ECONOMICALLY OPTIMAL WINTER WHEAT (TRITICUM AESTIVUM) SEEDING RATES FOR CONVENTIONAL AND NARROW ROW WIDTHS IN WEED FREE AND CHEAT (BROMUS SECALINUS) INFESTED FIELDS

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CHAPTER I

INTRODUCTION

Problem Statement

In Oklahoma, over seven million acres exceed the USDA's highly erodible classification. Much of the highly erodible cropland has traditionally been seeded to continuous hard red winter wheat (*Triticum aestivum*). The quantity of land seeded to wheat has increased from 5,910,000 acres in 1950, to 7,500,000 acres in 1990. The yield per acre harvested over that period of time increased from nine bushels in 1950 to 32 bushels in 1990 (Oklahoma Agricultural Statistics, 1989-1990, p. 16).

During the last decade changes in the area seeded to wheat have been related to changes in government programs such as the conservation reserve and the wheat commodity program. Beginning in 1995 farmers will be faced with the problem of complying with federal regulations designed to reduce erosion on highly erodible land to maintain eligibility for deficiency payments and other government programs. Farmers who produce continuous wheat on land classified as highly erodible and who choose to implement a residue management program will encounter another problem, that of cheat (*Bromus secalinus*) infestation. In the absence of conventional tillage, cheat can become a serious problem in fields in Oklahoma which are continuously seeded to wheat. Some traditional practices for controlling cheat infestations include late or delayed planting, deep plowing, and crop rotation.

Late planting helps in controlling cheat. This practice is effective when moisture is available in the fall to germinate cheat prior to the final wheat seedbed preparation (Greer et al.). However, an experiment conducted by Runyan showed that delayed planting did not eliminate the cheat problem but did result in reduced wheat yield if planting was delayed beyond October. Furthermore, this practice is not practical for farmers who use wheat to produce fall forage for grazing during the winter.

Rotation of crops is an effective cheat control practice (Greer et al.). However, because of climate and markets there are limited opportunities for crop rotations in the major wheat producing areas of Oklahoma.

The most widely used practice for controlling cheat in Oklahoma has been to use a moldboard plow in infested fields after harvest to reduce the cheat population in the subsequent crop (Runyan). Deep plowing is effective for cheat control if the soil is completely inverted. This practice buries most of the cheat seeds to depths from which they can not germinate and emerge. Conservation compliance guidelines, however, are expected to severely limit the frequency of use of moldboard plows on highly erodible land.

As tillage practices are adjusted to comply with the surface residue requirements imposed by the federal regulations, populations of cheat are expected to increase in wheat fields. In the absence of alternative controls, after several years, producers may be confronted with serious infestations of cheat. Potential alternative controls include the use of chemical herbicides. However, a chemical herbicide that is harmless to wheat, cost effective and consistently provides control of cheat in wheat fields is not available for the region (Greer et al.).

Two cultural practices have been hypothesized as potential substitutes for moldboard plowing to control cheat: 1) seeding wheat in narrow rows and 2) increasing the seeding rate. These suggested practices are based on the assumption that the ability of wheat plants to compete with cheat for water and nutrients is influenced by the number of wheat plants per land unit and pattern of placement.

The central objective of this research is to increase understanding of the impacts of alternative row spacing and alternative seeding rate on wheat grain yield for alternative levels of cheat infestation. The specific objective is to determine if the cultural practices of decreased row spacing and increased seeding rate, may be used to control populations of cheat in fields which are continuously cropped to winter wheat.

Literature Review

A review of prior research of wheat grain yield response to alternative factors (seeding rate, row spacing, herbicides, weedy grasses, and management practices) is presented in this section which is divided into three subsections. These are: tools for assessing economics of weed control, agronomic studies of weed control, functional structure of wheat yield response, and row spacing and seeding rate impacts on wheat grain yield.

Tools for Assessing the Economics of Weed Control

Presence of weeds in a given crop field causes a decrease in the crop yield and has economic consequences. Several tools can be used to assess the economics of the presence of weeds and their control in a given field. Common tools include: economic thresholds, budgeting, investment criteria, and comparison of risky outcomes (Auld et al.). This section includes a discussion of these alternative tools for assessing the economics of weed control.

Economic Thresholds: The threshold concept embodies the notion that some functional relationship exists between weed density, the intensity of control, and crop yield (Auld et al.). It allows the determination of weed densities at which it is just economic to treat the weed. That is, where the marginal value of incremental yield is equal to the marginal cost of control. The economic threshold method requires information including, yield loss function, price of the crop considered, costs of treatment of the weed including labor, and machinery costs.

This method was used by Stallman and Miller in a study conducted in Southeastern Wyoming and West-Central Kansas on irrigated and dryland sites to quantify yield loss from downy brome interference and approximate economic threshold levels. They found that densities of 24, 40,and 65 downy brome m^2 reduced wheat yield by 10, 15, and 20%, respectively. They reported potential monetary loss increased with increasing downy brome plant density. More specifically, increasing weed density up to 72 downy brome plants m^2 increased monetary losses for potential wheat yields of

1786 to 2676 pounds per acre to nearly \$20 and \$30 per acre, respectively. The same method was used by Gillespsie et al., and Donald and Prato in North Dakota.

Budgeting. This method uses enterprise or activity budgets. Here, the decision is one of choosing between alternative activities (select the least-cost weed control technique). An activity budget consists of: 1) a description of the activity, including the physical setting, and timing of operations; 2) a listing and quantification of the input requirements for the activity and their associated costs; and 3) a statement of activity output and its value. Ferreira et al. used budgeting (enterprise budgets) to assess economic returns from cheat control in winter wheat. A more sophisticated form of budgeting is linear programming (Auld et al.).

Investment Criteria. This method provides criteria to assist farmers with decisions that have long-term economic consequences. There are two basic types of criteria (Auld et al.): 1) net present value and 2) internal rate of return.

The investment in the weed control program should be undertaken if the net discounted present value is greater than zero, i.e if

$$\sum_{t=1}^{n} \frac{(B_t - C_t)}{(1+r)^t} > 0 \qquad (1)$$

where:

r = discount rate,

t = time in years,

B = benefits, and

C = costs.

If B, C, and t are known, the above expression may be set equal to zero, and solved for the discount rate which is known as the internal rate of return r^*. If $r^* > r$, then the investment should be undertaken. This method requires substantital information including benefits and costs per period of the proposed weed control program for each time period in the future which will be impacted.

Comparing Risky Outcomes. This method allows farmers to select from among alternative weed control strategies. The alternative strategies may be associated with different degrees of expected profitability E(T) and risk which can be measured by variance of net returns $E(\sigma^2)$. Managers who engage in weed control activities are generally regarded as being risk averse. They may be willing to sacrifice some expected profit for a reduction in risk (Auld et al.). If one weed control strategy (A) is characterized by both higher E(T) and lower $E(\sigma^2)$ than an alternative strategy (B), then strategy A will be preferred to B. This method requires information including levels of weed infestation, weather, prices, carryover effects, time interval effects, costs of control, yield improvement, and quality effects.

This method was used by Doyle et al. in a study conducted at the Grassland Research Institute and the AFRC Weed Research Institute in the United Kingdom to determine the long-term economic implications of controlling black-grass (*Alopecurus myosuroides Huds.*) infestations in winter wheat. They reported that a strategy of applying herbicides every year may tend to minimize the economic risks associated with a herbicide performing less satisfactorily than expected, even though it may not be the preferred strategy for risk neutral farmers. This method was used by Pannell at the University of Australia, and also by Pandey and Medd.

The decision regarding which method of economic assessment of weed-control strategy to use depends upon the availability of information. The more information is available, the more sophisticated the method of assessment may be.

Agronomic Studies of Weed Control

A study was conducted in Utah to determine if herbicides applied over the snow to winter small grains would consistently control weeds (Dewey et al.). Herbicide efficacy of over-snow applications was compared with conventional fall applications. The researchers reported that chlorsulfuron and metsulfuron applied with or without graphite in the fall were 91 to 100% effective in controlling weeds. Equivalent over-snow treatments provided 92 to 100% control. They also reported that adding graphite to sulfonylurea herbicide treatments appears essential to consistently control weeds with over-snow applications. These results are similar to those reported by Donald and Prato. The most effective winter wheat herbicide in both studies was a sulfonylurea herbicide.

Another study of herbicide application was conducted by Pannell at the University of Western Australia to find the determinants of optimal herbicide usage. The weed targeted was ryegrass (*Lolium rigidum*). The data used included wheat yield, wheat price, initial weed density, cost of herbicide, recommended dose of herbicide, herbicide application costs (labor, and machinery used), and costs from other inputs assumed fixed. The optimal herbicide rate was 0.26 kg active ingredient of diclofop-methyl per hectare.

Ferreira et al. conducted a field experiment in Oklahoma to determine the influence of winter wheat seeding date and forage removal on the efficacy of cheat control herbicides, forage and grain yields, and net returns. Cheat infestation was artificially induced by seeding cheat. Wheat was seeded at 74 kilograms per hectare (66 pounds per acre) in 20 cm (8 inch) rows on three dates at each location. The planting dates were: September 2 to 3 (early seeding), September 30 to October 11 (normal seeding period), and November 1 to 3 (delayed seeding). Herbicide treatments were metribuzin at 0.28 and 0.42 kilograms per hectare (0.25 to 0.0375 pounds per acre), ethyl-metribuzin at 0.84 and 1.3 kilograms per hectare (0.75 and 1.16 pounds per acre) and cyanazine at 0.45 and 0.67 kilograms per hectare (0.40 and 0.59 pounds per acre). They concluded that all herbicide treatments reduced the yield of wheat with delayed seeding. Metribuzin treatments reduced the yield more than other treatments. The results reported showed that neither metribuzin nor cyanazine were consistently effective herbicides capable of controlling cheat infestation without harming wheat yield. This finding is consistent with that reported by Greer et al.

Donald and Prato conducted a similar study in North Dakota to determine if three sulfonylurea herbicides (metsulfuron, chlorsulfuron, and CGA-131036) could be profitably substituted for glyphosate to control annual broadleaf weeds present at planting of no-till spring wheat. The data used included planting dates, weather measures, wheat seed, wheat yield, wheat price, and herbicide costs. They found that absolute net returns of different treatments varied among herbicides, but relative net returns were insensitive to changes in either herbicide or wheat price. They concluded that the three sulfonylurea herbicides controlled both emerged kochia (*Kochia scoparia*) and wild mustard (*Sinapis arvensis*) whether or not combined with glyphosate better than glyphosate alone.

Pandey and Medd developed a systems model for herbicide recommendations taking into account multi-period effects of current weed control decisions, stochastic influences, and farmers' attitude towards risk. They found that the optimal solution (optimal herbicide dose to apply) depends on weed density as well as seed density. They also reported that substantial economic gains can be realized if herbicide dose decisions are taken by considering future profit effects of current decisions, as opposed to the more common approach of only considering the current period effect. They used a dynamic stochastic programming framework. The weed grass targeted was wild oats (*Avena fatua*). The data used included weed density, seed density, herbicide dose, a measure of soil moisture, a measure of time, and wheat yield.

Another study using stochastic dynamic programming was conducted by Taylor and Burt. Their research was conducted to determine near-optimal multiperiod decision rules for controlling wild oats in spring wheat in North Central Montana. They found that wild oats seed germination was triggered by soil temperature, while planting of spring wheat was typically based on soil moisture conditions. That is, the later the planting time relative to the occurrence of the critical soil temperature for wild oats germination, the less likely a herbicide will be needed because many of the wild oats will be destroyed by planting operations.

Whatever the framework used, most of the literature cited confirms that herbicides help somewhat to control weeds in wheat fields. Few of the studies mention the possible harmful effects of herbicides on wheat yield.

Functional Structure of Wheat Yield Response

This section includes a description of alternative functional forms which have been used in the literature to address crop response to factors of production. The choice of a functional form is not an easy task. Different functional forms have been used to estimate wheat yield response to factors including herbicides, seeding rate, and row spacing. Wheat yield response functions allow researchers to determine significant relationships between factors (herbicides, seeding rate, row spacing, weeds, macronutrients, and management practices) and wheat yield, thereby helping farmers in their decision making process. That is, wheat yield response functions can help discriminate among different cultural practices.

A problem that researchers encounter in choosing a functional structure is whether to consider the crop response process as static or dynamic. In his presidential address to the Southern Agricultural Economics Association, Trapp argued that the single equation static production function is an obsolete research tool which should be replaced by dynamic production theory. Nevertheless, he recognized that there is still a very important need for the concepts of static production theory. The question that rises is: Does the use of dynamic theory in production help improve the decision making process? The debate on whether static production theory should be replaced by dynamic production theory is beyond the scope of this research. Indeed, for this research the static production theory will be used. Another problem that production economists encounter is the choice of a functional form. Different functional forms have been used to estimate crop growth response.

Tompkins et al. in their study of the effects of seeding rate and row spacing on grain yield and yield components of no-till winter wheat, used a modified inverse polynomial function to describe the relationship between wheat yield and seeding rate. The function they used was written as follows :

$$Y = \mu SR(1 - SR/s)/(SR + \mu/e) \tag{2}$$

where:

μ = the upper limit of yield (bushels per acre) when seeding rate is not limited,

SR = seeding rate (bushels per acre),

e = change in grain yield per unit of seeding rate, and

s = allows for depression of yield at high seeding rates. It is a measure of sensitivity to excess levels of seeding rates (larger s values indicate less sensitivity), and

Y = wheat yield (bushels per acre).

Non-linear regression procedures (SAS, 1985) were used to provide least-squares estimates of the regression coefficients μ, e, and s.

They argued that the inverse polynomial function provides a response curve that more appropriately describes the normal shape of wheat grain yield response to seeding rate than a traditional quadratic function. The functional form permits an initial rapid yield increase followed by a plateau region and eventually a yield decrease. The model has been used in the literature to describe grain yield response to macronutrients (fertilizer). It has also been shown that grain yield decreases at very high levels of macronutrients (Fowler et al.). The inverse polynomial function has been used in the literature to address crop response to a single factor (nitrogen, or seeding rate) (Fowler et al., and Tompkins et al.). However, the properties of a multiple factor inverse polynomial function have not been established.

Frank et al. compared alternative crop response models. The models compared include the quadratic specification and a linear plateau characterized by the Von Liebig function. A Von Liebig function starts with a linear portion and then reaches a maximum plateau. The quadratic function used was:

$$Y = \beta_0 + \beta_1 N + \beta_2 P + \beta_3 N^2 + \beta_4 P^2 + \beta_5 NP \qquad (3)$$

where:

β_i = estimated parameters (i=0,1,..,5),

Y = grain yield,

N = nitrogen applied, and

P = phosphorous applied.

The Von Liebig model used by Frank et al. was:

$$Y = Min(Y^*,\ \beta_1 + \beta_2 N,\ \beta_3 + \beta_4 P) \qquad (4)$$

where:

Y^* = maximum grain yield.

Frank et al. concluded that, for the data at hand, the growth plateau specification characterized by the Von Liebig function performed better than the quadratic specification. This result was also supported by Ackello-Ogutu et al. who tested a Von Liebig crop response function against a polynomial specification. The model based on a Von Liebig function was seldom rejected in favor of a polynomial. Their results support the idea that crop response to nitrogen fertilizer is characterized by a plateau growth.

Nonnested hypotheses tests were conducted by Grimm et al. to discriminate between the traditional polynomial response model and the Von Liebig specification. They failed to reject the Von Liebig model for wheat, corn, and cotton. They referred to a study conducted by Boyd to support the idea of plateau growth crop response. Indeed, after several studies of fertilization experiments with sugar beets, wheat, barley and potatoes, Boyd concluded that crop response can be characterized by a linear-plateau model. That is, over a range, yield responds linearly to additional levels of a variable input until the yield plateau is reached. The plateau indicates either the physiological yield limit, or the point at which some factors other than the variable factor is limiting yield.

The hypothesis of plateau growth crop response is also supported by Perrin who argued that the linear response and plateau (LRP) provides an approximation of phenomenon that many agricultural economists have noted (that response curves often tend to be quite flat on the top). While, many agricultural economists support the hypothesis that response curves often tend to be quite flat at the top, few support the maintained hypothesis of the LRP characterized by the Von Liebig that the initial portion of crop response curves are linear. Indeed, empirical plots of data in general reflect a curvilinear shape for crop response curves for input levels less than that required to achieve the plateau. Hence, a quadratic plateau function may be a more appropriate specification than a linear plateau function.

Griffin et al. evaluated several functional forms. They concluded that, "determination of the true functional form of a given relationship is impossible, so, the problem is to choose the best form for a given task" (Griffin et al. p. 220).

Agronomic Studies of Row Spacing and Seeding Rate

Impacts on Wheat Yield

Several studies have evaluated the relationship between row spacing and wheat grain yield. Solie et al. found that narrowing row spacing from 23.0 cm (9 inches) to 7.5 cm (3 inches) resulted in a 12.8% increase in wheat yield. Their work was conducted in Oklahoma at Stillwater, Orlando, Perkins, Lahoma, and Chickasha. They found that row spacing and wheat grain yield were inversely related in cheat-free field treatments at Stillwater and Orlando but not at Perkins and Lahoma. Their results for Perkins and Lahoma were not statistically significant. In the Chickasha experiment, row spacing and presence of cheat were not significant factors.

Joseph et al. in a field experiment conducted in the coastal plain of Virginia evaluated row spacing and seeding rate influences on winter wheat grown under intensive management (adequate supply of macronutrients). The seeding rate ranged from 186 to 558 seeds m^{-2} (1.2 square yards), and row spacings were 10 cm (4 inches) and 20 cm (8 inches). Additional treatments of 744 and 1116 seeds m^{-2} (1.2 square yards) in 10 cm (4 inches) row spacing were also included. They found that 10 cm (4 inches) row spacings produced 0.6 to 0.8 Mg ha^{-1} (536 to 714 pounds per acre) higher grain yields than 20 cm (8 inches) row spacings at identical seeding rates (approximately 12% yield increase). They also found that seeding rates of 372 to 744 seeds m^{-2} (1.2 square yards) in 10 cm (4 inches) rows were sufficient to produce high yields. Similar results were reported by Johnson et al. from a study conducted in the southeastern United States to determine the effects of row spacing and seeding rates on grain yield and yield components of five cultivars in a high yield environment. Seeding rate ranged from 288 to 576 seeds m^{-2} (1.2 square yards). Row spacings were 10 cm and 20 cm (4 and 8 inches). Their results showed that the 10 cm (4 inches) row spacing yielded 8% more than the 20 cm (8 inches) row spacing. They also reported that wheat yield was not influenced by seeding rates when averaged over years. Row spacing and seeding rate interactions on grain were found not to be statistically significant. Similar results of seeding rate effects on yields were reported by Roth et al. in Pennsylvania.

A study conducted in the northeastern United States by Frederick and Marshall to determine the effects of seeding rate, row spacing, seed depth and rate of spring nitrogen fertilization concluded that seeding rates above 101 kilograms per hectare (90 pounds per acre) increased grain yield in some locations. The seeding rate and row spacing used ranged from 101 to 235 kilograms per hectare (90 to 210 pounds per acre) and 12.7 to 17.8 cm (5 to 7 inches), respectively. They also reported that yield response to seeding rate was influenced by environment and that a high seeding rate produced the greatest yield response with late planting (severe winter). They concluded that averaged over environment, 168 kilograms per hectare (150 pounds per acre) was the optimum wheat seeding rate.

At West Lafayette, Indiana, yield response at two seeding rates and two row spacings were investigated by Marshall and Ohm. Seeding rates were 377 and 538 kernels m^{-2} (1.2 square yards) at row spacings of 6.4 cm and 19.2 cm (2.5 and 7.5 inches). They concluded that row spacings narrower than the conventional 19.2 cm (7.5 inches) significantly increase grain yield, but the response varied depending on cultivar and environmental conditions. They also reported that a combination of increased seeding rate and narrow row spacing was important for increasing grain yield (9.1% increase in grain yield).

An Ontario (Canada) experiment conducted by Stoskopf determined yield performance of upright-leaved selections of winter wheat in narrow row spacings. Row spacings ranged from 22.8 and 17.8 cm (9 and 7 inches) (wide) to 11.4 and 8.9 cm (4.5 and 3.5 inches) (narrow). Seeding rates were 60, 120, and 180 pounds per acre. He concluded that, at all three seeding rates, narrow rows produced 12.6% more grain than wide rows. Highest yields were obtained at a seeding rate of 120 pounds per acre.

In a review of experimental work on winter wheat conducted at Leeds University, Holliday concluded that, at constant seeding rates, narrow row spacing (4 to 8 inches) yielded more grain than wide row spacing (12 inches).

A study conducted by Freeze and Bacon in Arkansas evaluated three row spacings (4, 6, and 8 inches) and three seeding rates (13, 26,and 52 seeds per square foot). They concluded that row spacing effects on yield were not statistically significant. However, they did find that high seeding rates yielded more grain. Their conclusion on row spacing diverged from previous studies. Other studies have shown significant effects of changing row spacings on grain yield. A study in Canada using seeding rates of 35, 70, 105, and 140 kilograms per hectare (31, 62.5, 93.7 and 125 pounds per acre) and 9, 18, 27, and 36 cm (3.5, 7, 10.6,and 14 inches) row spacings found that narrowing row spacings increased grain yield under favorable climatic conditions (Tompkins et al.). They also reported that high seeding rates and narrow row spacings interact positively to increase grain yield.

Beuerlein and Lafever found similar results for row spacing but not for seeding rate. They found that increasing seeding rate from 45 to 180 pounds per acre in 7 inch rows caused a linear decrease in yield. Their study was conducted at Wooster in Ohio in 1982-1983. Only a few studies have focused on the effect of seeding rate on cheat population.

Summary of Literature Reviewed

The agronomic studies reviewed, showed that herbicides can be used to mitigate somewhat the deleterious effects of weeds (Dewey et al; and Greer et al.). However, a chemical herbicide which provides consistent control of cheat with little to no damage to wheat is not commercially available to farmers. Cheat is physiologically very similar to wheat. It thrives in conditions conducive to good wheat production. The vast majority of herbicides used to control cheat are also detrimental to the growth of wheat. Hence, the herbicides currently registered for use to control cheat in wheat such as metribuzin, are ineffective or damage the crop if conditions are less than ideal when applied.

The literature on functional structure showed that the choice of a functional form to model the production process is left to the researcher. However, theory and statistical tests can be used to assist with selecting an appropriate functional form to describe the information at hand.

The literature confirms that many studies have evaluated the relationships between row spacing and wheat yield, and seeding rates and wheat yield. However, the influence of seeding rate on wheat grain yield for alternative levels of cheat infestation has not been established.

The majority of studies have found that reducing row spacing from levels conventionally used with seeding rate held constant resulted in increased yield. A second finding showed that yield was a function of seeding rate. However, none of the studies attempted to estimate a continuous function of yield response to seeding rate. The seeding rate at which yield was maximized varied with climate, soil, and wheat class.

For example, Stoskopf whose study was conducted at Ontario reported highest yield at a seeding rate of 120 pounds per acre. But, Tompkins et al. reported highest yield with a seeding rate of 125 pounds per acre. Furthermore, Frederick and Marshall whose study was conducted in the northeastern United States reported highest yields at a seeding rate of 150 pounds per acre. None of the studies derived the economically optimal seeding rate.

A third finding was that the impact of seeding rate and row spacing on the wheat plant's ability to compete with cheat for water and nutrients has not been established. It is not known if increasing the wheat seeding rate or changing row spacing are viable methods for reducing the deleterious impact of cheat on wheat yield. Moreover, the economic consequences of alternative seeding rates, row spacings and cheat infestation levels have not been established.

CHAPTER II

THE DATA

Data were obtained from two trials conducted during the 1989-1990 growing season. Detailed descriptions of the experiments including the experimental design are provided in Solie et al. The trials were conducted at experiment stations near Lahoma, and Chickasha, Oklahoma. In both trials, treatments included three wheat seeding rates (60, 90, and 120 pounds per acre), three row spacings (3, 6, and 9 inches), and five levels of artificially induced cheat infestation. Cheat infestation was achieved by seeding cheat at rates of 0, 30, 60, 90, and 120 pounds per acre.

Severe cheat populations resulted from the 120 pound cheat seeding rates. Moderate cheat infestations, typical of that which naturally occurs under stubble mulch tillage, were achieved with the 60 pound cheat seeding rate. All treatments were replicated six times. Factors other than seeding rate and cheat level, including fertilizer applied were constant across all plots. A total of 972 observations were available for response function estimation. The 972 observations were composed of two groups. The Lahoma study was composed of three row spacings (3, 6, and 9 inches) by three seeding rates (60, 90, and 120 pounds) by five cheat levels (0, 30, 60, 90, and 120 pounds) by six replications supplemented by three row spacings by three seeding rates by twelve replications and by three row spacings by three seeding rates by six replications for a a total of 432 observations.

The Chickasha experiment included three row spacings (3, 6, and 9 inches) by three seeding rates (60, 90, and 120 pounds) by five cheat levels (0, 30, 60, 90, and 120 pounds) by six replications supplemented by three row spacings by three seeding rates by eighteen replications, and by three row spacings by three seeding rates by twelve replications for a total of 540 observations.

The Model

This section describes the procedures used in this research. Linear and non-linear regression procedures were used to provide estimates of wheat grain yield response functions.

Historically, a factor-product model has been characterized by a production function in which output is expressed as a function of the level of inputs:

$$Y = F(X_1, X_2, . . .) \tag{5}$$

where:

Y = total output,

F = function of variables X_i's, and

X_i = level of input i.

The wheat plant growth response model estimated for this research is of the form:

$$Y = F(SR, RS, CL, \Omega) \tag{6}$$

where:

Y = wheat yield (total output),

SR = seeding rate,

RS = row spacing,

CL = cheat, and

Ω = other factors influencing wheat plant growth such as fertilizer, which was fixed rather than a treatment variable in the field experiments, and weather.

The literature contains only a few studies that report an explicit model to describe the functional relationship between grain yield and seeding rate (Tompkins et al). Unlike Tompkins et al., Guitard et al., and Boyd describe graphically wheat yield response to seeding rate. Boyd's study was conducted at Rothamsted Experiment Station in Harpenden (England) in 1952. The standard seeding rate was 120 pounds per acre. Guitard's study was conducted at the experimental farms at Beaverlodge and Fort Vermillion in Alberta (Canada) from 1954 to 1956. In both studies, wheat yield response to seeding rate was characterized by an initial rapid increase followed by a plateau region. An explicit model treating wheat grain yield response to seeding rate and cheat infestation at alternative row spacings has not been reported. For a better understanding of the variables affecting wheat grain yield, consider Figure 1.

Figure 1 shows factors which may directly affect wheat grain yield. These factors are: natural factors, macronutrients, seeding rate, row spacing, cheat infestation level, management practices, capital, and pesticides. Natural factors include rainfall, climate, and the type of soil. Macronutrients include nitrogen, phosphorus, and potassium fertilizers. Management practices effects on wheat grain yield can be positive as well as negative. Similarly, capital and pesticides in economically optimal quantities are directly related to wheat yield. But excessive amounts of some pesticides may harm the

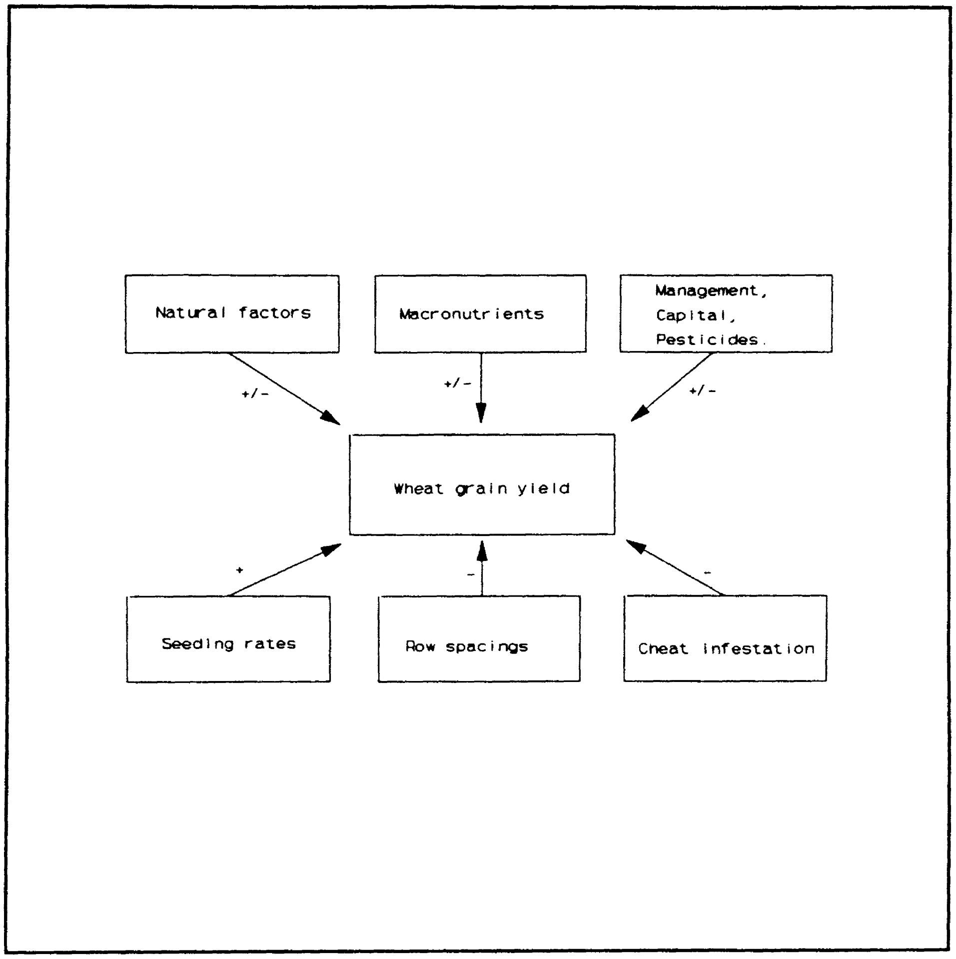

Figure 1. Variables Affecting Wheat Grain Yield.

crop. The effects of these variables on wheat yield are indicated on the flow chart by arithmetic signs. In this research, the treatment variables of concern are seeding rate, row spacing, and cheat infestation level.

For this research, two functional forms were used to estimate equation (6): the quadratic, and the quadratic response plateau model (QRP). The choice of the quadratic function was based on its curvilinear and bell shape which describes initial rapid growth as the level of the factor of production is increased, followed by a maximum and then declining yield, its computational simplicity and its ability to statistically represent the data. Its marginal products are linear and unrestricted in sign. That is, the marginal products can be either positive or negative. The LRP characterized by the Von Liebig specification exhibits unrestricted but constant marginal products. That is, they do not allow model estimation to determine at what input level output begins to decrease but rather maintain the hypothesis of everywhere positive or zero marginal productivity (Griffin et al.).

As mentioned in Chapter I, the properties of the inverse polynomial function when dealing with crop response to several factors have not yet been established. That is, it was not considered as a functional structure of crop response in this research.

The quadratic specification is also characterized by variable elasticity of substitution of RS for SR. That is, the corresponding isoquants are elliptical. Thus, there may be areas of positive, negative, zero, and infinite slope (Beattie and Taylor). The substitutability of seeding rate and row spacing can be tested given the variable elasticity of substitution assumption. This hypothesis is more realistic than assuming constant elasticity of substitution or zero elasticity of substitution as the LRP (characterized by the Von Liebig specification) does.

Another advantage of the quadratic functional form is the relative ease in estimating with conventional statistical methods. The mathematical expression of the model is as follows:

$$Y = \beta_0+\beta_1 SR+\beta_2 CL+\beta_3 RS+\beta_4 SR^2+\beta_5 SRCL+\beta_6 CL^2 \\ +\beta_7 RS^2+\beta_8 RSCL+\beta_9 RSSR+\beta_{10} RSSRCL+e_t \tag{7}$$

where:

Y = wheat grain yield expressed in bushels per acre,

β_i = parameters to be estimated,

SR, CL, and RS are as previously defined,

SRCL = seeding rate and cheat level interaction,

RSCL = row spacing and cheat level interaction,

RSSR = row spacing and seeding rate interaction,

RSSRCL = row spacing, seeding rate, and cheat level interaction, and

e_t = unobservable random variable.

Plateau response model estimation is not as convenient as that of the quadratic. However, it may provide a better description of wheat grain yield response to alternative seeding rates, row spacing, and levels of cheat infestation. For that reason, a QRP model was selected as an alternative specification of wheat grain yield response to seeding rate, row spacing, and levels of cheat infestation. The decision was to use both functional forms and conduct a nonnested hypothesis test to discriminate between the two specifications. The mathematical expression for the QRP model considered is as follows:

$$Y = \beta_0+\beta_1 SR+\beta_2 CL+\beta_3 RS+\beta_4 SR^2+\beta_5 SRCL+\beta_6 CL^2$$
$$+\beta_7 RS^2+\beta_8 RSCL+\beta_9 RSSR+\beta_{10} RSSRCL+e \text{ if } SR \leq SR_0 \quad (8)$$
$$Y = Y_M + e \quad \text{if } SR > SR_0$$

where:

Y_M = plateau yield,

SR = seeding rate, and

SR_0 = minimum seeding rate required to achieve the plateau yield.

At Y_M the assumed optimum cheat level and row spacing are zero and three inches, respectively. The QRP model as described by equation (8) forces a linear plateau which is smoothly grafted to a quadratic segment. Smoothness and continuity of the function are obtained by placing continuity and smoothness restrictions upon the model (Epplin and Schatzer).

Ordinary Least Squares Procedure for Estimating β

The general form of the model to be estimated is:

$$Y = X\beta+e \quad (9)$$

where:

X = a (T x K) observable nonstochastic matrix,

β = a (K x 1) vector of parameters to be estimated,

Y = a (T x 1) observable random vector, and

e = a (T x 1) unobservable random vector with the following properties:

E(e) = 0 and E(ee') = ϕ = diag($\sigma_1^2, \sigma_2^2, \ldots, \sigma_T^2$)

Using OLS techniques to estimate (9) leads to the estimator

$$b = (X'X)^{-1}X'Y \tag{10}$$

Given that the data contain information from two different trials, the OLS assumption of constant and identical variance of residuals, that is, $E(e_t e_t') = \sigma^2$ for all t could be violated. If that is the case, and if OLS methods are used to estimate the model, the estimates will be unbiased, asymptotically unbiased, and consistent. However, they will not be efficient. In other words they will not necessarily have the minimum variance relative to other unbiased estimators (Judge et al.; Kennedy; Kmenta). Consequently, confidence intervals and hypothesis tests based on those estimates would not be valid. The violation of this OLS assumption is known in the literature as heteroskedasticity.

Once b is obtained via OLS, a test for homoskedasticity is conducted to confirm the assumption of identical variances of residual variables. Several tests are described in the literature including Goldfeld-Quandt, White, Breusch-Pagan, Glejser, and Harvey (Judge et al.). For this research, the Breusch-Pagan (B-P) was used to test for the presence of heteroskedasticity. The choice of B-P does not require any ordering of observations as with the Goldfeld-Quandt test. The B-P and White tests are very similar.

Using equation (9), assume that under the hypothesis of heteroskedasticity:

$$\sigma_t^2 = h(z_t'\alpha) = h(\alpha_1 + Z_{t-1}^{*\prime}\alpha^*) \tag{11}$$

where:

Equation (11) describes the form that the heteroskedasticity takes if it is present.

$z'_t = (1, z^{*\prime}_t) = (1, z_{t2}, \ldots, z_{tT})$ = a vector of observable explanatory variables,

$\alpha = (\alpha_1, \alpha^{*\prime}) = (\alpha_1, \ldots, \alpha_T)$ is a vector of unknown coefficients (Judge et al.), and

z'_t = the independent variable X or a group of independent variables other than X (Pindyck and Rubinfeld).

Under the null hypothesis that the variance of the residuals are identical ($\alpha^* = 0$), if errors are normally distributed, one-half the difference between the total sum of squares and the residual sum of squares from the regression

$$\frac{\hat{e}_t^2}{\tilde{\sigma}^2} = z_t \alpha + v_t \tag{12}$$

is distributed asymptotically as a chi-square with (T-1) degrees of freedom.

$$\tilde{\sigma}^2 = \sum_{t=1}^{T} \frac{\hat{e}_t^2}{T} \tag{13}$$

where:

$\hat{e}_t$ = least squared residuals from the OLS regression (Judge et al.), and

v_t = unobservable random vector with the same properties as e_t.

The relevant statistic is RSS/2 $\approx \chi^2_{(t-1)}$.

where:

RSS = regression sum of squares, and

$\chi^2_{(t-1)}$ = chi square with (t-1) degrees of freedom.

If RSS/2 is greater than the critical value for a given level of significance, the null hypothesis of homoskedasticity is rejected and it is concluded that heteroskedasticity is present.

The estimator described in equation (10) is an unbiased and consistent estimator, but, in the absence of non-identical variance of the random variables it is not efficient. Given this inefficiency of b, the possibility of developing a best linear unbiased estimator for ß was investigated (Judge et al.).

The first step in developing that estimator is to transform (9) by multiplying both sides by a (TxT) matrix P which has the property that

$$P\psi P' = I_T \tag{14}$$

where:

ψ = variance-covariance matrix of equation (9), and

I = identity matrix. ψ is a positive definite matrix such that $P \psi P' = I_T$ always exists (Judge et al.). Using P to transform (9) yields:

$$PY = PX\beta + Pe \tag{15}$$

or

$$Y^{*} = X^{*} \beta + e^{*} \tag{16}$$

where:

$Y^{*} = PY$,

$X^{*} = PX$, and

$e^{*} = Pe$

e^{*} is such that $E(e^{*}) = E(Pe) = PE(e) = 0$

and $E(e^{*}e^{*\prime}) = E(Pee'P') = PE(ee')P' = \sigma^2 P \psi P' = \sigma^2 I_T$

Thus, e^{*} has the same properties as e in (9).

Hence, the least squares estimator

$$\hat{\beta} = (X^{*\prime}X^{*})^{-1}X^{*\prime}Y^{*} \tag{17}$$

is the best, linear, unbiased estimator of the unknown parameter β.

Writing (17) in terms of the original observations gives:

$$\hat{\beta} = (X'P'PX)^{-1}X'P'PY \tag{18}$$

Because $P\psi P' = I_T$, $\psi = P^{-1}P^{-1\prime}$.

Rearranging the above equality yields $\psi^{-1} = P'P$. Thus, least squares applied to the transformed observations is given by:

$$\hat{\beta} = (X'\psi^{-1}X)^{-1}X'\psi^{-1}Y \tag{19}$$

where:

β = the Generalized Least Squares estimator (GLS).

β is obtained assuming that ψ is known. But, in general ψ is not known, and it must be estimated. Hence, ψ in equation 19 is replaced by $\hat{\psi}$ in (20) which leads to the Estimated Generalized Least Squares (EGLS) estimator denoted by:

$$\hat{\beta} = (X'\hat{\psi}^{-1}X)^{-1}X'\hat{\psi}^{-1}Y \tag{20}$$

It has been proven that β is an unbiased estimator. However, it is neither "best" nor "linear" (Judge et al.). Consistency and asymptotic normality of β have been established (Judge et al., pp. 353-356). Hence, in the presence of heteroskedasticity, the EGLS procedure may be used to estimate parameters of the model considered. Other procedures to estimate parameters in the presence of heteroskedasticity are available, including, the maximum likelihood estimation procedure.

Maximum Likelihood Procedure for estimating β

The maximum likelihood procedure may be used to estimate equation (9) in the presence of heteroskedasticity. The first step in using maximum likelihood (ML) is to make a distributional assumption. The second step is to set up a log-likelihood function. For this research, it is assumed that the unobserved variable is distributed normally with mean zero and variance $\sigma^2\Omega$. The log-likelihood function, excluding the constant terms, is given as follows:

$$L = -\frac{T}{2}\ln\sigma^2 - \frac{1}{2}\ln|\psi| - \frac{1}{2\sigma^2}(Y-X\beta)'\psi^{-1}(Y-X\beta) \tag{21}$$

where:

ln = symbol for the natural log.

The objective in ML, is to find β and σ^2 which maximize the probability of obtaining the sample actually observed. In equation (21) only the last term contains β Hence, maximizing equation (21) with respect to β is equivalent to maximizing

$$-\frac{(Y-X\beta)'\psi^{-1}(Y-X\beta)}{2\sigma^2} \tag{22}$$

Given the negative sign and the constant term $2\sigma^2$, maximizing equation (22) is equivalent to minimizing

$$S = (Y-X\beta)'\psi^{-1}(Y-X\beta) \tag{23}$$

with respect to β. S in equation (23) is the least squares criterion (Judge et al., pp. 223-225).

Thus, we can write

$$\tilde{\beta} = [X'\psi^{-1}X]^{-1}X'\psi^{-1}Y \tag{24}$$

To obtain σ^2, derive the first order condition of the maximization problem with respect to σ^2:

$$\frac{\partial L}{\partial\sigma^2} = -\frac{T}{2\sigma^2} + \frac{1}{2\sigma^4}(Y-X\beta)'\psi^{-1}(Y-X\beta) = 0 \tag{25}$$

Solving equation (25) for σ^2 gives:

$$\frac{1}{2\sigma^4}(Y-X\beta)'\psi^{-1}(Y-X\beta) = \frac{T}{2\sigma^2} \tag{26}$$

$$\frac{(Y-X\beta)\psi^{-}1(Y-X\beta)}{(\sigma^2)} = T \tag{27}$$

$$\tilde{\sigma}^2 = \frac{[Y-X\tilde{\beta}]'\psi^{-1}[Y-X\tilde{\beta}]}{T} \tag{28}$$

Substituting equation (24) and the expression of σ^2 into equation (21) and rearranging terms gives:

$$L = -\frac{T}{2}\ln(Y-X\tilde{\beta})'\psi^{-1}(Y-X\tilde{\beta}) + \frac{T}{2} lnT - \frac{1}{2}\ln|\psi| - \frac{T}{2} \tag{29}$$

Excluding constant terms leads to

$$L(\theta) = -\frac{T}{2}(Y-X\tilde{\beta}(\theta))'\psi^{-1}(\theta)(Y-X\tilde{\beta}(\theta)) - \frac{1}{2}\ln|\psi(\theta)| \tag{30}$$

The maximum likelihood estimator (MLE) for θ, $\tilde{\theta}$, is that value of θ for which L(θ) is maximum. Define

$$\tilde{\psi} = \psi(\tilde{\theta}) \tag{31}$$

then, the maximum likelihood estimators for β and σ^2 (not conditional on θ) are given by

$$\tilde{\beta} = \tilde{\beta}(\tilde{\theta}) = (X'\tilde{\psi}^{-1}X)^{-1}X'\tilde{\psi}^{-1}Y \tag{32}$$

$$\tilde{\sigma}^2 = \tilde{\sigma}^2(\tilde{\theta}) = \frac{(Y-X\tilde{\beta})'\tilde{\psi}^{-1}(Y-X\tilde{\beta})}{T} \tag{33}$$

Thus, the MLE for β is of the same form as the EGLS estimator. But, instead of using an estimate of ψ based on least squares residuals, it uses an estimate of ψ obtained by maximizing equation (30) with respect to θ. Because the MLE $\tilde{\beta}$ is also an EGLS estimator, the properties of the EGLS estimators hold for the MLE. However, in the MLE case, the estimator $\tilde{\beta}$ is asymptotically efficient (Judge et al., pp. 180-182).

Non-linear Regression Procedure for Estimating
the Quadratic-Plateau Model

For the quadratic-plateau model, a direct numerical search procedure known as Gauss-Newton method was used. This method is also known as the linearization method. It uses a Taylor series expansion to approximate the nonlinear regression model (Neter et al.). The Gauss-Newton method helps in simultaneously estimating the parameters and selecting the graft point which minimizes the sum of squared errors (Epplin and Schatzer). Continuity and smoothness restrictions are imposed for the function to be continuous and smooth at the graft point. The continuity restriction, for instance, forces the values of the segments to be equal at the grafted point. The smoothness constraint forces the first derivatives of the two segments to be equal at the point of graft. The quadratic-plateau model was given by equation (8).

The restrictions that the plateau function be continuous and smooth at SR_0 result in:

$$Y = ß_0 + ß_1\, SR_0 + ß_2\, CL + ß_3\, RS + ß_4\, SR_0^2 + ß_5\, SR_0CL + ß_6\, CL^2 + ß_7\, RS^2 + ß_8\, RSCL + ß_9\, RSSR_0 + ß_{10}\, RSSR_0CL \qquad (34)$$

where:

$$SR_0 = -0.5*(ß_1+ß_5*CL+ß_9*RS+ß_{10}*RS*CL)/ß_4 \qquad (35)$$

which requires that:

$$Y_M = \beta_0 + \beta_2 CL + \beta_3 RS + \beta_6 CL^2 + \beta_7 RS^2 + \beta_8 RSCL - \frac{1}{4\beta_4}(\beta_1 + \beta_5 CL + \beta_9 RS + \beta_{10} RSCL)^2 \tag{36}$$

Testing the Traditional Quadratic Specification

Against the Quadratic-Plateau Specification

A nonnested hypothesis test was conducted to discriminate between the traditional quadratic and the quadratic-plateau specification. Procedures for nonnested hypothesis testing are found in Pesaran and Deaton, Davidson and Mackinnon (1981, 1993), Pesaran, Godfrey and Pesaran, and Fisher and McAleer. For this research, the P-test developed by Davidson and MacKinnon was used.

Let our two models be as follows:

The quadratic specification:

$$Y = Z_0 = \beta_0 + \beta_1 SR + \beta_2 CL + \beta_3 RS + \beta_4 SR^2 + \beta_5 SRCL + \beta_6 CL^2 + \beta_7 RS^2 + \beta_8 RSCL + \beta_9 RSSR + \beta_{10} RSSRCL + e \tag{37}$$

The quadratic-plateau specification:

$$Y = \begin{cases} Z_1 = \gamma_0 + \gamma_1 SR + \gamma_2 CL + \gamma_3 RS + \gamma_4 SR^2 + \gamma_5 SRCL + \gamma_6 CL^2 + \\ \gamma_7 RS^2 + \gamma_8 RSCL + \gamma_9 RSSR + \gamma_{10} RSSRCL + e \quad if\ SR \le SR_0 \\ Z_1 = Z_M + e \quad if\ SR > SR_0 \end{cases} \tag{38}$$

where:

$Y = Z_0 = Z_1$ = wheat yield,

Z_M = plateau wheat yield, and

B_i and γ_i = parameters to be estimated (i= 1,...,10).

Both specifications must be differentiable to conduct the nonnested hypothesis test. However, the plateau model is not differentiable throughout. Thus, the test will be conducted on the part of the plateau function that is differentiable.

Let the hypotheses be as follow:

$H_0 : Y = Z_0(\beta) + e$

$H_1 : Y = Z_1(\gamma) + e$

Z_0 and Z_1 are (n x k_0) and (n x k_1) matrices of observations, and β and γ are (k_0 x 1) and (k_1 x 1) matrices of parameters, respectively. To test H_0, consider the Gauss-Newton regression from the original estimations:

$$Y - \hat{Z}_0 = \hat{Z}b + a(\hat{Z}_1 - \hat{Z}_0) + e \qquad (39)$$

where:

$\hat{Z}_0$ = the predicted value from Z_0,

$\hat{Z}_1$ = the predicted value from Z_1,

$\hat{Z}$ = by definition $Z(\hat{\beta})$, and

$$\text{Diff} = \hat{Z}_1 - \hat{Z}_0 \qquad (40)$$

$Z(\beta)$ is the (n x k_0) matrix of derivatives of $Z_0(\beta)$ with respect to β, and β is the estimate of β under H_0. The P-test uses the t-statistic for a = 0 from the Gauss-Newton regression to test H_0 against H_1. The same test is conducted to test H_1 against H_0.

If the null hypothesis of a = 0 is rejected the alternative, H_1 is selected as the correct specification. Because each hypothesis may or may not be rejected, four possible outcomes are possible from the test. If both hypotheses (H_0 and H_1) are rejected, neither model is satisfactory. Each model may possess unique information. Failure to reject either hypotheses, suggests that both models fit the data equally well and that neither provides evidence that the other is misspecified. This result may be because the two models are very similar, or because the data set is not informative (Davidson and MacKinnon 1993).

Variability of Predicted Wheat Grain Yields

Once estimates of the parameters of a response function are available (equation (9)), the function may be used to predict the dependent variable for selected values of the independent variables. The justification of this section is that farmers may be concerned about the variability in wheat grain yields for alternative levels of row spacing, seeding rate, and cheat infestation. Within this context, consider equation (9)

$$\hat{Y} = X\beta \quad = X\beta + e \tag{41}$$

Using the estimated model

$$\hat{Y} = X\hat{\beta} \tag{42}$$

The value of the dependent variable $\hat{Y}$ is determined for each set of explanatory variables. $\hat{Y}$ represents the predicted values from the estimated equation. To investigate the variability in predicted yields, consider the prediction error, that is $(Y - \hat{Y})$. The variability of an individual observation

$$(Y_t - \hat{Y}_t) = \hat{e}_t \tag{43}$$

is a random variable, normally distributed, with mean zero. The variance of the prediction error can be estimated as follows:

$$VAR(Y-\hat{Y}) = VAR(Y) + VAR(\hat{Y}) - 2COV(Y,\hat{Y}) \tag{44}$$

given that

$$COV(Y,\hat{Y}) = E[Y-E(\hat{Y})][\hat{Y}-E(\hat{Y})] \tag{45}$$

and that

$$Y = X\beta + e$$

$$E(Y) = E(X\beta + e) = X\beta + E(e)$$

$$E(e) = 0$$

$$E(Y) = X\beta \tag{46}$$

Consequently,

$$Y - E(Y) = X\beta + e - X\beta = e \tag{47}$$

$$if \quad \hat{Y} = X\hat{\beta}$$

$$E(\hat{Y}) = E(X\hat{\beta}) = X\beta \tag{48}$$

then $\hat{Y} - E(\hat{Y}) = X\hat{\beta} - X\beta = X(\hat{\beta}-\beta)$ (49)

Thus $COV(Y,\hat{Y}) = E[e(\hat{\beta}-\beta)] = XE[e(\hat{\beta}-\beta)]$ (50)

given that $E(e) = 0$ we have

$$COV(Y\ ,\ \hat{Y}) = 0 \tag{51}$$

Finally, we have

$$\text{VAR}\ (Y-\hat{Y}) = VAR(Y) + VAR(\hat{Y}) \tag{52}$$

$$\text{VAR (Y)} = \sigma^2 \tag{53}$$

$$\text{VAR}\ (\hat{Y}) = \sigma^2[X_0(X'X)^{-1}\ X_0 + \frac{1}{n}] \tag{54}$$

where:

X_0 = vector of the independent variables (seeding rate, row spacing, and cheat levels) used to compute the predicted yield,

X = matrix of seeding rate, row spacing, and cheat level observations, and

n = number of observations.

$$VAR(Y-\hat{Y}) = VAR(\hat{e}) = \sigma_f^2 = \sigma^2 + \sigma^2[X_0(X'X)^{-1}\ X_0 + \frac{1}{n}] \tag{55}$$

$$\sigma^2{}_f = \sigma^2[1 + \frac{1}{n} + X_0(X'X)^{-1}X_0] \tag{56}$$

An unbiased estimator of σ_f^2 is obtained by replacing σ^2 by s^2 (Kmenta, pp. 426-427). Using the resulting estimator (s_f^2) it is possible to construct the following test statistic:

$$\frac{(Y-\hat{Y})}{S_f} \sim t_{T-k} \tag{57}$$

From the above statistic a prediction interval can be constructed for each individual predicted value of wheat yield with a selected probability. Designating that probability α, we can write

$$\hat{Y} - t_{T-k,\frac{\alpha}{2}} * S_f \leq Y \leq \hat{Y} + t_{T-k,\frac{\alpha}{2}} * S_f \tag{58}$$

which is the confidence interval or prediction interval at $(1-\alpha)100\%$ for Y. With a bound on the error of predicting Y, we would expect the error to be less, in absolute value, than $(t_{T-k},\alpha/2)*S_f$ with probability equal to $(1-\alpha)$ (Mendenhall et al.). S_f is the standard deviation of the prediction error. An F-test can be constructed. Since

$$\frac{\hat{\sigma}_f^2(T-K)}{s_{1_f}^2} \sim \chi_{1_{(T-K)}}^2 \tag{59}$$

A chi-square can be defined for the alternative cheat infestation levels as described by equation (60). Consider the following test statistic:

$$\hat{\sigma}_f^2\ \frac{(T-K)}{s_{2_f}^2} \sim \chi_{2_{(T-K)}}^2 \tag{60}$$

which is different from the one in equation (59). Using these two statistics an F-test is constructed to test wheat yield variability:

$$\frac{s_2^2}{S_1^2} \sim F_{(T-K,T-K)} \tag{61}$$

Substituting (59) and (60) into (61) yields the following result

$$\frac{\chi_1^2/(T-K)}{\chi_2^2/(T-K)} \sim F_{(T-K,T-K)} \tag{62}$$

which can be used to test for differences in wheat yield variability across different levels of row spacing, cheat level, and seeding rate.

Methods for Conducting Economic Analysis of Weed Control Alternatives

This section presents methods for conducting economic analysis of weed control alternatives. As mentioned in Chapter I, different tools to assess the economics of weed control are available (economic thresholds, budgeting, investment criteria, and comparison of risky outcomes). Either tool of assessment requires the existence of an objective function. The type of objective function may vary from the simple single equation static deterministic objective function to a complicated dynamic stochastic objective function. This section includes alternative objective functions and information needed for their estimation.

Consider a single equation static deterministic objective function.

$$\pi(X_i,\ldots,X_i,\ldots,X_n) = P\ F(X_i,\ldots,X_i,\ldots,X_n) - \sum_{i=1}^{n} r_1 X_i \qquad (63)$$

where:

π = value of the objective function,

$F(X_1,\ldots,X_i,\ldots,X_n)$ = concave production function,

P = output price,

X_i = level of input i, and

r_i = price of input i.

The necessary conditions for profit maximization are obtained by taking the partial derivatives of the objective function with respect to the input variables and setting them equal to zero.

$$\frac{\partial \pi}{\partial X_i} = P \frac{\partial F}{\partial X_i} - r_i = 0 \tag{64}$$

For a given set of prices (P and r) the level of X_i that maximizes π can be determined by solving equation (64) for the optimal X_i. The information needed for the above analysis includes output and input prices, and the response function, $F(X_1,\ldots,X_i,\ldots X_n)$.

To allow for the impact of weeds on crop yield, include a weed variable in the single equation static deterministic response function:

$$Y = F(X_1,\ldots,X_i,\ldots X_n,W) \tag{65}$$

where:

W = weed density.

$$\frac{\partial Y}{\partial W} < 0 \tag{66}$$

The objective function will be:

$$\pi(X_1,\ldots,X_i,\ldots X_n,W) = P\ Y - \sum_{i=1}^{n} r_i X_i \tag{67}$$

where:

The first order conditions for profit maximization are given by:

$$\frac{\partial \pi}{\partial X_i} = P \frac{\partial Y}{\partial X_i} - r_i = O \tag{68}$$

The information needed for this analysis includes, in addition to the data needed for the first method, weed density as an argument in the response function.

The model may be expanded to include a weed control variable in the crop response function. The weed control variable can be a chemical herbicide or a cultural practice. The response function with the weed control variable can be written as follows:

$$Y = F(X_1,\ldots,X_i,\ldots,X_n,W,H) \tag{69}$$

where:

H = weed control variable.

The objective function is:

$$\pi(X_1,\ldots,X_i,\ldots,X_n,W,H) = P\ Y - \sum_{i=1}^{n} r_i X_i - cH \tag{70}$$

where:

c = cost of weed control.

The first order condition for profit maximization is as follows:

$$\frac{\partial \pi}{\partial X_i} = P \frac{\partial Y}{\partial X_i} - r_i = 0 \tag{71}$$

$$\frac{\partial \pi}{\partial H} = P \frac{\partial Y}{\partial H} - c = 0 \tag{72}$$

At the optimum, the value of using an additional unit of X_i and H should be just equal the price of input i and the cost of weed control, respectively. The additional information needed for the above objective function includes: herbicide dose (if herbicide is used as weed control agent), and the costs of treatment. The weed density at which it is just economical to apply the herbicide is referred to in the literature as the economic threshold.

The static model may be modified to include time in the response function.

$$Y_t = F_t(X_{it},\ldots,W_{it},\ldots,X_{nt},W_t,H_t) \tag{73}$$

where:

t = time period (1,2,...,T).

Let π_t be the expected profit at time period t. The objective of the farmer will be to maximize the present value of the expected profit in time period t. Thus, we need a multi-period profit function.

$$\pi_t(X_{1t},\ldots X_{it},\ldots,X_{nt},W_t,H_t) = P_t\ Y_t - \sum_{i=1}^{n} r_{it}X_{it} - c_tH_t \tag{74}$$

Let u, be the discount rate at which future profits are discounted, and $G(W_t, H_t)$ be a function measuring change in weed seed density. G is known as the equation of motion (Pandey and Medd).

$$\frac{\partial G}{\partial H_t} \leq 0 \tag{75}$$

$$\frac{\partial G}{\partial W_t} \text{ is unrestricted in sign.} \tag{76}$$

The net discounted present value of future profits is given by:

$$\sum_{t=1}^{T} \frac{\pi_t(X_{1t},\ldots,X_{it},\ldots,X_{nt},W_t,H_t)}{(1+u)^t} \tag{77}$$

The objective function assuming profit maximization for a multi-period crop response function is to maximize net discounted present value (NDPV) where:

$$NDPV = \sum_{t=1}^{T} \frac{\pi_t(X_{1t},\ldots,X_{it},\ldots,X_{nt},W_t,H_t)}{(1+u)^t} \tag{78}$$

subject to:

$$W_{t+1} - W_t = G(W_t, H_t) \tag{79}$$

Equations (78) and (79) can be written as follows:

$$L = \sum_{t=1}^{T} \frac{\pi_t(X_{1t},\ldots,X_{it},\ldots,X_{nt},W_t,H_t)}{(1+u)^t} + \lambda_{t+1} G(W_t,H_t) \tag{80}$$

The first order conditions for profit maximization are as follows:

$$\frac{1}{(1+u)^t} \quad \frac{\partial \pi_t}{\partial X_{it}} = 0 \tag{81}$$

$$\frac{1}{(1+u)^t} \quad \frac{\partial \pi_t}{\partial H_t} + \lambda_{t+1} \frac{\partial G}{\partial H_t} = 0 \tag{82}$$

λ_{t+1} = marginal change in net discounted present value caused by a marginal change in the seed density at the beginning of time period t. $\lambda_{t+1} < 0$ because, *ceteris paribus*, an increase in the current weed density will reduce future profits. The solutions to the first order conditions equations are X_{it}^* = the level of input i in time period t necessary to maximize NDPV; W_t^* = the level of weed density at which it is just economical to control the weed; H_t^* = the level of the weed control variable in time period t necessary to maximize NDPV. The additional information needed for this multi-period analysis include: a finite time period, herbicide dose, herbicide bank in the soil over the time period considered (for carryover effects), a discount rate, a set of output and input prices over the time period, and data on the crop production, and input used. Beside the investment criteria, other tools such as budgeting (for dynamic programming) can be used.

The model may be expanded to account for uncertainty. Uncertainty in the crop-weed-control system arises mainly from the variability in the performance of control measures, variability in the weed-free yield and variability of weed density (Pandey and Medd). In addition those factors, causes of uncertainty include: weather, output and input prices, the system of production, and all other factors that affect crop production but cannot be predicted with certainty. The multi-period profit function is the same as equation (74). The presence of uncertainty is reflected in uncertainty in crop yield and return in the next time period. Indeed, the current cropping decision whether to control weeds affects future decisions through the equation of motion. The equation of motion takes the form described in equation (79). Because of the uncertainty, P_t, Y_t, and W_t become stochastic variables with the following probability density functions (Deen et al.):

$$P_t \sim p(P_t) \tag{83}$$

$$Y_t \sim y(Y_t) \tag{84}$$

$$W_t \sim w(W_t) \tag{85}$$

incorporating the probability distributions of the stochastic variables in equation (74) results in the following expected profit function:

$$\begin{aligned} & E\,[\pi_t\,(X_{1t},\ldots,X_{it},\ldots,X_{nt},W_t,H_t)] \\ & = E\,\{p(P_t)\;y\;(Y_t,w(W_t)) - \sum_{i=1}^{n} r_{it}X_{it} - c_tH_t\,\} \end{aligned} \tag{86}$$

The net discounted present value of expected future profits

$$\begin{aligned} & \sum_{t=1}^{T} \frac{1}{(1+u)^t}\; Ep(P_t)\; y(Y_t,w(W_t)) - \\ & \qquad \sum_{i=1}^{n} r_t X_{it} - c_t H_t \end{aligned} \tag{87}$$

is used to setup the objective function.

Let

$$p = \frac{1}{(1+u)^t} \tag{88}$$

That is, the objective function takes the same form as in equations (78) and (79). The Lagrangian for the maximization problem is as follows:

$$\begin{aligned} L &= p\ E\ \{p(P_t)\ y(Y_t, w(W_t)) \\ &- \sum_{i=1}^{n} r_t X_{it} - c_t H_t\ \} + \lambda_{t+1}\ G(W_t, H_t) \end{aligned} \tag{89}$$

The first order conditions for maximization of NDPV of expected future profits are as follows:

$$P_t \frac{\partial Y_t}{\partial X_{it}} - r_{it} = 0 \tag{90}$$

$$P_t \frac{\partial Y_t}{\partial H_t} - c_t + \lambda_{t+1} \frac{\partial G}{\partial H_t} = 0 \tag{91}$$

Equations (90) and (91) are equivalent to setting marginal profit equal to zero. In equation (91), marginal profit is equal to zero if either λ_{t+1} or $\frac{\partial G}{\partial H_t}$ is assumed to be zero. The additional information needed for this analysis include: probability distribution for the stochastic variables. This can be done using Monte Carlo simulations assuming that prices and yields are jointly (negatively correlated) distributed normally, and that weed densities approximate a negative binomial distribution (Deen et al.). The tools of analysis include budgeting (for dynamic stochastic programming).

For this research, given the data available an economic threshold method will be used (equations (65) and (67)). The standard objective is to maximize profit. The economic threshold method implies the existence of a functional relationship between the crop yield and the factors involved in the production of that crop. The functional structure considered for this research is the one described in equation (7), and it is assumed to possess certain properties: 1) marginal products are unrestricted in sign; 2) nonzero elasticity of substitution between SR and RS; and 3) the production function is strictly concave (Henderson and Quandt).

The decision to control weeds is influenced by the most probable increase in benefit, especially the increased value of production (Auld et al.). The value of increased production is equal to the quantity of increased production multiplied by the market price received for each unit of production. The decision to control weeds is economical if the increased value of production is greater or equal to the increased cost of control. For this research, increased costs of control include only the increased dollar amount used to purchase the additional wheat seed. Given the functional structure considered, the problem can be written as follows:

$$\pi(SR,RS,CL,\Omega) = PF(SR,RS,CL,\Omega) - r_1 SR - r_2 RS \tag{92}$$

where:

π = the objective function value,

P = the per unit price of wheat,

r_1 = the per unit cost of wheat seed,

r_2 = cost of changing the row spacing width, and

The first order conditions for a maximum π consists of the marginal conditions for optimization:

$$P\frac{\partial \pi}{\partial SR} - r_1 = 0 \tag{93}$$

$$P\frac{\partial \pi}{\partial RS} - r_2 = 0 \tag{94}$$

Solving the above equations for SR, RS, and CL gives the economically optimal seeding rate, row spacing, and level of cheat infestation, which are functions of wheat seed and wheat prices. The second order conditions for maximum π are fulfilled given the strict concavity assumption.

CHAPTER III

RESULTS

This chapter includes the results of the statistical and economic analysis conducted to complete the objectives of the study.

Expected Results

Based on information reported in the literature, the seeding rate variable is hypothesized to be positively related to wheat yield. Thus, the coefficient associated with the seeding rate variable is expected to be positive. The presence of cheat is hypothesized to decrease wheat yield. Based on previous studies and given the range of row spacings used in the field experiments, the row spacing variable is expected to be negatively related to wheat yield. That is, narrow row spacing is hypothesized to result in increased yields. Quadratic terms for seeding rate, cheat level, and row spacing are expected to be negative, positive, and positive, respectively.

The seeding rate and cheat level interaction is hypothesized to be positively related to wheat yield. That is, it is hypothesized that increasing seeding rate in a cheat infested field results in increased yields. The row spacing cheat level interaction term is hypothesized to be negatively related to wheat yield. That is, narrow row spacing in a cheat infested field is hypothesized to result in increased wheat yields.

Empirical Results

The quadratic functional form depicted in equation (8) was used to estimate wheat production response to alternative seeding rate, cheat level, and row spacing. A total of five models were estimated for each location. An additional five models were estimated with data pooled from the two locations. Results of the statistical estimates are reported in sections which follow.

The Chickasha Experiment

Table 1 contains statistical results obtained from the data generated in the field trial conducted at Chickasha. The full model was estimated with methods described in Chapter II. A series of t-tests were conducted to select variables for omission from successive reduced models.

All five models reported in Table 1 resulted in poor statistical fits. Indeed, none of the parameter estimates for any of the models are statistically significantly different from zero at the 0.05 level of probability. However, the seeding rate and cheat level variables have the expected signs. The interaction of cheat level and seeding rate is positive. The pathetic statistical fits may be a function of physical factors including the variable soil across replications at the experiment station location and weather conditions which prevailed during the year of the study.

Graphical presentations of the parameter estimates of Model E in Table 1 are included in Figures 2, 3, and 4 for three, six, and nine inch row spacing, respectively. The graphs reflect the estimated lack of differences between wheat yield for the alternative row spacings. That is, changing row spacing from conventional to narrow

Table 1. Ordinary Least Squares Estimates of Wheat Yield Response to Alternative Seeding Rates, Row Spacing, and Levels of Cheat Infestation at Chickasha.

	Model				
Variable	A	B	C	D	E
Intercept	36.682492 (3.229)	37.506196 (3.457)	38.033089 (3.862)	34.608339 (3.894)	33.859688 (3.849)
Seeding Rate	0.090380 (0.423)	0.090380 (0.424)	0.084526 (0.408)	0.122578 (0.608)	0.122578 (0.608)
Cheat Level	-0.082361 (-0.731)	-0.082361 (-0.732)	-0.093338 (-1.524)	-0.093338 (-1.525)	-0.077741 (-1.400)
Row Spacing	-0.239566 (-0.140)	-0.569048 (-0.531)	-0.656830 (-0.864)	-0.086071 (-0.306)	0.038704 (0.202)
Seeding Rate Squared	-0.000597 (-0.537)	-0.000597 (-0.538)	-0.000597 (-0.538)	-0.000597 (-0.538)	-0.000597 (-0.539)
Seeding Rate x Cheat Level	0.000546 (0.481)	0.000546 (0.482)	0.000668 (1.560)	0.000668 (1.561)	0.000668 (1.562)
Cheat Level Squared	-0.000297 (-0.793)	-0.000297 (-0.794)	-0.000297 (-0.794)	-0.000297 (-0.795)	-0.000297 (-0.795)
Row Spacing Squared	-0.027457 (-0.247)				
Row Spacing x Cheat Level	0.000770 (0.047)	0.000770 (0.047)	0.002599 (0.607)	0.002599 (0.608)	
Row Spacing x Seeding Rate	0.005366 (0.466)	0.005366 (0.467)	0.006342 (0.808)		
Row Spacing x Seeding Rate x Cheat Level	0.000020 (0.116)	0.000020 (0.116)			
Adj. R-square	0.0387	0.04	0.0422	0.0433	0.0439

Values in parentheses are t-statistics of the estimated coefficients.

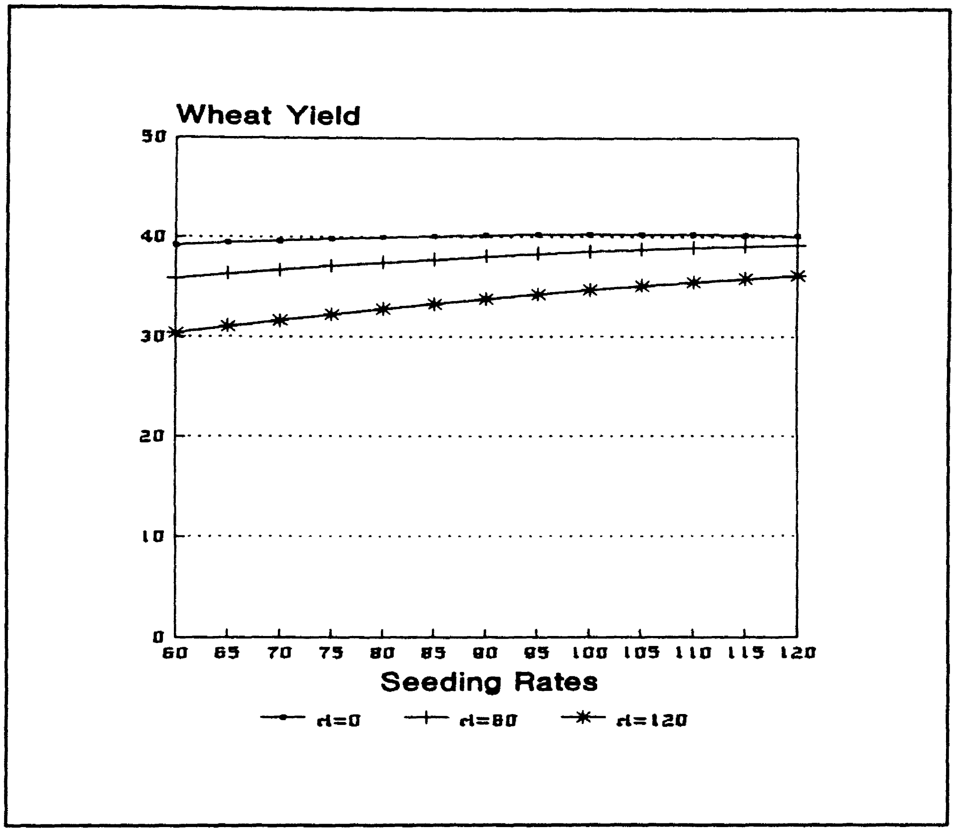

Figure 2. Impacts of Cheat on Wheat Yield in a Three Inch Row Spacing Field at Chickasha.

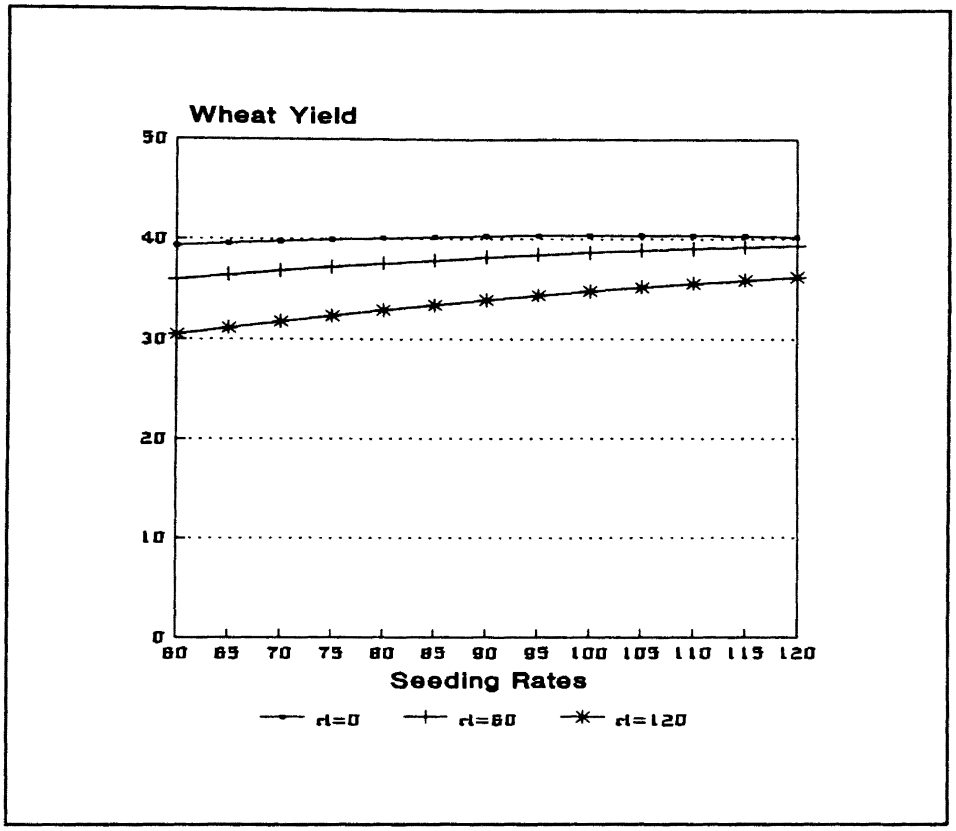

Figure 3. Impacts of Cheat on Wheat Yield in a Six Inch Row Spacing Field at Chickasha.

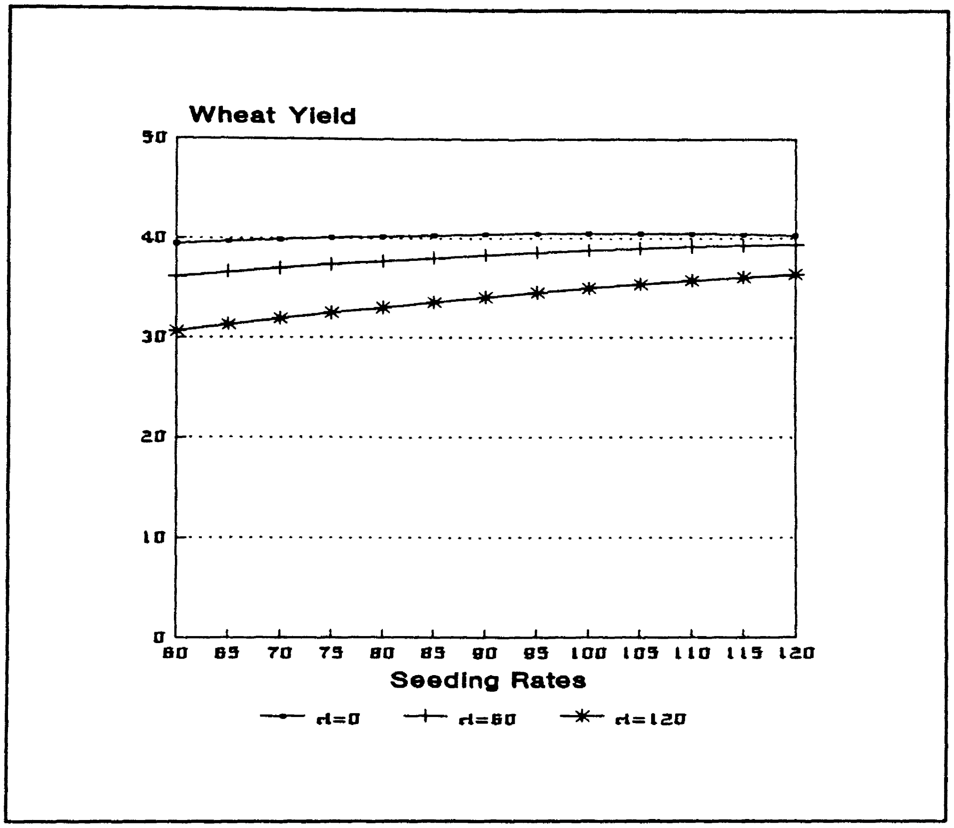

Figure 4. Impacts of Cheat on Wheat Yield in a Nine Inch Row Spacing Field at Chickasha.

widths did not reduce wheat yield loss as a result of cheat infestation. The graphs reflect the positive (but statistically insignificant) impact of seeding rate on wheat yields.

The positive sign of the seeding rate by cheat level interaction variable is manifested in Figures 2, 3, and 4. For example, for a seeding rate of 60 pounds per acre, estimated wheat yield is 39 bushels per acre in a cheat free field and 31 bushels (8 bushels less) per acre in a field with severe cheat infestation. However, for a seeding rate of 120 pounds per acre the estimated wheat yield is 40 bushels in a cheat free field, and 36 bushels (4 bushels less) per acre in field with severe cheat infestation. That is, increasing wheat seeding rate can help mitigate the negative effect of infestations of cheat.

The Lahoma Experiment

Results from the Lahoma experiment are presented in Table 2. The full model, including all the interaction terms, is reported as model A. The variables that were not significant (in a statistical sense at 0.05 probability level) in the full model were dropped one at a time and four reduced models were estimated.

Model E, which includes seeding rate, cheat level, row spacing, seeding rate by cheat level interaction, and quadratic terms for seeding rate and cheat level was selected for further analysis. All parameter estimates for Model E are significant at the five percent probability level. In addition, all estimated coefficients have the expected signs.

Seeding rate is positively related to wheat yield. That is, over a range of the data, wheat yield can be increased by increasing the seeding rate. However, the

Table 2. Ordinary Least Squares Estimates of Wheat Yield Response to Alternative Seeding Rates, Row Spacing, and Levels of Cheat Infestation at Lahoma.

	Model				
Variable	A	B	C	D	E
Intercept	35.081424 (3.730)	37.216262 (4.140)	36.342366 (4.468)	36.590479 (4.988)	36.175069 (4.985)
Seeding Rate	0.386473 (2.192)	0.386473 (2.193)	0.396183 (2.318)	0.393426 (2.366)	0.393426 (2.369)
Cheat Level	-0.307942 (-3.327)	-0.307942 (-3.329)	-0.290130 (-5.848)	-0.290130 (-5.855)	-0.281609 (-6.293)
Row Spacing	0.142753 (0.101)	-0.711183 (-0.796)	-0.565533 (-0.901)	-0.606886 (-2.594)	-0.537650 (-3.398)
Seeding Rate Squared	-0.002085 (-2.273)	-0.002085 (-2.274)	-0.002085 (-2.277)	-0.002085 (-2.280)	-0.002085 (-2.282)
Seeding Rate x Cheat Level	0.001461 (1.559)	0.001461 (1.560)	0.001263 (3.572)	0.001263 (3.577)	0.001263 (3.580)
Cheat Level Squared	0.000583 (2.047)	0.000583 (2.048)	0.000583 (2.050)	0.000583 (2.053)	0.000583 (2.055)
Row Spacing Squared	-0.071161 (-0.776)				
Row Spacing x Cheat Level	0.004389 (0.325)	0.004389 (0.326)	0.001420 (0.402)	0.001420 (0.402)	
Row Spacing x Seeding Rate	0.001159 (0.121)	0.001159 (0.121)	-0.000459 (-0.071)		
Row Spacing x Seeding Rate x Cheat Level	-0.000033 (-0.228)	-0.000033 (-0.228)			
Adj. R-square	0.3146	0.3153	0.3168	0.3184	0.3197

Values in parentheses are t-statistics of the estimated coefficients.

quadratic term for seeding rate is negative. This indicates that yield increases with seeding rate at a decreasing rate. As hypothesized, the cheat level variable has a negative sign. The presence of cheat significantly reduces wheat yield. The quadratic term for cheat level is positive. This means that wheat yield decreases with cheat infestation at an increasing rate.

Over the data range, row spacing is negatively related to wheat yield. That is, wheat yield can be improved by planting wheat in narrow rows. The lack of significance for the row spacing by cheat level interaction term indicates that a change in row spacing will not reduce the negative impacts of cheat on wheat yield. In other words, wheat yield loss to cheat infestation is insensitive to changes in row spacings.

The seeding rate by cheat level interaction variable has a positive sign. That is, as seeding rate is increased, the negative effect of cheat is reduced. The above results for Model E are reflected by the graphs included in Figures 5, 6, and 7.

Results for the Pooled data from Chickasha and Lahoma

The results for the pooled data are presented in Table 3. Five models which included the same variables as those estimated for the location specific models were estimated. All five models were supplemented with an intercept shifting dummy variable which was included to allow for linear differences across locations.

Model E of Table 3 has the expected signs for all variables except for the quadratic term for cheat infestation. The presence of cheat significantly reduce wheat yield. Reducing row spacing from conventional to narrow widths results in increased yields. However, reducing row spacing is not an effective cheat control practice. The

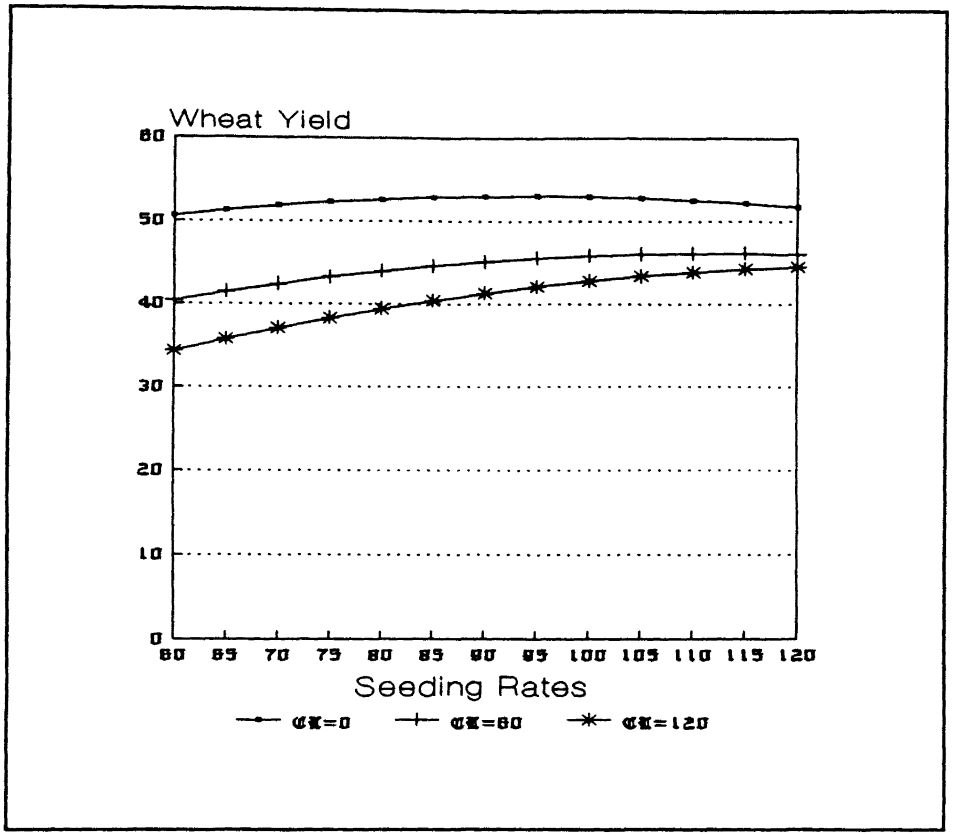

Figure 5. Impacts of Cheat on Wheat Yield in a Three Inch Row Spacing Field at Lahoma.

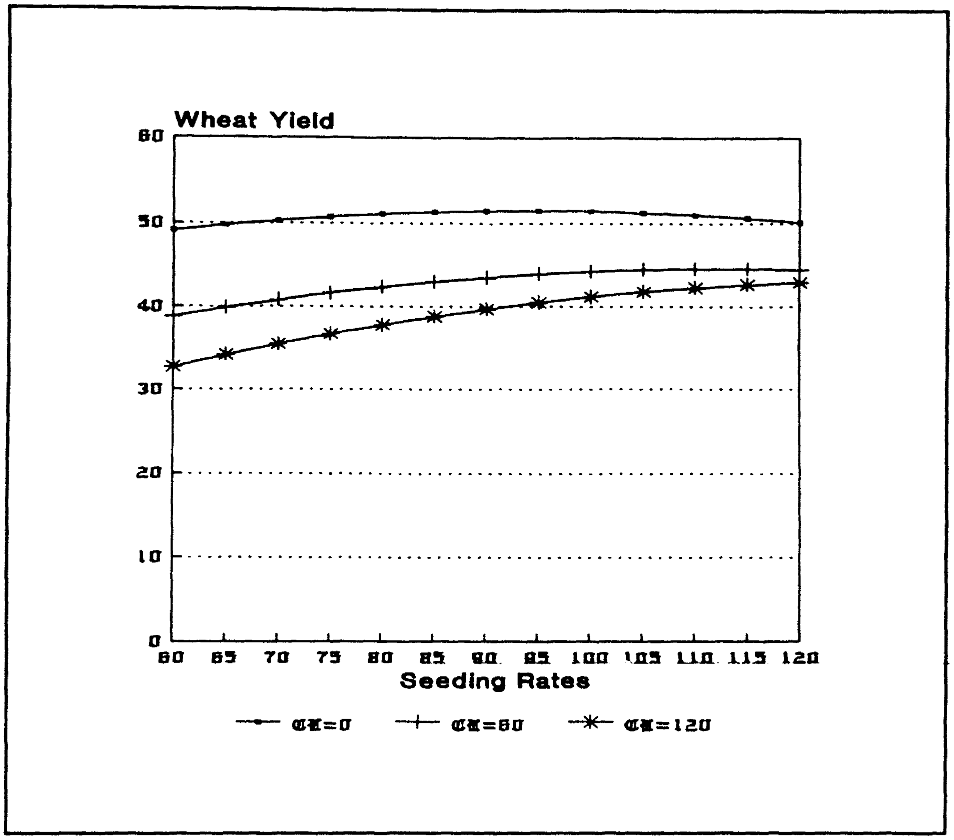

Figure 6. Impacts of Cheat on Wheat Yield in a Six Inch Row Spacing Field at Lahoma.

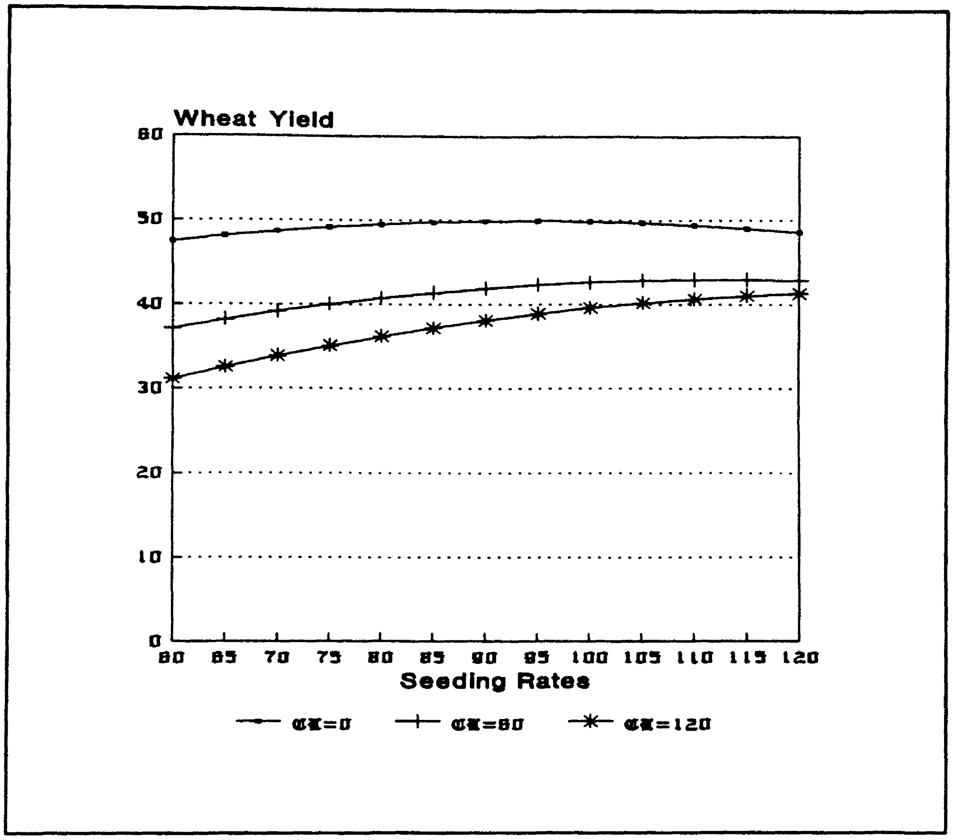

Figure 7. Impacts of Cheat on Wheat Yield in a Nine Inch Row Spacing Field at Lahoma.

Table 3. Estimated Generalized Least Squares Estimates of Wheat Yield Response to Alternative Seeding Rates, Row Spacing, and Levels of Cheat Infestation at Chickasha and Lahoma.

	Model				
Variable	A	B	C	D	E
Intercept	37.002000 (4.897)	38.738000 (5.345)	37.539000 (5.829)	36.607000 (6.295)	35.849000 (6.240)
Seeding Rate	0.119370 (0.855)	0.117910 (0.844)	0.131340 (0.975)	0.141830 (1.082)	0.144010 (1.098)
Cheat Level	-0.125950 (-1.796)	-0.126090 (-1.792)	-0.104140 (-2.679)	-0.103420 (-2.666)	-0.090410 (-2.575)
Row Spacing	-0.084202 (-0.074)	-0.583280 (-0.795)	-0.387660 (-0.788)	-0.237450 (-1.219)	-0.125810 (-1.018)
Seeding Rate Squared	-0.000736 (-1.022)	-0.000730 (-1.014)	-0.000730 (-1.014)	-0.000732 (-1.016)	-0.000744 (-1.033)
Seeding Rate x Cheat Level	0.001108 (1.551)	0.001112 (1.551)	0.000859 (3.182)	0.000856 (3.171)	0.000857 (3.174)
Cheat Level Squared	-0.000502 (-2.268)	-0.000504 (-2.275)	-0.000499 (-2.256)	-0.000501 (-2.263)	-0.000509 (-2.299)
Row Spacing Squared	-0.055286 (-0.772)				
Row Spacing x Cheat Level	0.005726 (0.571)	0.005774 (0.573)	0.002088 (0.771)	0.002035 (0.752)	
Row Spacing x Seeding Rate	0.003824 (0.486)	0.003849 (0.487)	0.001666 (0.331)		
Row Spacing x Seeding Rate x Cheat Level	-0.000041 (-0.377)	-0.000041 (-0.379)			
Location Dummy (Lahoma)	4.5444 (7.323)	4.5499 (7.329)	4.5489 (7.327)	4.5485 (7.326)	4.5456 (7.319)
Adj. R-square	0.1873	0.1878	0.1893	0.1889	0.1895

Values in parentheses are t-statistics of the estimated coefficients.

results of Model E are reflected in the graphs of Figures 8, 9, and 10.

Nonnested Hypothesis Test

The parameters reported for Model E of Table 2 which were estimated from the data generated in the Lahoma experiment were used to initialize the search procedure to fit a quadratic-plateau functional form. The iterative search procedure failed to fulfill convergence requirements. Terminal parameter estimates are reported in Table 4.

Data obtained from the three and nine inch row spacing treatments were deleted and a QRP model was estimated with data from the six inch row spacing Lahoma treatments. Results are reported as Model C in Table 5.

Models A and B of Table 5 were estimated with conventional linear methods to generate initial parameters for the nonlinear iterative search procedure used to estimate the QRP model. Since all observations used to estimate Model C of Table 5 were obtained with data generated in six inch row spacings, row spacing was not included as a variable. The quadratic term for cheat level was not included in Model C since it was not significant in Model A.

To determine the most appropriate functional form, results generated by Models B and C were used to conduct a nonnested hypothesis test. Results of the Gauss-Newton regression used to conduct the test are presented in Table 6. The coefficient of variable Diff, which is the difference between the predicted values of the quadratic specification (Model B of Table 5) and those of the quadratic-plateau functional form (Model C of Table 5) is the parameter of interest. The t-value of that parameter obtained when testing H_o versus H_1 is not significantly different from zero. That is, the test fails to reject the

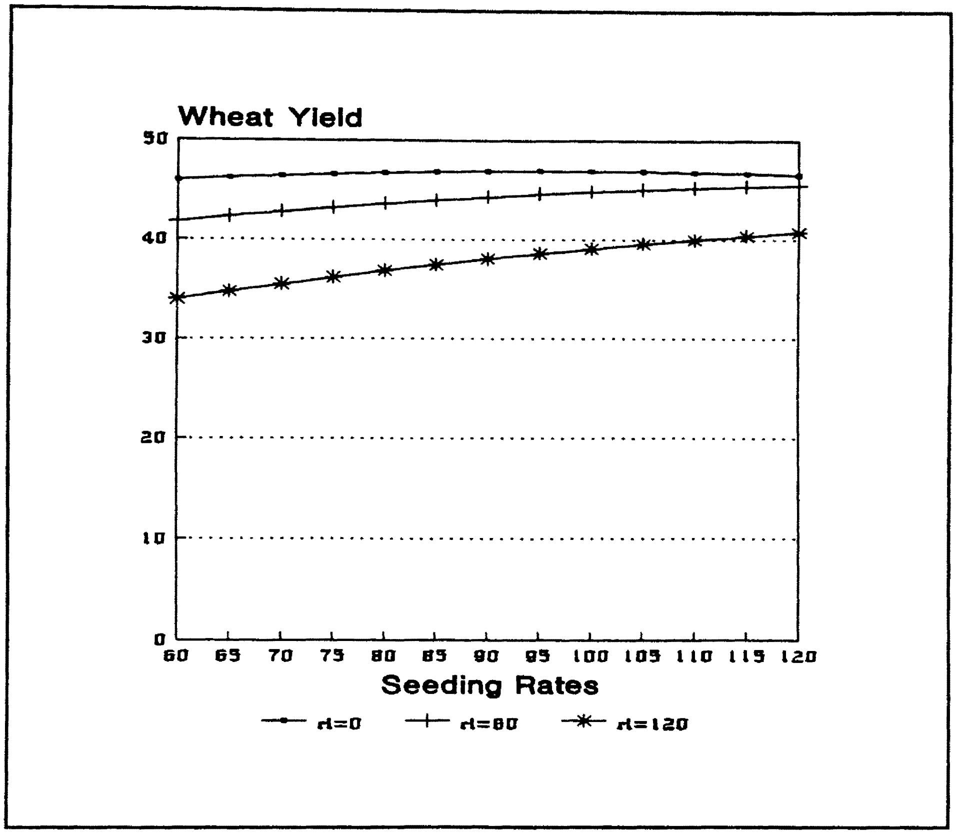

Figure 8. Impacts of Cheat on Wheat Yield in a Three Inch Row Spacing Field for the Pooled Data from Chickasha and Lahoma.

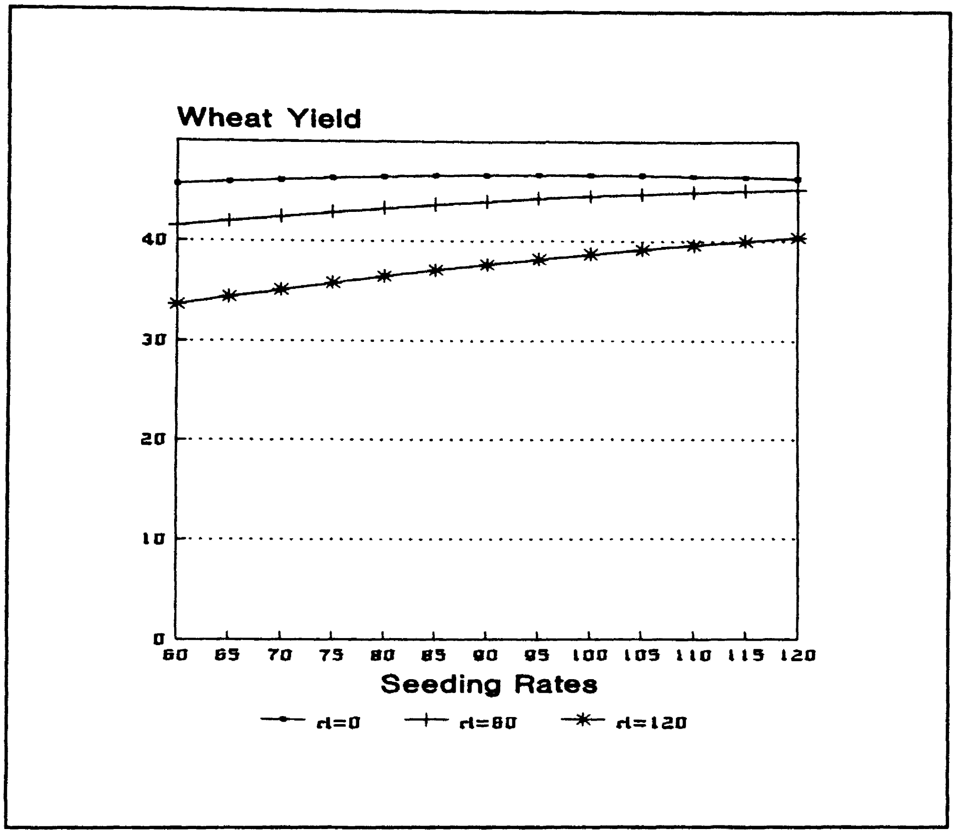

Figure 9. Impacts of Cheat on Wheat Yield in a Six Inch Row Spacing Field for the Pooled Data from Chickasha and Lahoma.

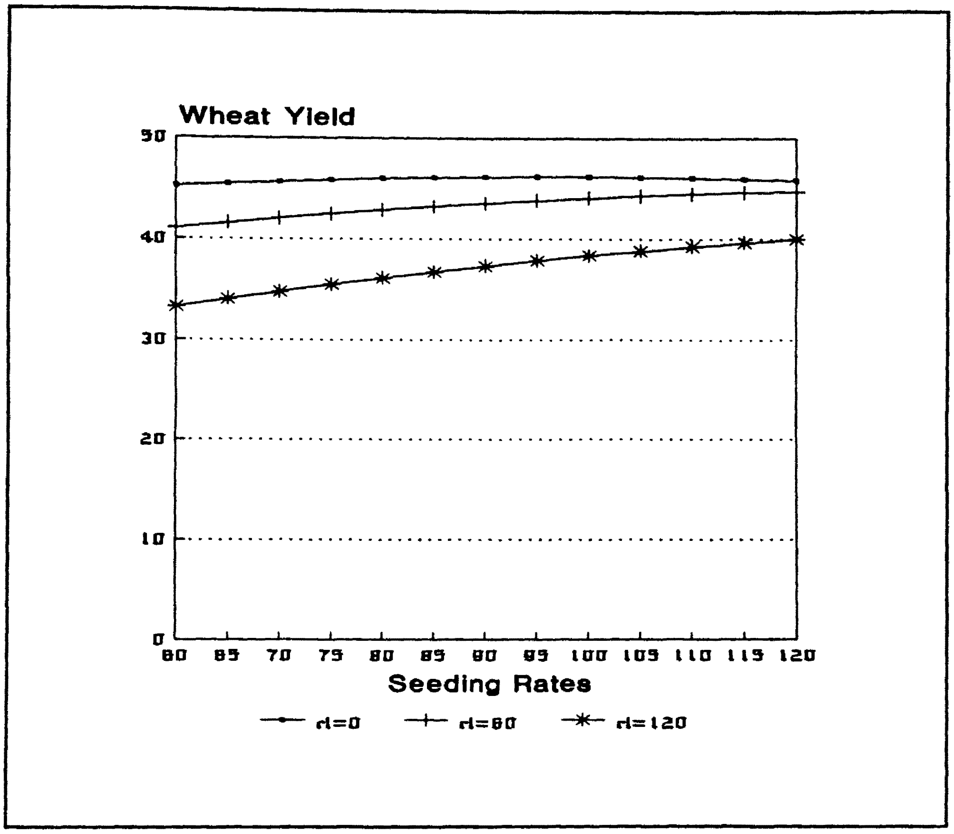

Figure 10. Impacts of Cheat on Wheat Yield in a Nine Inch Row Spacing Field for the Pooled Data from Chickasha and Lahoma.

Table 4. Nonlinear Least Squares Estimates of Wheat Yield Response, with a Quadratic-Plateau Functional Form.

Model	Plateau specification fails to converge
Variable	
Intercept	36.175069 (5.174)
Seeding Rate	0.393426 (2.202)
Cheat Level	-0.281609 (-5.693)
Row Spacing	-0.537650 (-3.507)
Seeding Rate Squared	-0.002085 (1.783)
Seeding Rate x Cheat Level	0.001263 (2.213)
Cheat Level Squared	0.000586 (1.972)
Estimated Plateau Yield	49.895
Minimum seeding rate required to achieve the plateau in a cheat free field	94.347

Values in parentheses are t-statistics of the estimated coefficients.

Table 5. Ordinary Least Squares Estimates of Wheat Yield Response, to Alternative Seeding Rate and Levels of Cheat Infestation for Six Inch Row Spacings at Lahoma.

Model	Polynomial specification		Plateau specification
Variable	A	B	C
Intercept	19.414637 (1.438)	19.090953 (1.417)	12.44982 (0.276)
Seeding Rate	0.771920 (2.477)	0.771920 (2.481)	1.003995 (0.766)
Cheat Level	-0.320423 (-3.816)	-0.278178 (-4.512)	-0.32904 (-2.211)
Seeding Rate Squared	-0.004400 (-2.567)	-0.004400 (-2.571)	-0.00653 (-0.690)
Seeding Rate x Cheat Level	0.001891 (2.857)	0.001891 (2.861)	0.002826 (1.279)
Cheat Level Squared	0.000396 (0.743)		
Adj. R-square	0.2974	0.2997	
Estimated Plateau Yield			51.039
Minimum seeding rate required to achieve the plateau in a cheat free field			76.855

Values in parentheses are t-statistics of the estimated coefficients.

Table 6. Gauss-Newton Regression Estimates for Testing the Quadratic Functional Form Versus the Quadratic-Plateau Specification.

Variables	Testing H0	Testing H1
Intercept	-0.00779	-0.00779
	(-0.001)	(-0.001)
Z(β)	0.000173	0.000173
	(0.001)	(0.001)
Diff	0.003637	0.996363
	(0.006)	(1.724)*

* Significant at 0.10 probability level

quadratic specification. An additional statistical test confirms this result.

The results as reported in Table 6, show that the t-value associated with the coefficient of the variable Diff is significantly different from zero at the 0.10 probability level. The null hypothesis H_1 is therefore rejected. That is, given the data set evaluated, the quadratic functional form is a more appropriate specification of wheat yield response to seeding rate than the quadratic-plateau functional form. The QRP model was rejected. Hence, Model E of Table 2 was selected and used to determine the optimal seeding rate for selected prices and levels of cheat infestation.

Test of Wheat Yield Variability

Standard errors of the predicted yields for selected levels of seeding rate and cheat infestation are reported in Tables 7 and 8. Model E of Table 2, which was generated from data obtained in the Lahoma experiment, was used to compute the predicted yields, standard errors, and damage in terms of wheat yield loss, attributable to cheat infestation. These results are included in Table 7. Model B of Table 5 was used to compute the predicted yields which are reported in Table 8.

Statistical analysis was conducted to test the null hypothesis of equal variance of predicted yields across alternative levels of cheat, wheat seeding rate, and row spacing. The hypothesis testing procedure for conducting the test was described in Chapter II.

The specific test for the 60 pound seeding rate between a cheat free field and a field with a moderate level of cheat with three inch row spacing was conducted as described by equation (64). The test statistic is the ratio of variances which has an F-distribution. In this case s_1^2 is the variance of the predicted yields in the cheat free

Table 7. Predicted Yields, Estimated Standard Errors of Predicted Yield, and Estimated Yield Loss Due to Cheat for Alternative Seeding Rates Based on Parameter Estimates of Model E in Table 2.

Seeding Rate (lbs/ac)	Row Spacing (inch)	Cheat Level (lbs/ac)	Predicted Yield (bu/ac)	Standard Error of Predicted Yield (bu/ac)	Estimated Yield Loss Due to Cheat (bu/ac)
60	3	0	50.7	7.9	0
90	3	0	53.1	7.9	0
120	3	0	51.8	7.9	0
60	3	60	40.4	7.9	10.3
90	3	60	45.1	7.9	8
120	3	60	46.1	7.9	5.7
60	3	120	34.4	7.9	16.3
90	3	120	41.3	7.9	11.8
120	3	120	44.6	7.9	7.2
60	6	0	49.1	7.9	0
90	6	0	51.5	8	0
120	6	0	50.1	7.9	0
60	6	60	38.8	8	10.3
90	6	60	43.5	8	8
120	6	60	44.4	8	5.7
60	6	120	32.8	7.9	16.3
90	6	120	39.7	7.9	11.8
120	6	120	42.9	7.9	7.2
60	9	0	47.4	7.9	0
90	9	0	49.8	7.9	0
120	9	0	48.5	7.9	0
60	9	60	37.2	7.9	10.2
90	9	60	41.9	7.9	7.9
20	9	60	42.8	7.9	5.7
60	9	120	31.1	7.9	16.3
90	9	120	38.1	7.9	11.7
120	9	120	41.3	7.9	7.2

Table 8. Predicted Wheat Yield, Estimated Standard Errors of the Predicted Yields, and Estimated Yield Loss Due to Cheat for Alternative Seeding Rates Based on Parameter Estimates of Model B, of Table 8.

Seeding Rate (lbs/ac)	Cheat Level (lbs/ac)	Predicted Yield (bu/ac)	Standard Error of Predicted Yield (bu/ac)	Estimated Yield Loss Due to Cheat (bu/ac)
60	0	49.6	8.5	0
90	0	52.9	8.6	0
120	0	48.4	8.5	0
60	60	39.7	8.6	9.9
90	60	46.4	8.6	6.5
120	60	45.3	8.6	3.1
60	120	29.8	8.4	19.8
90	120	40	8.5	12.9
120	120	42.2	8.4	6.2

field and s_1^2 is the variance of the predicted yields in the field with moderate cheat.

$$F_2 = \frac{(7.9)^2}{(7.9)^2} = 1$$
$$F_{(0.05,425,425)} = 1.14 \tag{64}$$

The critical value for a 95 percent level of probability with 425 degrees of freedom is greater than the computed value. The null hypothesis of equal variances of the predicted wheat yields between a cheat free field and a field with a moderate level of cheat is not rejected. Similarly, none the null hypotheses of equal variances across the three seeding rates, three cheat levels, and the three row spacings were rejected. In other words, the presence of cheat in the treatments did not increase or decrease yield variability across the levels of seeding rate and row spacing investigated.

Optimal Seeding Rates

Model E of Table 2, and Model B of Table 5 were used to determine the physically, and economically optimal seeding rates for several combinations of wheat seed and wheat grain prices (Tables 9, 10, and 11). These models were also used to estimate the damage in terms of wheat grain yield loss due to cheat infestation (Tables 7 and 8).

In the absence of cheat, the physically optimal seeding rate is 94.3 pounds per acre. The expected wheat yield from this seeding rate is 53.1, 51.5, and 49.9 bushels per acre for 3, 6, and 9 inch row spacings, respectively. In the statistical models the row spacing by seeding rate interaction term was not significant. Hence, the physically optimal seeding rate is the same across the three row spacings.

Table 9. Physically Optimal Wheat Seeding Rate (pounds per acre) for Alternative Levels of Cheat Infestation and Row Spacings Based on Parameter Estimates of Model E in Table 2.

Cheat Infestation (Lbs/ac)	Physically Optimal Seeding Rate (Lbs/ac)	Row Spacing	Expected Yield (bu/ac)
		3	53.1
0	94.3	6	51.9
		9	49.9
		3	46.2
60	112.5	6	44.5
		9	42.9
		3	44.8
120	130.7	6	43.2
		9	41.6

Table 10. Optimal Wheat Seeding Rate (pounds per acre) for Selected Prices and Levels of Cheat Infestation Based on Parameter Estimates of Model E in Table 2.

Seed Price ($/bu)	Cheat Infestation (Lbs/ac)	Wheat Price ($/bu)			
		2.50	3.00	3.50	4.00
6	0	85	86	87	88
9	0	80	82	84	85
6	60	103	105	106	107
9	60	98	101	102	104
6	120	121	123	124	125
9	120	116	119	120	122

Table 11. Optimal Wheat Seeding Rate (pounds per acre) for Selected Prices and Levels of Cheat Infestation Based on Parameter Estimates of Model B, in Table 8.

Seed Price ($/bu)	Cheat Infestation (Lbs/ac)	Wheat Price($/bu)			
		2.5	3	3.5	4
6	0	83	84	84	85
9	0	81	82	83	83
6	60	96	97	97	98
9	60	94	95	96	96
6	120	109	110	110	111
9	120	107	108	109	109

For a moderately infested field, the optimal seeding rate is 112.5 pounds per acre which is expected to generate yields of 46.2, 44.5, and 42.9 bushels per acre in 3, 6, and 9 inch row spacings, respectively. For severe cheat infestations, the estimated physically optimal wheat seeding rate of 130.7 pounds per acre is beyond the data range available for this research. Nevertheless, if that level of wheat seed was used, by extrapolation, expected yields are 44.8, 43.2, and 41.6 bushels per acre for 3, 6, and 9 inch row spacings, respectively.

A comparison of the information in Tables 10 and 11, and 7 and 8 reveals that there are few practical differences between the economically optimal seeding rate and predicted yields obtained from Model 6 in Table 2, and the economically optimal seeding rate and predicted yields obtained from Model B of Table 5. Both models were estimated from data generated in the Lahoma experiment. However, data across all row spacings were used to estimate Model E, whereas only six inch row spacing data were used to estimate Model B. Hence, Model B was used to compute the economically optimal wheat seeding rates reported in Table 11.

Economically optimal seeding rates are presented in Tables 10 and 11 for a selected set of prices. For a relatively low wheat price ($2.50 per bushel) and a relatively high price of wheat seed ($9 per bushel) the economically optimal seeding rate of 80 pounds per acre (with a row spacing of three inches) is expected to result in a yield of 53 bushels per acre in the absence of cheat (Table 10). Alternatively, for relatively high wheat ($4 per bushel) and wheat seed prices ($9 per bushel), 85 pounds of seed per acre is economically optimal.

The economically optimal wheat seeding rate is relatively insensitive to wheat seed and wheat grain prices. For example, with zero cheat, for a relatively high seed price of $9 per bushel and low wheat price of $2.50 per bushel the optimal wheat seeding rate is 81 pounds per acre (Table 11). On the other hand, for a relatively low seed price of $6 per bushel and high wheat price of $4 per bushel, the optimal seeding rate is 85 pounds per acre. The difference in optimal seeding rate is only four pounds per acre across the range of prices investigated.

Expected yields are approximately 53 bushels per acre across all economically optimal seeding rates for zero cheat, 47 bushels per acre for moderate infestations of cheat, and 42 bushels per acre for severe infestations of cheat. Severe infestations of cheat reduce the economically optimal yield by approximately 11 bushels per acre across the range of wheat seed and wheat market prices used.

The economically optimal seeding rate is sensitive to the level of cheat infestation. In general, for a given set of wheat seed and wheat grain market prices, the optimal wheat seeding rate is 13 and 26 pounds per acre more for moderate and severe infestations of cheat, respectively.

For a wheat seed price of $6 and a wheat market price of $3 per bushel, the economically optimal seeding rates are 84, 97, and 110 pounds per acre for zero, moderate, and severe levels of cheat infestation, respectively. With an 84 pound seeding rate, moderate levels of cheat would be expected to reduce yield by 7.15 bushels per acre relative to the cheat-free yield. However, if the farmer confronted moderate levels of cheat adjusted seeding rate to 97 pounds per acre, the expected yield decline would be reduced to 5.99 bushels per acre. The economic significance of the cultural practice of adjusting the seeding rate, which is expected to result in an additional 1.16 bushels per acre, depends upon the wheat market price net of harvesting costs.

For severe infestations of cheat, the economic benefits of adjusting the seeding rate are more pronounced. With an 84 pound seeding rate, severe levels of cheat would be expected to reduce yield by 14.3 bushels per acre relative to the cheat-free field. However, if the farmer responded to severe levels of cheat by seeding 110 rather than 84 pounds per acre, the expected yield would increase by 3.8 bushels, from 38.6 to 42.4 bushels per acre. For a net market price of $3 per bushel the economic benefit of the practice would exceed $10 per acre.

CHAPTER IV

SUMMARY AND CONCLUSION

Infestation of weeds, especially cheat, have hampered the adoption of residue management programs on soils which are continuously cropped to winter wheat in the southern plains. Periodic use of the moldboard plow, typically every third year, is the primary cheat control practice. Information regarding alternatives to intensive tillage is necessary to assist farmers confronted with the requirement to restrict moldboard plowing on highly erodible soil and for farmers in general who are evaluating less intensive tillage systems on land which is not highly erodible.

The objective of this research was to determine the economically optimal wheat seeding rate for fields which are continuously cropped to winter wheat and have severe, moderate, and zero levels of cheat infestation. The work was initiated to determine if the relatively inexpensive and environmentally neutral cultural practice of altering seeding rates, and changing patterns of placement can be used to mitigate the deleterious effects of cheat on wheat yield.

Seventeen wheat grain yield response functions were estimated from data generated in experiment station trials. Yield was estimated as a function of wheat seeding rate, row spacing, and level of cheat infestation. Cheat infestation was artificially induced by seeding cheat in the plots. Level of cheat infestation varied from zero to severe.

A traditional quadratic response function was used as well as a quadratic-plateau functional form. A nonnested hypothesis test was conducted to discriminate between the two specifications. Wheat yield variability for alternative levels of cheat infestations was estimated. Finally, physically and economically optimal seeding rates were determined.

Conclusion

The nonnested hypothesis test conducted failed to reject the quadratic specification. The statistical analysis based on the quadratic specification of the yield response function confirmed that the presence of cheat reduces wheat yield, and that changing row spacing from nine to three inches increases yield. For a seeding rate of 90 pounds per acre, moderate to severe levels of cheat reduced yield by 6 to 13 bushels per acre. This result confirmed the potential economic consequences of cheat infestation. It also explains why farmers are concerned about cheat and why they have continued to use moldboard plows in tillage rotations.

The hypothesis of equal variance of wheat yield for alternative levels of cheat was not rejected. The statistical analysis also confirmed the hypothesis that increasing seeding rate reduces the wheat yield loss in cheat infested fields. Changing row spacings influences wheat yield but is not an effective response to cheat. The economically optimal seeding rate is relatively insensitive to the price of seed and the price of wheat. However, it is sensitive to the level of cheat infestation. In general, for a given set of wheat seed and market prices, the optimal seeding rate was 13 to 26 pounds per acre more for moderate and severe levels of cheat relative to zero cheat. Increasing seeding rate is an appropriate strategy for farmers confronted with the cheat problem. However, even with the increased seeding rate, yield losses exceeding 10 bushels per acre can be expected from severe cheat infestations.

While the study does illustrate the serious nature of the cheat problem and confirms that the environmentally benign practice of adjusting the seeding rate is appropriate, it does not address the very relevant issue of whether farmers should continue to use moldboard plows. Additional research is necessary to consider the long run consequences of plowing on cheat levels, farm income, soil loss, and soil productivity over time.

Most studies based upon agronomic data obtained from experiment station plots have shortcomings. This study does as well. An underlying assumption is that fertility level and management practices used in the field experiments are similar to those of farms in the region. Additional work is necessary to confirm the estimates over several years and locations, and to calibrate the level of artificially induced cheat to actual field situations.

In recent decades, agronomists have been reluctant to artificially introduce weeds on an experiment station except to evaluate chemical herbicides. Efforts to evaluate alternatives to chemicals, such as the one described in this research, are rare.

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