net return than the high input scenario across the field was 57%. Using the greenhouse data-derived parameters, these probabilities were 57% and 66% for the variable rate producing a greater net return than the low input and high input cases, respectively.

Average whole field net return values were \$348, \$125, and \$94 per hectare for the variable rate, low input, and high input scenarios respectively for yield optimization using the greenhouse-derived data. Average whole field net return values were \$3115, \$636, and \$548 per hectare for the variable rate, low input, and high input scenarios respectively for yield optimization using the field-derived data. As illustrated by the suspiciously large average net return value for the variable rate scenario based on field parameters (i.e. \$3115 ha⁻¹), the field data parameters tended to overestimate predicted yields and net returns as compared to estimates using the greenhouse data-derived parameters. Net returns averaged over the 35 management zones from the two parameter sources were graphically compared (Figures 4.4). Figure 4.5 was presented to more clearly show discrepancy between the scenarios for model output using the greenhouse parameters. Synonymous with the large standard deviations for the variable rate scenarios shown in Figure 4.4, the residual sum of squares (RSS) of the yield values (e.g.

$RSS = \sum (Y_{predicted, i} - Y_{observed, i})^2$) using the field data parameters were nearly twice as

large as the RSS using the greenhouse data parameters. These RSS values were 6186 and 3306 for the two parameter sources, respectively.

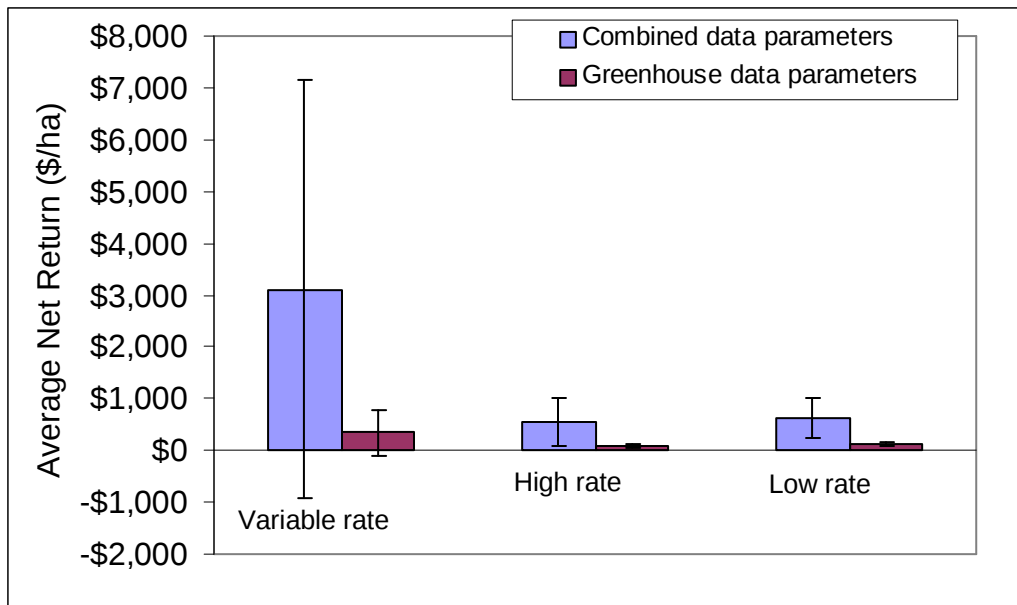


Figure 4.4. Mean yield values for each of the three scenarios indicated by the bars. Error bars indicate the mean $\pm$ one standard deviation for each scenario. “Mean” yield refers to the average yield across all the 35 management zones within each scenario.

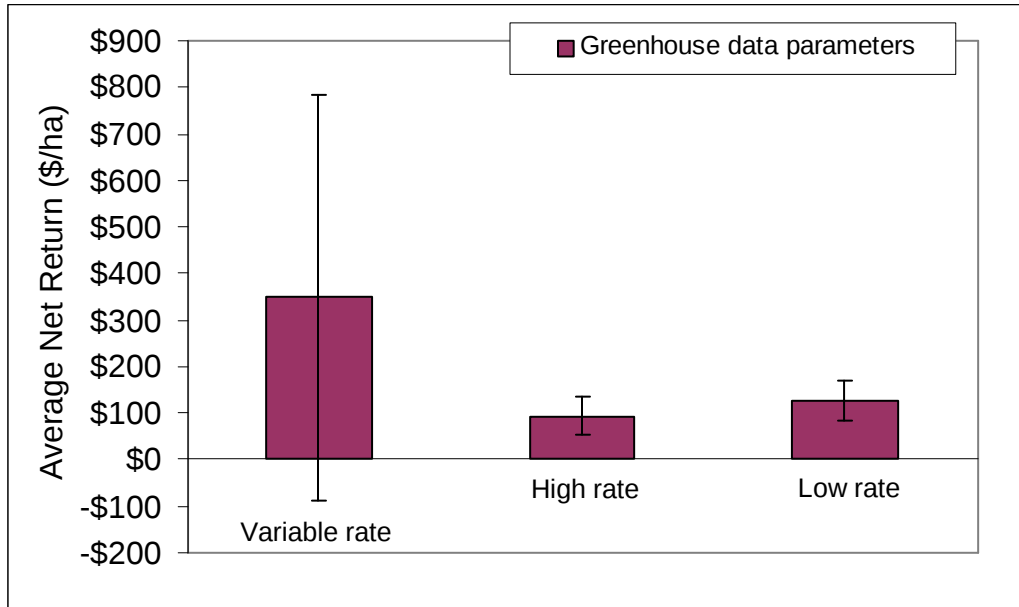


Figure 4.5. Mean net return values for each of the three scenarios indicated by the bars. Error bars indicate the mean $\pm$ one standard deviation for each scenario. “Mean” net return refers to the average yield across all the 35 management zones within each scenario.

Discussion

The five-variable model we have proposed was the first known empirical model that optimizes fertilizer and herbicide rate based on early season soil water measurements and wheat and wild oat densities. Results from simulations show that the variable rate scenario was the most efficient management scheme for increased net return in at least 48% of the management zones of the virtual field, and at most 66%, using two data sources of parameter estimates. Thus, the simulation presented here somewhat supports the hypothesis that localized variable-rate management can increase net return values over broadcast input application, further supporting previous research on site-specific

input management (Schueller 1992, Nordbo et al. 1994, Brown and Steckler 1995, Johnson et al. 1995, Christensen et al. 1996, Gerhards et al. 1999, Heisel et al. 1999, Peters et al. 1999, Luschei et al. 2001). While variability was shown surrounding each scenario, the greenhouse parameter estimates showed greater support for localized variable rate management.

Besides achieving a major step in agronomic predictive modeling, the results of this demonstration make a strong case for the readiness of the model to be applied to real farm fields. Parameter estimates will undoubtedly improve in accuracy with added data collection, and model accuracy can possibly be improved with the addition of the interactions of variables and nonlinear terms. Nonetheless, this demonstration hypothesizes that even with the current model form and parameter estimates applied to a farm field, the variable rate strategy is likely to generate greater net returns than high-rate and low-rate prophylactic management in at least 57% and 66% of the management zones, relatively, when greenhouse parameter estimates were used. A proposed additional benefit of the VR strategy over low-rate input management plan is the eradication of more wild oat plants ensuring fewer wild oat seeds entering the seedbank.

While the model can be used to make variable rate recommendations in real farm scenarios, on-farm experimentation would further refine the model by updating parameter estimates and could be used to alter the model's form for improved prediction. The large RSS surrounding yield revealed parameter estimate inaccuracies as well as the necessity for investigating model form improvement. Increased data from on-farm experimentation would allow further investigation into the discrepancy shown between initial net return values for the two original sources of parameter estimates and the sizable

standard deviations for net return output values that were found with these demonstration data sets (Figures 4.4 and 4.5). The cost of such data is relatively cheap as compared with competition study data on small plots on agricultural experiment stations (Luschei and Maxwell, in review). Proposed is a future on-farm experimentation plan to be implemented in concert with an empirical model to make site-specific variable rate management decisions for increased net returns on a *real* farm (Table 4.4).

A benefit of on-farm experimentation is that site-specific parameter estimation eliminates extrapolation from experiment stations and builds a local temporal frequency distribution for each parameter. The skepticism associated with parameterizing a model in one specific geographic location and then applying those estimates to another location is avoided. Secondly, with every year current year information can update prior years' information in a Bayesian framework, such that the value of past years' information is included to make inference. Thirdly, on-farm experimentation can address how weed infestation, including the potential for resistance, responds under a variable herbicide rates, thus influencing long-term yields and net returns. With such information, our current-year optimization model can be updated to maximize yield and net return over several years. By optimizing inputs over a three-year period, for example, the influence of current management strategies on future weed densities and consequential management costs are addressed.

Table 4.4. On-farm experimentation plan for model and parameter estimate improvement.

Spring, Year 1	Within 1 week after emergence, measurements of wheat and wild oat seedling densities are taken. Greenhouse parameters and the above measurements are input into the model for the output of optimized nitrogen and herbicide rates. Output site-specific variable rates of nitrogen and herbicide are applied.
Fall, Year 1	Harvested (observed) and predicted yield values are compared. Net returns are compared to previous year's net return. The model is refit to the observed yield values for a new set of parameter means and standard deviations. Improved model forms are investigated such as the addition of interaction terms and nonlinear terms especially concerning nitrogen, herbicide and water. The model's fit to predicted yield values is compared with the original model's fit.
Spring, Year 2	Early spring plant density and soil water measurements are taken. If the model has been revised to include interaction and/or nonlinear terms, it and the new parameter estimates are used for the current year's variable rate management strategy. Variable rate application is carried out according to the model's output.
Fall, Year 2	Observed and predicted yield values are compared. Net returns are compared to previous year's net return. Parameter estimates and model form is updated.
Years 3+	The on-farm experimentation process is continued until parameters stabilize.

References Cited

- Auernhammer, H., and M. Demmel. 1993. Lokale Ertragsermittlung beim Mahdrusch. *Landtechnik* 48:315-319.
- Bell, A.R., and J.D. Nalewaja. 1968. Competition of wild oat in wheat and barley. *Weed Science* 16:505-508.
- Bowden, B.A., and G. Friesen. 1967. Competition of wild oats (*Avena fatua* L.) in wheat and flax. *Weed Research* 7:349-359.
- Brown, R.B., and J.P.G.A. Steckler. 1995. Prescription maps for spatially variable herbicide application in no-till corn. *Transactions of the ASAE* 38:1659-1666.
- Carlson, H., Hill, J., and Baghott, K. 1982. Wild oat competition in spring wheat. *In* 33rd Annual Californian Weed Conference, pp. 13-24.
- Chancellor, R.J., and N.C.B. Peters. 1974. The time of the onset of competition between wild oats (*Avena fatua* L.) and spring cereals. *Weed Research* 14:197-202.
- Christensen, S., T. Heisel, and A.M. Walter. 1996. Patch spraying in cereals. *Proceedings from the 2nd International Weed Control Congress*.
- Cousens, R. 2000. Greenhouse studies of interactions between plants: the flaws are in interpretation rather than design. *Journal of Ecology* 88:352-353.
- deJong, E., and D.A. Rennie. 1967. Physical soil factors influencing the growth of wheat. *Can. Cent. Wheat Symp. Pub. Western Co-op Fertilizers Ltd., Calgary, Canada*.
- DiTomaso, J.M. 1985. Approaches for improving crop competitiveness through the manipulation of fertilization strategies. *Weed Science* 43:491-497.
- Engel, R., D. Long, and G. Carlson. 2001. Nitrogen requirement and yield potential of spring wheat as affected by water. *MSU Extension Service Agricultural Experiment Station*.
- Freckleton, R.P. and A.R. Watkinson, 2000. Designs for greenhouse studies of interactions between plants: an analytical perspective. *Journal of Ecology* 88: 386-391.
- Fleming, K.L. and D.G. Westfall. 1999. Farmer developed management zone maps for variable rate fertilizer application. *Proceedings from the 2nd European Conference on Precision Agriculture, J. V. Stafford (ed.). Odense Congress Center, Denmark. July 11-15, 1999.*

- Gerhards, R., M. Sokefeld, C. Timmermann, S. Reichart, and W. Kuhbauch. 1999. Results of a four-year study on site-specific herbicide application. Proceedings from the 2nd European Conference on Precision Agriculture, J. V. Stafford (ed.). Odense Congress Center, Denmark. July 11-15, 1999.
- Gerowitt, B., and R. Heitefuss. 1990. Weed economic thresholds in cereals in the Federal Republic of Germany. *Crop Protection* 9:323-331.
- Gotway-Crawford, C.A., D.G. Bullock, F.J. Pierce, W.W. Stroup, G.W. Hergert, and K.M. Eskridge. 1997. Experimental design issues and statistical evaluation techniques for site-specific management. *In: The State of Site-Specific Management for Agriculture*. p. 301-335, F. J. Pierce and E. J. Sadler, eds. American Society of Agronomy/Crop Science Society of America/Soil Science Society of America, Madison, WI.
- Government of Alberta. Agriculture, Food and Rural Development. Estimated herbicide application costs worksheet. 2003.
<http://www1.agric.gov.ab.ca/app23/pesticides/herbicides/getherbicidecosts.jsp>
- Haahr, V., R.N. Jorgensen, and A. Jensen. 1999. A method for optimal site-specific nitrogen fertilisation. Proceedings from the 2nd European Conference on Precision Agriculture:709-717.
- Heisel, T., S. Christensen, and A.M. Walter. 1997. Validation of weed patch spraying in spring barley--preliminary trial. Proceedings of the 1st European Conference on Precision Agriculture. pp. 879-886.
- Heisel, T., S. Christensen, and A.M. Walter. 1999. Whole-field experiments with site-specific weed management. The 2nd European Conference on Precision Agriculture:759-768.
- Heisel, T., A.K. Ersboll, and C. Andreasen. 1999. Weed mapping with co-kriging using soil properties. *Precision Agriculture* 1:39-52.
- Johnson, G.A., D.A. Mortensen, and A.R. Martin. 1996. Spatial and temporal analysis of weed seedling populations using geostatistics. *Weed Science* 44:704-710.
- Luschei, E. 2001. An assessment of the use of site-specific weed control for improving prediction-based management decisions and automating on-farm research. Ph.D Thesis, Montana State University.
- Luschei, E. and B.D. Maxwell. *in review*. Ecological justification for site-specific weed management.

- Martin, R.J., B.R. Cullis, and D.W. McNamara. 1987. Prediction of wheat yield loss due to competition by wild oats. *Journal of Agricultural Research* 38:487-499.
- Moore, G.A., and J.P. Tyndale-Busoe. 1999. Estimation of the importance of spatially variable nitrogen application and soil moisture holding capacity to wheat production. *Precision Agriculture* 1:27-338.
- Nordbo, E., S. Christensen, K. Kristensen, and M. Walter. 1994. Patch spraying of weeds in cereal crops. *Asp. Appl. Biol.* 40:325-334.
- O'Donovan, J.T., E.A.d.S. Remy, P.A.O. Sullivan, D.A. Dew, and A.K. Sharma. 1985. Influence of the relative time of emergence of wild oat (*Avena fatua* L.) on yield loss of barley (*Hordeum vulgare*) and wheat (*Triticum aestivum*). *Weed Science* 33:498-503.
- O'Donovan, J.T. 1993. Weed economic thresholds: useful agronomic tool or pipe dream? *Phytoprotection* 77:13-28.
- Peters, M.W., I.T. James, R. Earl, and R.J. Godwin. 1999. Nitrogen management strategies for precision farming. *Proceedings from the 2nd European Conference on Precision Agriculture* p.719-728.
- Prices paid for production in the Northern Plains. 2003. National Agricultural Statistics Service. <http://www.nass.usda.gov/sd/bulletin/ab03060.pdf>
- Prices received by farmers, market year average. 2003. Montana Agricultural Statistics Service. <http://www.nass.usda.gov/mt>.
- Radford, B.J., B.J. Wilson, O. Carthedge, and F.B. Watkins. 1980. Effect of wheat seeding rate on wild oat competition. *Aust. Journal of Experimental Agriculture and Animal Husbandry* 20:77-81.
- Sadler, E.J., and G. Russell. 1997. Modeling crop yield for site-specific management, *In* The state of site-specific management for agriculture. F. J. Pierce and E. J. Sadler, eds. p. 69-79. ASA, CSSA, and SSSA, Madison, WI.
- Schmerler, J., and M. Basten. 1999. Cost/benefit analysis of introducing site-specific management on a commercial farm. *The 2nd European Conference on Precision Agriculture*.
- Schueller, J.K. 1992. A review of integrating analysis of spatially-variable control of crop production. *Fertilizer Research* 33:1-34.
- Streibig, J.C. 1980. Models for curve-fitting herbicide dose response data. *Acta Agriculturae Scandinavica* 30:59-64.

- Thurston, J.M. 1962. The effect of competition from cereal crops on the germination and growth of *Avena fatua* L. in a naturally infested field. *Weed Research* 2:192-207.
- Welsh, J.P., G.A. Wood, R.J. Godwin, J.C. Taylor, R. Earl, B.S. Blackmore, G. Spoor, and G. Thomas. 1999. Developing strategies for spatially variable nitrogen application. *Proceedings from the 2nd European Conference on Precision Agriculture*.
- Wilkerson, G.G., L.J. Wiles, and A.C. Bennett. 2002. Weed management decision models: pitfalls, perceptions, and possibilities of the economic threshold approach. *Weed Science* 50:411-424.
- Williams, M.M., R. Gerhards, S. Reichart, D.A. Mortensen, and A.R. Martin. 1998. Weed seedling population responses to a method of site-specific weed management. *Proceedings of the 4th International Conference on Precision Agriculture*.
- Wilson, B.J., and N.C.B. Peters. 1982. Some studies of competition between *Avena fatua* and spring barley. I. The influence of *Avena fatua* on yield of barley. *Weed Research* 22:143-148
- Wilson, B.J., R. Cousens, and K.J. Wright. 1990a. The response of spring barley and winter wheat to *Avena fatua* population density. *Annals of Applied Biology* 116:601-609.

EPILOGUE

This thesis reveals the progression of model development from assessment of prior knowledge (Chapter 1), collection of data (field data in Chapter 2 and greenhouse data in Chapter 3), development of models (based on field data in Chapter 2 and greenhouse data in Chapter 3), assessment of models (Chapters 2, 3, and 4), to recommendations for future work (Chapter 4 and Epilogue). Every step is and has been critical to the entire process of what is called “modeling”, and the strength of each step strengthens the final product—the proposed model to be used for fertilizer and herbicide management in wild oat infested small grain production fields.

Model Building and Model Fitting

What is typically associated with modeling in ecology is the simulation of biological processes over time with the objective of scientific inquiry and/or management recommendations. Specifically, such a model is a simulation of an organism or group of organisms that grow, reproduce, interact, are possibly managed, and die or are harvested within a specified environment, complete with parameters that describe these mechanisms. While developing a simulation plays a major role in the realm of modeling, this thesis details another important component of what is referred to as “modeling”—the development of an equation that describes a system.

The reason for this approach, empirical equation building based on pattern in data rather than simulation building based on process through time, is steeped in the objective

of helping farmers make optimal management decisions. Agricultural systems are unique from other managed biological systems because fertilizer and herbicide management are conducted once a year early in the annual growing season often before other environmental factors begin to influence yield. As explained in the prologue of this thesis, an empirical model simply and more concisely attempts to answer the question: what is the optimal localized variable rate strategy for fertilizer and herbicide in a wild oat infested wheat field?

As evident by the amount of literature, debate, and effort in assessing model performance (Akaike 1973, Linhart and Zucchini, 1986, Lehmann 1990, Chatfield 1995, Royall 1997, Hilborn and Mangel 1997, Burnham and Anderson 1998, Bozdagan 2000, Forster 2000, Taper, in press), model fitting, steeped in statistics and philosophy, remains challenging. While there is an ever-growing body of literature written on model fitting, performance and uncertainty, little is written on *how* to develop an empirical equation. I believe this thesis represents a set of instructions that is absent from the literature. If I were to advise a graduate student to build an empirical model, the following is my brief set of instructions:

1. Assess prior knowledge of the system's mechanisms and decipher the most important predictor variables. Assessing prior knowledge includes knowledge in the form of experimental results and any models that have been developed to describe the system of interest. Realize that this is a big task that increases exponentially with every predictor variable added to the model.
 - a. Explore known linear and nonlinear influences and possible interactions of the predictor variables on the dependent variable in the literature.
2. Ask whether or not the data with which to build your proposed model exists. If it does, or if you are unsure if it does, gather previously collected data sets not utilized specifically for this purpose of model building with the predictor variables of interest. Then, follow the subsequent steps.

- a. Explore the pattern(s) in the collected disjoint data sets through scatter plots.
 - b. Conduct standardized regression analysis to reveal the strength of the predictor variables individual influences on the dependent variable and each other.
 - c. Develop hypotheses of the processes of the system and develop a candidate set of models based on prior experimental data and theoretical models.
 - d. Fit models to data sets, making observations and assumptions about error structure and model uncertainty.
 - e. Assess model performance with statistics such as AIC, AICc, BIC, and/or ICOMP depending on the number of observations, correlations among parameters, and confidence intervals of parameter values.
 - i. Explore increasing model performance (i.e. accuracy of predicted values to observed values) by transformations and by including and/or omitting variables and interaction terms.
3. Assess whether additional data is necessary for model development.
 - a. If additional data is necessary, conduct an experiment to collect further data and continue to Step 4.
 - b. If more data is not necessary, go to Step 5 and use the model for the intended purpose. Investigate how well the model predicts the outcome or describes the system investigated using statistics such as coefficient of determination, means square error, AIC, BIC, and ICOMP.
 4. Explore data and fit, repeating steps 2a – 2c. Update the candidate set of models based on steps 2a – 2c and continue with model assessment (steps 2d – 2e) by fitting the updated models to the new collection of data.
 5. Use the model for its intended purpose (e.g. prediction, management strategy recommendation, scientific inquiry).
 6. Conduct model validation and sensitivity analysis.
 7. Does the model require *significant* improvement?
 - a. If the answer is no, use the model for intended purpose.

- b. If the answer is yes, ask, “how could the model be improved?” Explore improvement through simulation of pertinent biological processes and/or through more data collection. Build simulation and/or collect more data. Go back to step 2a and continue the process.

Inherent in all steps described above is the importance of collaboration among researchers, students, advisors, and in the case of agroecological modeling, farmers.

Taper (in press) eloquently makes this point:

Determining adequate model structure is an elusive component of modeling. It requires deep knowledge of the natural system, a subtle understanding of the behavior of models, a clear statement of the questions to be explored, and a command of statistical methods by which data can be queried by models. Rarely do all these qualities reside in a single scientist. Collaboration is generally the most effective way to probe nature with models.

Future Work

The performance of the proposed model and parameter estimates described in Chapter 4 reveal the power of model fitting by making the case for on-farm experimentation rather than collecting expensive field data. Thus, the next step beyond this thesis is Step 5—to apply this model to farmers’ fields with the experimental plan outlined in Table 4.3. The application of the prediction model to make recommendations and the annual field data collection by precision agricultural machinery allows model form and parameter estimates to be updated. This process is a continuation of the classic scientific method from hypothesis (model) formulation, to hypothesis (model) testing, and hypothesis (model) refinement (Popper, 1959).

If the model requires further improvement after application to farmers' fields and subsequent updating, I propose two main direction for future research: one is improving the model by including soil characteristics and the other is building an individual based model (IBM). The first research direction would incorporate existing mapping technologies to create maps made during planting of soil moisture and aerial maps of soil type. Maps of available spring soil moisture could more accurately relate localized spring soil water to final yield while incorporating weed density and nitrogen and herbicide inputs at corresponding locations. In addition soil moisture maps together with aerial maps of soil type could more accurately develop management zones rather than simply dividing a field into a grid as was done in Chapter 4.

The other research direction of IBM development would allow further investigation of competition mechanisms with varying controlled inputs and environmental factors by investigating competition between a plant and its neighbors. Outcomes of competition with varying combinatorial levels of inputs and with varying time of input application in a virtual IBM setting could elucidate mechanisms not revealed in previous experiments. Such flexibility would allow differences in time of emergence between individual plants, for example, to be incorporated into the model. An IBM could allow the investigation of many levels of inputs that have not been examined in the field or greenhouse due to time, space, and monetary constraints. An IBM can incorporate previous research results on the behavior of individual wheat and wild oat plants, e.g. the parameters used in models such as CERES-wheat and INTERCOM. An IBM would also allow for investigation of the most efficient management zone size, and optimal spacing and arrangement of crop plants. In addition, IBMs can allow for quick

simulated replication, and the incorporation of the effects of management of population dynamics over time as focused on individual plants. Results from such a model would help to update the form of a predictive empirical model to be used for the development of localized variable rate input recommendations.

The prologue of this thesis mentioned the “Achilles heel” of our proposed model that it does not include time. Rather, it makes assumptions that predicted yield is a function of inputs being applied at the specified ideal time, that wheat and wild oat plants emerge at the same time, and that predicted yield values are not diminished after input application by environmental scenarios such as a late flush of localized weed patches, adverse weather conditions, and/or a disease/pathogen outbreak. The IBM framework allows exploring what happens after inputs are applied, thus updating the prediction of yields based on the occurrences within the rest of the growing season until harvest. Furthermore, an IBM could explore yield outcomes when inputs are applied at less than ideal times. Given the currently proposed empirical model, we could add an efficiency coefficient on herbicide to account for late applications on herbicide, however, nitrogen is more tricky, especially since less is known about the influence of nitrogen and water together as a function of time. An IBM would allow the investigation of such complex scenarios as well as the influence of time of emergence and the role localized soil characteristics play on yield. Through such simulation, our proposed model can be updated.

“Everyday Thinking”

The whole of science is nothing more than a refinement of everyday thinking. It is for this reason that the critical thinking of the physicist cannot possibly be restricted to the examination of the concepts of his own specific field. He cannot proceed without considering critically a much more difficult problem, the problem of analyzing the nature of everyday thinking.

–Albert Einstein

Farming, critical to our modern existence, has existed since approximately 8000BC, occupying everyday thinking in some way. While this thinking about food production is done by a smaller percentage of the population today, it is critical to the goal of developing ecologically based sustainable farming practices. My thesis research has attempted to incorporate everyday thinking in the form of collaboration among scientists and farmers for the development of a model to be used to recommend sustainable management prescriptions. As an agroecologist I hope to continue this endeavor for the development of increased environmental, social, and economic sustainability of agricultural production.

References Cited

- Bozdogan, H. 2000. Akaike's Information Criteria and recent developments in Information Complexity. *Journal of Mathematical Psychology* 44:62-91.
- Burnham, K.P., and D.R. Anderson. 1998. *Model Selection and Inference: a practical information-theoretic approach* Springer-Verlag New York Inc., New York.
- Chatfield, C. 1995. Model uncertainty, data mining and statistical inference. *Journal of the Royal Statistical Society, Series A* 158: 419-466.
- Forster, M. R. 2000. Key concepts in model selection: Performance and generalizability. *Journal of Mathematical Psychology*.
- Hilborn, R. and M. Mangel, 1997. *The Ecological Detective: confronting models with data*. Princeton University Press, Princeton, New Jersey.
- Lehmann, E.L. 1990. Model specification: the views of Fisher and Neyman, and later developments. *Statistical Science* 5: 160-168.
- Linhart, H. and W. Zucchini. 1986. *Model Selection*. John Wiley and Sons, New York.
- Popper, K.R. 1959. *The Logic of Scientific Discovery*. Hutchinson & Co., London.
- Royall, R. 1997. *Statistical Evidence: A likelihood paradigm*. Chapman and Hall, London.
- Taper, M., and S. R. Lele. in press. The nature of scientific evidence: a forward looking synthesis. In: *The Nature of Scientific Evidence: Empirical, Statistical, and Philosophical Considerations*. University of Chicago Press.

APPENDICES

APPENDIX A
FOUR-WAY SCATTER PLOTS

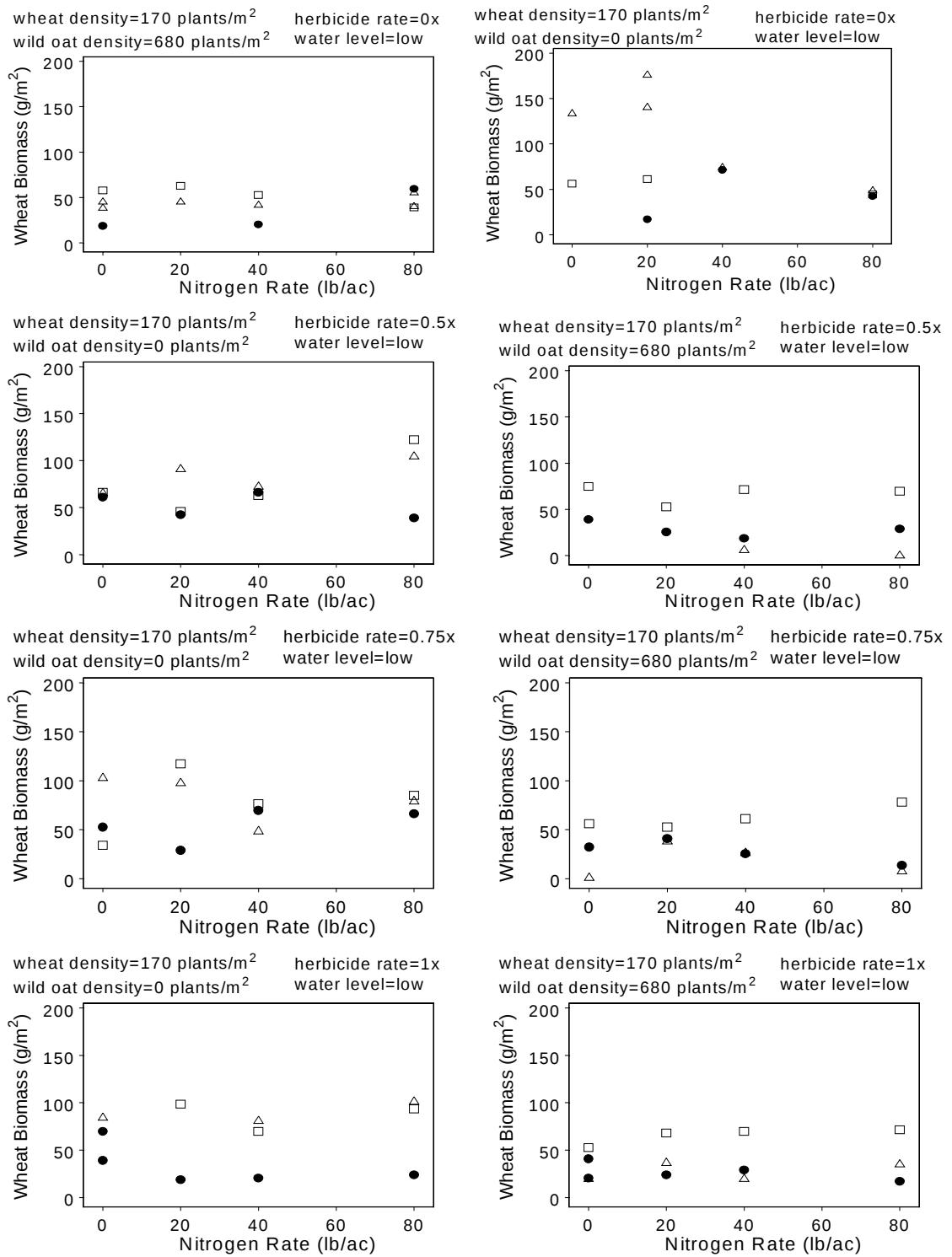


Figure A.1. Wheat biomass vs. nitrogen rate scatter plots at low wheat density, low water level, low and high wild oat densities, and all four herbicide rates.

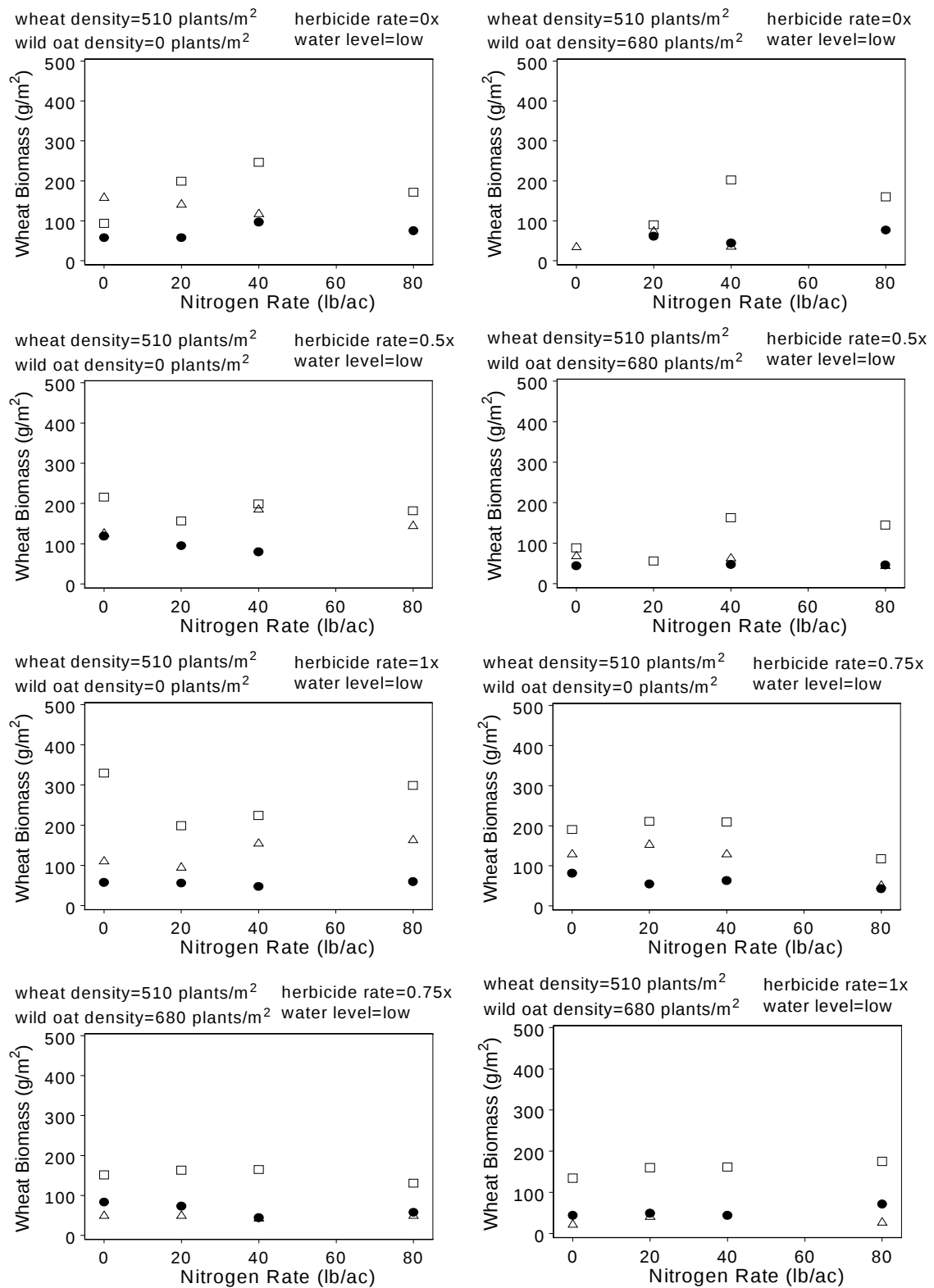


Figure A.2. Wheat biomass vs. nitrogen rate scatter plots at high wheat density, low water level, low and high wild oat densities, and all four herbicide rates.

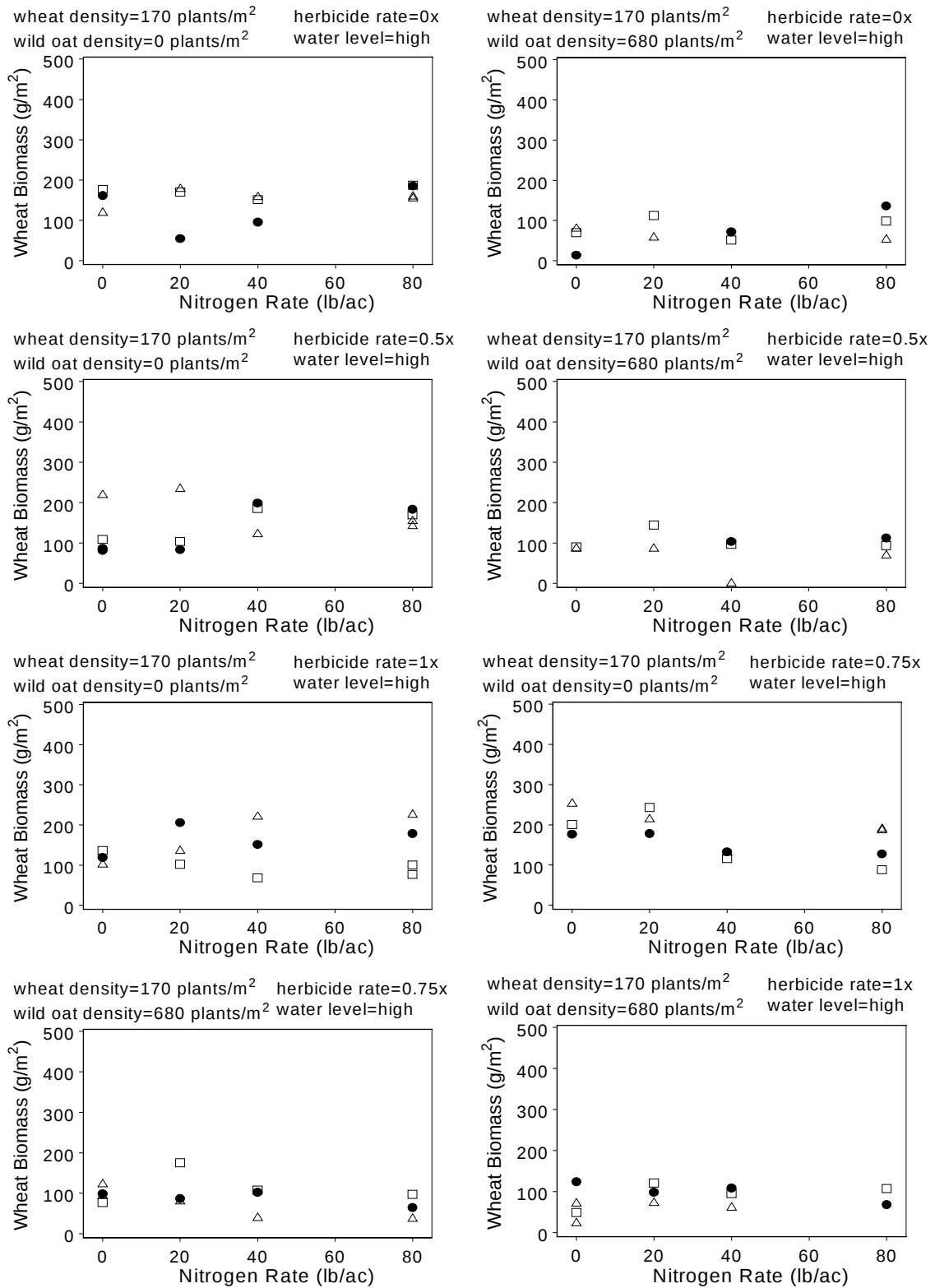


Figure A.3. Wheat biomass vs. nitrogen rate scatter plots at low wheat density, high water level, low and high wild oat densities, and all four herbicide rates.

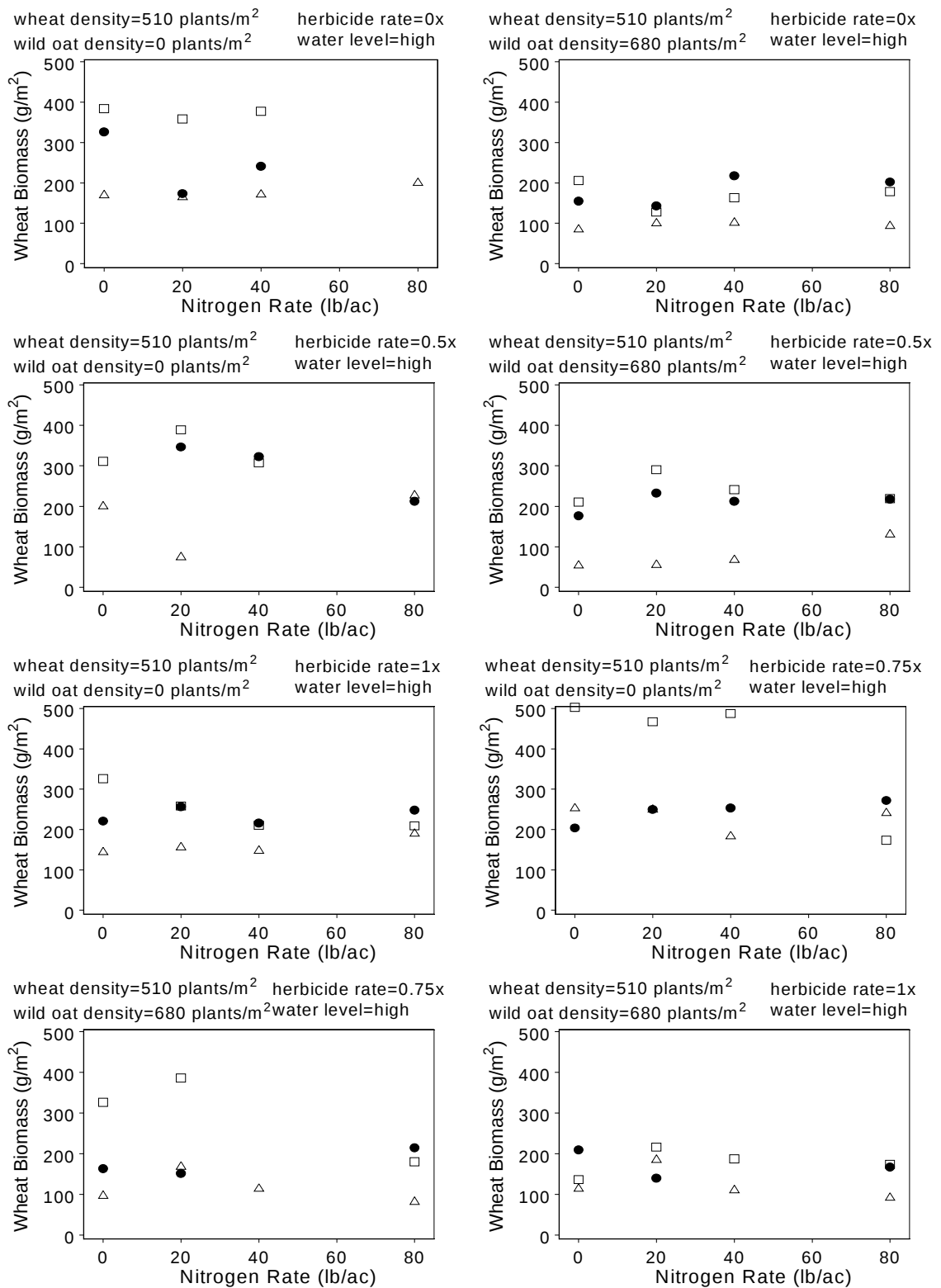


Figure A.4. Wheat biomass vs. nitrogen rate scatter plots at high wheat density, high water level, low and high wild oat densities, and all four herbicide rates.

APPENDIX B

REGRESSION MODELS FOR THE HIGH WATER TREATMENT

Table B.1. Regression models for the high water treatment. Model C includes wild oat density and model D includes wild oat biomass.

Regression model C	Regression model D
<i>total wheat biomass</i> = 1.1 + 0.25 <i>wheat density</i> – 0.23 <i>oat density</i> + 0.20 <i>water</i> + 0.05 <i>herb</i> – 0.002 <i>nitrogen*</i> – 0.04 <i>wheat density</i> ² – 0.04 <i>nitrogen</i> ² + 0.02 <i>water</i> ² – 0.04 <i>water:nitrogen</i> n = 418 AIC = 41 R _a ² = 0.61	<i>total wheat biomass</i> = 1.0 – 0.27 <i>oat biomass</i> + 0.26 <i>water</i> + 0.23 <i>wheat density</i> + 0.04 <i>herb</i> + 0.006 <i>nitrogen*</i> – 0.06 <i>wheat density</i> ² + 0.04 <i>oat biomass</i> ² – 0.04 <i>nitrogen</i> ² – 0.04 <i>water:nitrogen</i> n = 418 AIC = 52 R _a ² = 0.50