THE VALUE OF INFORMATION IN INTEGRATED PEST MANAGEMENT OF CORN ROOTWORM AND EUROPEAN CORN BORER IN MINNESOTA

A Thesis

Submitted to the Faculty of the Graduate School

by

Anita Regmi

In partial fulfillment of the requirement
for the degree of

Doctor of Philosophy

June, 1990

Anita Regmi (271 words)

ABSTRACT

The value of information in integrated pest management (IPM) of corn rootworm (CRW) and European corn borer (ECB) on continuous corn is estimated in this research. A bioeconomic model for corn is developed considering CRW and ECB. Economic thresholds are estimated for each pest, and the sensitivity of the estimated thresholds to relative corn and pesticide price changes is analyzed. The value of pest information to individual farmers and the economic justification of scouting data collection methods are also examined.

A bioeconomic simulation model is used to generate net revenue distributions under different management strategies and economic conditions. To incorporate stochastic behavior into the model, the performance of each strategy is simulated under many random states of nature. By evaluating a wide range of strategies, the model is used to identify preferred pest management strategies for CRW and ECB. Changes in producer welfare associated with different pest management strategies are measured by changes in the levels of certainty equivalents.

The results indicate that flexible decision rules which base CRW control actions on information are preferrable to fixed CRW decision rules of routine control and routine no-control. Hence, scouting for CRW information are economically justifiable. When the cost of acquiring information is considered, CRW beetle counts are better sources of information than egg counts, and combined egg and beetle counts. Based on this study, the best control action for ECB is routine no-control, and scouting for ECB information is not economically justifiable. The results also indicate that the value of information differs with producer risk preferences. However, the optimal pest control action is invariant to different levels of absolute risk aversion.

ACKNOWLEDGEMENTS

I wish to express my gratitude to the all the individuals and organizations who assisted in this research and to the members of my committee for their encouragement and support. In particular, I wish to accord special thanks to four members of my committee; Rob King, Dave Andow, Ken Ostlie and Sharon Lohr. Despite my long absence from campus, the encouragement, guidance, and patience of my major advisor, Rob King, supported me throughout my research. I consider myself very fortunate to have had the opportunity to work under Rob for whom I hold deep respect. Dave and Ken assisted me with the entomological aspects of my dissertation. I am further indebted to Dave for his contribution of data. Sharon showed amazing interest and care by her long distance statistical guidance to me in Rwanda.

In addition to the members of my committee, several other individuals have directly assisted in this research. Some of these who helped with data collection are Gabe Horner, Craig Longtine, Tim Schenk and Sanjeev Chadda, all from the Department of Entomology. I also wish to acknowledge Jaya Raj Joshi at the Department of Soil Science and Bruce Potter at the Department of Plant Pathology who provided me with assistance. I wish to extend my thanks to those crop consultants from Minnesota who participated in the survey conducted. In addition, this research would not have been possible without the cooperation of the farmer, Donald Nord from Goodhue, Minnesota to whom I extend my sincere thanks.

This research was partially supported by USDA (contract number 87-CRSR-2-3015), the University of Minnesota Agricultural Experiment Stations and the University of Minnesota Doctoral Dissertation Fellowship.

Finally, I wish to thank all my friends and family without whose love and support I would not have been able to accomplish this major task.

CONTENTS

ACKNOWLEDGEMENTS iii
LIST OF FIGURES vii
LIST OF TABLES viii

CHAPTER

1. INTRODUCTION 1
   1.1 Background 1
   1.2 Objectives 5
   1.3 Organization of the Dissertation 5

2. PEST BIOLOGY AND DESCRIPTION OF THE MODEL 7
   2.1 Pest Biology 7
      2.1.1 CRW 7
      2.1.2 ECB 9
   2.2 Brief Review of Modeling IPM 10
   2.3 Description of the Model 16
      2.3.1 The Biological Component 16
      2.3.2 The Economic Component 18
   2.4 Brief Review on Estimating the Value of Information 19
   2.5 Summary 24

3. MODEL SPECIFICATION AND ESTIMATION 25
   3.1 Data Source for Model Building 25
   3.2 Model Specification 26
      3.2.1 Yield Equation 26
      3.2.2 Yield Component Equations 27
      3.2.3 Pest Damage Prediction Equations 28
   3.3 Parameter Estimates 32
      3.3.1 Yield Equation 32
      3.3.2 Yield Component Equations 33
      3.3.3 Pest Damage Prediction Equations 36
      3.3.4 Correlation and Standard Deviation of Regression Residuals 38
   3.4 Summary 42

4. MODEL VALIDATION 44
4.1 Data Source for Model Validation 44
4.2 Methodology of Model Validation 46
4.3 IPM Model Validation 49
4.3.1 Yield Equation 50
4.3.2 Yield Component Equations 51
4.3.3 Pest Damage Prediction Equations 53
4.4 Summary 55

5. THE SIMULATION MODEl 57
5.1 The Bioeconomic Model 58
5.1.1 Strategies 60
5.1.2 Model Inputs for the Simulation Experiment 62
5.1.3 Simulation Experiments 71
5.2 Calculating the Value of Information 72
5.3 Cost of Acquiring Information 74
5.4 Summary 77

6. VALUE OF INFORMATION AND THE ECONOMIC THRESHOLD 79
6.1 The Estimated Value of Pest Information 80
6.1.1 Value of CRW Information 80
6.1.2 Value of ECB Information 90
6.2 Sensitivity of the Value of Information to Errors in Relating Pest Damage to Yield Loss .. 91
6.3 Estimating the Economic Threshold 102
6.4 Sensitivity of the Estimated Economic Thresholds to Errors in Damage-Yield Loss Relationship ... 104
6.5 Summary 104

7. SUMMARY AND CONCLUSIONS 107

APPENDICES
APPENDIX 1: EXPERIMENTAL DESIGN 118
A1.1 A Representative Plot 118
A1.2 Mean and Standard Deviation of Variables 120

A1.2.1 Overall Mean and Standard Deviation of Variables 120
A1.2.2 Mean and Standard Deviation by Block 121
A1.2.3 Mean and Standard Deviation by Tillage 123
A1.2.4 Mean and Standard Deviation by Whole Plot 124

APPENDIX 2: DERIVATION OF GLS TRANSFORMATION 128
A2.1 Methodology 128
A2.2 Estimation of Variance Components 129
A2.2.1 Yield Equation 131
A2.2.2 Yield Component Equation 132
A2.2.3 CRW Damage Equation 136
A2.2.4 ECB Damage Equation 141

APPENDIX 3: SIMULATION COMPUTER PROGRAM 146

APPENDIX 4: SCOUTING COST SURVEY QUESTIONNAIRE AND RESULTS 168
A4.1 Scouting Cost Survey Questionnaire 168
A4.2 Survey Results 170

REFERENCES 174

FIGURE

1.1 Illustration of the Corn-Pest Relationship 8

A1.1 A Representative Plot Design 119

TABLES

3.1 Estimation of Yield Equation 33
3.2 Estimation of Yield Component Equations 35
3.3 Estimation of CRW Damage Prediction Equations 37
3.4 Estimation of ECB Damage Prediction Equations 39
3.5 Correlation Matrix of the Regression Residuals ... 41
3.6 Standard Deviation of the Disturbance Term 42
4.1 Forecast Errors of the Estimated Equations 51
4.2 Model Validation Results 52
5.1 Initial Levels of Pest Counts 64
5.2 Estimated Costs for Different Tillage Systems 66
5.3 Estimated Costs of Treatments 67
5.4 Estimated Scouting Costs 77
6.1 Certainty Equivalent for Chisel Plow 81
6.2 Certainty Equivalent for Ridge Till 83
6.3 Certainty Equivalent for No-Till 85
6.4 Routine Control for CRW 87
6.5 Routine No-Control for CRW and ECB 88
6.6 Routine Control for CRW and ECB 89
6.7 Routine Control for ECB alone 92
6.8 Certainty Equivalent for Chisel Plow with Damage Parameters Raised by one Standard Deviation 94
6.9 Certainty Equivalent for Ridge Till with Damage Parameters Raised by one Standard Deviation 95
6.10 Certainty Equivalent for No-Till with Damage Parameters Raised by one Standard Deviation 96
6.11 Routine Control for CRW and ECB with Damage Parameters Raised by one Standard Deviation 97
6.12 Routine No-Control for CRW and ECB with Damage Parameters Raised by one Standard Deviation 99
6.13 Routine Control for CRW alone with Damage Parameters Raised by one Standard Deviation 100
6.14 Routine Control for ECB alone with Damage Parameters Raised by one Standard Deviation 101

6.15 The CRW Threshold Levels 103

6.16 CRW Economic Threshold Levels with Damage Parameters Raised by one Standard Deviation 105

CHAPTER 1

INTRODUCTION

1.1 Background

Over the past thirty years reliance on pesticides has increased dramatically in U.S. agriculture. Statistics indicate (Swanson and Dahl, 1989) that the U.S. pesticide industry grew at an annual rate of 6% between 1965 and 1974 and fluctuated throughout the remainder of the 70s. During the 80s, however, the sales dropped, with a decrease of 33% from 1980 to 1986. This recent downward trend in sales may, in addition to acreage reduction and lower prices, be attributed to the growing awareness and concern about the potential harm pesticides may have on human health and the environment. According to a study conducted jointly by the state of Minnesota Departments of Health and Agriculture, 39% of all rural wells sampled between July 1985 through June 1987 showed low levels of pesticide residue. Another estimate (Farm Chemicals, 1985) indicated that in the U.S. alone, 5,000 people are treated each year for some form of acute pesticide poisoning. In addition to the direct harm on humans, excessive use of pesticides may permanently change the farm ecology. Along with the pest, pesticides often kill natural enemies of crop pests and other beneficial organisms.

Notwithstanding these concerns, pesticides have routinely prevented major crop losses due to insect pest damages. Hence, there exists a need for a system of agriculture which does not decelerate economic growth and at the same time adopts judicial use of pesticides. Integrated pest management (IPM) is an attempt at meeting this demand. IPM has been defined by Smith (1978, p. 41-42) as "a multi- disciplinary ecological approach to pest population management which utilizes numerous control tactics in a single coordinated compatible system." As evident under this definition, the objective of IPM is to incorporate ecological factors into the farm decision making mechanism. Most of the studies conducted on IPM have dealt with static, single-crop, single-pest models. However, a multi-pest model might be a better representation of the complexity of agro-ecosystem.

IPM typically relies on pest population information to decide whether pest control should be adopted. This information is acquired through scouting data collection methods. Information in the form of monitored pest or damage counts at early stages of crop growth can be used to forecast potential pest damage at later stages. These forecasts can then be used to predict the potential yield at harvest. Comparison of net revenues with and without the use of pesticide ultimately determines the optimal strategy. Benefits from the use of information accrue directly to the farmer and indirectly to the society. Direct benefits are realized through increased profit to the farmer, either due to a lower operating cost with less pesticide use or due to an increase in the yields as a result of timely application of pesticide in response to pest outbreak forecasts. In addition, society benefits indirectly through the control of ground water pollution, conserved farm ecology, and a decrease in pesticide residue in food. Scouting data collection methods can be economically justified for individual farms if the monetary benefits from the use of information is greater than its cost.

The rationale for a market in pest management information has been established by Feder (1979). He argues that farmers will be willing to pay a certain amount for pest information as long as the cost of acquiring it does not lower their expected returns. He notes that the existence of uncertainty has been considered as a major motivation for the application of pesticide. Some of the uncertainty perceived by farmers is real, due to the random nature of pest population and damage. A significant component of the uncertainty, however, is due to their ignorance of prevailing levels of pest population. This uncertainty can be reduced considerably by the provision of information. Since the removal of uncertainty increases expected returns and decreases its variance, a farmer will be willing to pay for this information as long as the cost of acquiring it does not exceed the expected gain.

Feder further notes that another source of uncertainty in pest management is the lack of knowledge regarding the effectiveness of pesticide. Adoption of different schedules of pesticide application may improve the effectiveness. With improved effectiveness, a given quantity of pesticide generates greater pest control and therefore results in an increase in the level of expected returns. Information from scouting agencies may help achieve this improved pesticide efficiency.

Feder's analysis assumes that information from scouting can be substituted for pesticide. However, information (or scouting) may also be a complement to pesticides. Scouting is a substitute for pesticide when it leads to no application of pesticide on a crop or in a region where pesticide is routinely applied. In such a case, assuming that the cost of scouting is less than that of pesticide application, benefits to a farmer accrue in the form of reduced production cost. In the case where routine application is not followed, scouting will lead to application of pesticide when the scouted pest levels are significantly high. Here scouting can be considered a complement. The benefit to a farmer, in this case, is realized through higher yields. Grube (1979) analyzed the economics of field scouting in cotton production. His results are consistent with the above dual role of scouting. He further concluded that farmers are more likely to adopt scouting when a greater potential benefit is associated with scouting. The adoption of scouting also increased with the management skills of farmers. A positive effect of scouting was also noticed on cotton yields. Hence, he stated that scouting is a practice with a very high marginal return to each hour devoted to it. Or in other words, better information enables farmers to adjust other inputs so that cotton output can be increased significantly.

Grube's observation has to be accepted with qualifications.

Detailed information may lead to higher yields as a result of more accurate forecasts of potential pest damage, but this gain may not always be sufficient to offset the added cost of scouting. Therefore, the conditions under which the added cost of scouting is warranted need to be identified. To use L.Murrell's words (1986, p. 32), there exists a need for "hard and fast data on how much a service like that (scouting) was worth to a grower". In other words, "...show what the loss in income would be from a farmer's making a wrong decision because of lack of a qualified scouting...". Murrell addresses scouting in general and the degree or the intensity of scouting is not his focus. However, the same may be said about the intensity of scouting, i.e. show how much *better* information is worth to a grower.

There have been several studies (Nyrop, Foster and Onstad, 1986; Foster, Tollefson and Steffey, 1986; Steffey and Tollefson, 1982; Steffey, Tollefson and Hinz, 1982) on optimal scouting procedures for corn-rootworm (CRW). Steffey, Tollefson and Hinz state that visual beetle counts on corn plant provide the most precise estimate for the least cost. Plant beetle counts were observed to have performed better than egg samples or sticky-trap beetle counts. In general, soil treatment or crop rotation is recommended if more than one beetle per plant are observed through scouting the previous season. There do not appear to be any similar studies on scouting methods for European Corn Borer (ECB). However, the general rule followed in recommending insecticide use is to apply insecticide if over 50% plant injury is observed due to either the first or the second generation ECB (Andow and Ostlie 1989).

In this research the value of information in integrated pest management of corn rootworm (CRW) and European corn borer (ECB) in continuous corn is estimated. These are two of the major corn pests in the Midwest. In Minnesota alone (Ostlie, Noetzel and Sreenivasam, 1985), the average annual production loss attributable to these pests is estimated to be $111 million. Farmers in Minnesota are estimated to spend an average of $17.50 million annually on pesticides for their control. The bio-economic model developed in this study provides decision rules for different levels of pest information. This should provide useful advice to farmers, and guidance to policy-makers and private crop consultants in deciding whether some relevant pest information should be monitored and disseminated to farmers.

If the value of scouting is positive, gains may accrue to farmers either through a reduced cost of production or an increase in corn yield. When the gain is through a lower level of pesticide usage, society also gains with a lower level of pesticide residue in the environment. If no value of scouting is discerned, it may be worthwhile for the private and public agencies involved in scouting to seriously reconsider scouting.

1.2 Objectives

The overall objective of this research is to estimate the value of different levels of pest information in integrated pest management of CRW and ECB in continuous corn. More specific objectives can be summarized as follows:

1. To develop a stochastic bioeconomic integrated pest management model for corn simultaneously considering the two pests, CRW and ECB,
2. To estimate the value of monitored pest data to individual farmers with different levels of risk preferences,
3. To estimate economic threshold levels for each pest and to analyze the sensitivity of the estimated thresholds to relative corn and pesticide price changes
4. To examine the economic justification of scouting data collection methods (by private or public agencies).

1.3 Organization of the dissertation

The biology of CRW and ECB in relation with corn is presented in chapter 2. This chapter also reviews some relevant literature dealing with IPM modeling. In addition, a description of the bio-economic model of CRW and ECB on continuous corn is specified. Finally, a brief review of literature dealing with estimating the value of information is presented.

In chapter 3, the biological component of the specified IPM model is estimated. This estimated model is validated in chapter 4. Chapters 5 and 6 deal with incorporating the economic component into the biological component of the model. A description of the simulation experiment used in generating distributions of net revenue for different management strategies is presented in chapter 5. This chapter describes the various inputs required for the simulation and its operational procedure. The methods and costs involved in acquiring CRW and ECB population information are also presented.

The results from the simulation experiment are presented in chapter 6. From these results the value of pest information and the economic threshold levels of pest population are obtained considering different levels of producer risk preferences. Finally a summary and conclusions of this study are outlined in chapter 7.

CHAPTER 2

PEST BIOLOGY AND DESCRIPTION OF THE MODEL

This chapter initially reviews the biology of CRW and ECB in relation with corn. Next, a brief review of literature dealing with IPM modeling is presented. An IPM model of CRW and ECB on continuous corn is also specified. This is modeled in two components, biological and economic. At the end of the chapter, following the description of the economic component, a brief review on estimating the value of information is presented.

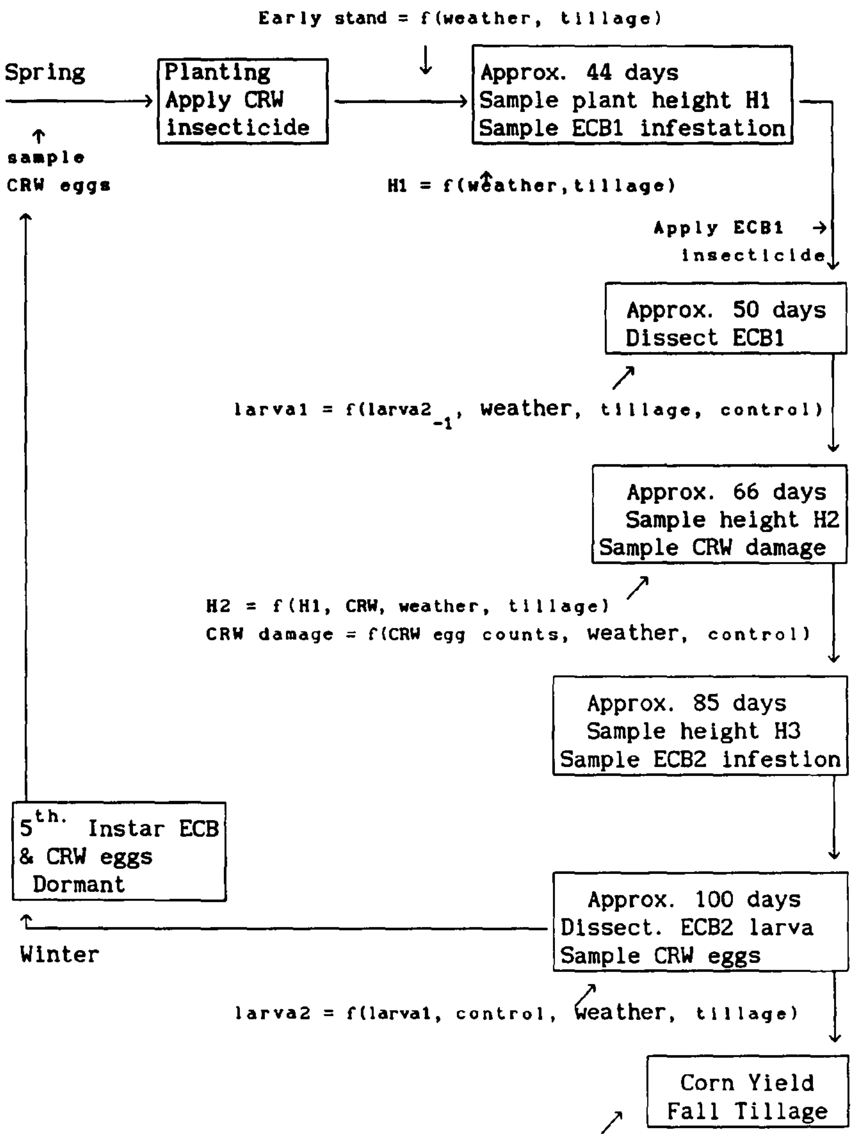
2.1 Pest Biology

Figure 1 gives a diagrammatic illustration of the corn-pest relationship together with the time clock of corn growth. Figure 1 also indicates the stages at which various plant components and pest levels were monitored in the data used for model building. A brief description of the biology of the pests considered in this study i.e.; northern corn rootworm, *Diabrotica barberi* Smith and Lawrence, western corn rootworm *Diabrotica virgifera virgifera* LeConte and European corn borer *Ostrinia nubilalis* (Hübner) is given below.

2.1.1 Corn Rootworm

Three species of corn rootworm (CRW) attack corn throughout the Corn Belt; western CRW, northern CRW and southern CRW. Northern and western CRW are the major pests in North Central region of the U.S. (NCR publication No. 98). These have only one generation per year. Eggs of both species are deposited in the soil in mid to late summer and pass the winter in this stage. Eggs are more concentrated in the top 6 inches and in rows at the base of plants in unirrigated fields. Egg hatch may commence by mid May depending on the soil temperature. Some eggs can hatch the same year in which laid, if the fall is warm and prolonged. Egg counts taken in spring and fall

Figure 2.1 Illustration of the Corn-Pest Relationship.



$$\left\{\begin{array}{l}
\text{Corn Yield} = f\left(\dfrac{\text{\#of plants}}{\text{sample}},\ H2,\ \dfrac{\text{\#of ears per plant}}{\text{sample}},\ \text{weather},\ \text{tillage}\right) \\[2ex]
\dfrac{\text{number of plants}}{\text{sample}} = f(\text{early stand, ECB damage, CRW damage, weather}) \\[2ex]
\dfrac{\text{\# of ears per plant}}{\text{sample}} = f(\text{ECB damage, weather, tillage})
\end{array}\right.$$

generally differ due to winter mortality. Eggs of northern CRW have been shown to be able to go through 2 winters before hatching (Chiang, 1973). Therefore, crop rotation may not always be a viable solution, especially in fields dominated by northern CRW.

The hatched larvae move to the corn roots and begin to feed. They die if a corn root is not found within a few inches. After about three weeks the larvae stop feeding and transform to the pupal stage in soil. In Minnesota, pupae have been observed as far as 25 inches from main root and 9 inches deep (Chiang, 1973). This explains the difficulty encountered in sampling pupae. Depending on the temperature, in about 5 to 10 days, adult beetles emerge from the pupae. Damage to corn occurs either in the larval stage or in the adult stage. Lodging of the plant as a result of larval feeding is a typical symptom. Lodged corn is more difficult to harvest. Older larvae burrow into tissue and damage vascular tissue and brace roots which causes yield loss. Larval feeding reduces yield but does not destroy the crop completely. Adults feed on silk, pollen and corn leaves. Silk feeding can interfere with pollination and cause yield loss. Yield loss is generally greater when the plants are under other stress, such as drought.

2.1.2 European Corn Borer

The European corn borer (ECB) has two generations (ECB1 and ECB2) in the Central Corn Belt (NCR publication No. 98). Mature larvae spend winter in corn stubble and during spring transform into the pupal stage. After about two weeks adult moths emerge. These mate and lay eggs on the undersides of leaves of early planted corn. Young larvae hatch in about six days. They move to the whorl zone and feed for several days. Older larvae bore into leaves, tassels and stalks. Once larvae are inside the plant, all potential for chemical control is lost, therefore treatments must begin several days before larvae bore into plants. The pupal stage is spent inside the plant or in the leaf axils. After about one to two weeks, moths emerge. These mate and lay eggs for the second generation, seeking the latest planted corn to deposit eggs. As the development time during the first generation is highly variable, adults and new larvae emerge over an extended period. This makes it difficult to evaluate the population to determine if treatment is necessary and to treat effectively. ECB damage occurs near the ear zone. Stalk breakage and ear drops are also generally seen. The second generation larvae overwinter in the stalks and come out as adults the following spring. Since overwintering occurs in the stubble, tillage may influence the intensity of the first generation population next season.

Chiang and Hodson (1959) establish that the developmental success of one stage is not related to that of the other stages during the same generation in a given year. In other words, the borer populations of different stages fluctuate in a random fashion and it may be difficult to predict any given stage of one generation using the sampled population of its preceding stage. They also observed that the population sizes of the first and second generations were independent. A very high level of first generation in a given year did not necessarily lead to a high level of the second generation. These previous findings indicate the difficulty involved in modeling ECB. Chiang and Hodson analyzed the population levels using two dimensional graphs. This does not take into account other environmental factors which may influence the resulting population levels. It is possible that some relations between stages may be observed in a more complete approach where previous stage samples are only one of the explanatory variables used in predicting the next stage.

2.2 Brief Review of Modeling IPM

IPM seeks to minimize the tradeoff observed with the use of pesticides between increased crop yields and reduced environmental quality (Carlson, 1970; Regev, Gutierrez and Feder, 1976). This is generally achieved by substituting pest information and management skills for chemical pesticides (Musser, Tew and Epperson, 1981) or by the adoption of what may be considered as responsive control rather than pre-emptive (prophylactic) control (Vandermeer and Andow, 1986). Vandermeer and Andow have defined pre-emptive control as referring to the application of insecticide to control a pest whether the pest will yield loss or not, whereas, responsive control implies that the pesticide application occurs in response to pest population levels.

A fundamental approach in modeling IPM has been to consider the economic injury level and the economic threshold level of pest population. Stern (1959) has defined *the economic injury level* to be the pest population density level at which the damage caused by the pest exceeds the cost of controlling it. This is the measure generally used in the study of population ecology. Cochran and Robison (1981) have defined *the economic threshold level* as the pest population density level at which the pest must be controlled to prevent it from reaching the economic injury level. Economic threshold can be thought of as representing the time for control i.e. when it is probable that the future pest injury will cause economic damage (Pedigo, Hutchins and Higley, 1986). Pedigo, Hutchins and Higley define economic threshold as "the injury equivalency of a pest population corresponding to the latest possible date for which a given control tactic could be implemented to prevent increasing injury from causing economic damage." Unlike entomologists, economists tend to approach from a marginal analysis point of view which focuses on economic thresholds rather than the economic injury levels.

The benefit from adopting a control measure can be considered in terms of avoidance of damage that would have been caused if the control had not been applied. Relevant ecological information can be included in the IPM model by defining a yield equation which incorporates both the pest population dynamics and the control measures. In general, IPM models can be broken down into three components: the *yield equation*, the *pest population prediction equation*, and the *kill efficiency equation*. Several studies have been conducted using this approach or its many modifications (Osteen, Johnson and Dowler, 1982; Hall and Norgaard, 1973).

Osteen, Johnson and Dowler constructed an IPM model for estimating the profit maximizing dosages of aldicarb to control lesion nematodes on corn. Using this model they estimated the economic threshold level of nematode population and checked the sensitivity of the estimated threshold to output price changes. They found that the optimal aldicarb dosage increases at a decreasing rate as the population level of lesion nematode increases and as the price of corn relative to the cost of aldicarb increases. They also noted that the pest population prediction was the weakest component of their model. Due to lack of reliable data (with sufficient variation) on pest population at different stages of growth, most bioeconomic models suffer from this limitation.

Osteen, Johnson and Dowler deal only with one pest and one control measure (although two different methods of applying nematicide were considered) and the questions that may arise with multi-species multi-control models are not addressed. In addition, no allowance is made for risk preferences of the decision maker. The issue of the feasibility of sampling for pest population information at different stages to estimate the population dynamics is also not addressed.

A second approach, used in modeling, is to divide the model into two major components: a biological system and an economic system (Cousens *et al.*, 1986; King *et al.*, 1986; Feder and Regev, 1975). The biological component models pest dynamics and the effect of pest on yield. The economic component models costs and returns associated with alternative pest management strategies. The biological system can be further subdivided into appropriate components to facilitate model building. Optimal decision rules can be obtained using dynamic programming (Taylor and Burt, 1984; Zacharias and Grube, 1986) or other methods of dynamic optimization (King *et al.*, 1986; Cousens *et al.*, 1986; Moffitt and Farnsworth, 1987).

Taylor and Burt use a partially decomposed stochastic dynamic model to obtain near-optimal multiperiod decision rules for the management of wild oats in spring wheat in North Central Montana. Similarly, Zacharias and Grube deal with IPM strategies for estimating approximately optimal control of CRW and soybean cyst nematode (SCN) using a stochastic dynamic programming model. This model allows for intertemporal effects and for uncertainty in pest population levels and in output price. The model simultaneously considers the optimal control of two pests in two different crops allowing some degree of interaction to occur. Several control options were considered with crop rotation as one of the viable options. Risk preferences of decision makers were, however, not considered in the study nor was the cost of monitoring population levels mentioned.

King *et al.* present a bioeconomic model of continuous corn cropping system for weed control. They consider four weed management strategies; two fixed strategies, one mixed, and one flexible. The first fixed strategy is annual application of pre-emergence herbicide. The second fixed strategy is application of pre-emergence herbicide in alternate years. The mixed strategy calls for application of pre-emergence herbicide in alternate years and the application of post emergence herbicide based on observed weed levels. The flexible strategy bases control on observed weed conditions. Weed control is adopted only if the expected benefit from control exceeds its cost. This model has two components, a biological component and an economic component. The biological component models weed population dynamics and the effects of weed on crop yield. The economic component models costs and returns associated with alternative weed management strategies.

King *et al.* use their model to evaluate weed management strategies under high and low initial weed conditions. All strategies are simulated over a 6 year period for 50 randomly selected sample states of nature, defined by a sequence of disturbance terms for each equation used in the model. Disturbance terms were drawn at random from a multivariate normal distribution. Adding these disturbance terms into the model introduces stochastic behavior, and after a large number of simulations for different states of nature, the resulting performance time paths define a probability distribution of outcomes. The analysis was conducted for a 200 ha. farm assumed to have a continuous corn production system. The comparison of performance of the four weed management strategies indicates that the flexible strategy outperforms the fixed strategy.

A similar simulation approach was taken by Cousens *et al.* in their economic analysis of *Avena fatua* in winter wheat. Moffitt and Farnsworth present a model for developing pest management advice to farmers when treatment decisions are related through time. A dynamic optimization model is used where the objective function represents the present value of profit, and pest and crop dynamics are reflected by stochastic difference equations. The objective function is reduced to an unconstrained function for the given conditional expectations and probabilities by incorporating the difference equations into it. The solution to the model provides the best intra-seasonal decision rule for pesticide treatment under the given conditions. Two separate methods of obtaining optimal decision rules are considered. The first considers a simple rule where at each period a given dosage of pesticide P^n is used if the pest population exceeds a certain level B^n. The second method uses dynamic programming where dosages are varied optimally at each time period. Since this requires the involvement of numerous state variables, the computational burden is higher than for the former method. The case of intraseasonal pest management involving Egyptian alfalfa weevil was used to illustrate the model. The empirical outcome from the two decision rules were similar. Therefore, in many cases where it may be difficult to apply dynamic programming, a dynamic optimization model as illustrated by Moffitt and Farnsworth may be simpler to use.

Increasing pest resistance to insecticides has been a major concern of many authors (Regev *et al.*, 1983; Lazarus and Dixon, 1984; Briggs, 1989). This aspect of pest control is also closely related to the common property nature of mobile insect pests. Each individual farm unit may regard the total regional insect pest population size and characteristics as largely unaffected by its actions. However, each operator's actions are assumed to impose insecticide resistance costs on neighboring farms. These studies use various forms of optimal control methodologies in their analysis. A common approach in such studies is to compare the optimal strategy of the individual farmer with the socially optimal strategy. The study by Feder and Regev (1975) also adopts the common property approach in pest management. Instead of pest resistance, the externality under consideration in this study is the environmental effect.

An optimal management model of northern corn rootworm (NCR), in the presence of dynamic externalities, has been developed by Briggs. The management strategies considered are soil insecticide application and crop rotation, and the externalities considered are pest resistance and pest population growth. Assuming perfect knowledge, optimal strategies are developed for a representative farmer and a social planner over a ten year planning horizon. The potential for pest resistance together with the common property nature of the pest population suggest that private and public pest management choices will diverge. When control options are restricted to soil insecticide in continuous corn, Briggs found that the social optimal strategy suggested greater insecticide use than the individual farmer's optimal strategy. Briggs' finding is in direct conflict with the traditional belief that farmers in general are risk averse and tend to over use pesticides. His finding, however, should be taken with some qualification since the potential environmental cost of pesticide usage is not considered in the study.

Another factor generally considered in integrated pest management is the risk preferences of farmers. As mentioned above the traditional belief is that individual farmers are risk averse and that this leads to overuse of pesticides. Lazarus and Swanson (1983), however, point out that if crop rotation to a less profitable, non-host crop is one of the alternatives present, greater risk aversion may lead to greater acreage alloted for rotation and a decrease in the overall pesticide usage. In such scenarios, the availability of crop insurance may lead the more risk averse farmers to allot greater acreage to corn ultimately resulting in an overall increase in pesticide usage. Other IPM studies involving risk have been conducted by Feder (1979) and Musser, Tew and Epperson (1981).

The literature discussed above covers various approaches in modeling pest management. Except for the study by King *et al.*, none of these studies estimates the value of pest information in IPM decision making. The following section outlines the model used in this study. The model used closely follows several of the references mentioned above.

2.3 Description of the model

As in many of the references above, the overall model can be divided into two components: biological and economic. The biological component models pest dynamics and the effect of pest population on plant and subsequently its yield. The economic component models costs and returns associated with alternative CRW and ECB management strategies.

2.3.1 The biological component

The biological model used in this study is recursive in nature. To define the model it is simpler to use a sequential procedure. First the visible impacts of pest population on the crop such as, fewer ears, sparse stand and shorter plants are identified. The next stage is to identify how these yield determinants vary under different weather conditions and under different pest density levels. The final step is to identify different factors influencing pest density levels, including the adopted control measures. To facilitate modeling, the biological component is further divided into two systems: yield equation and pest damage prediction equations.

The parameters of the biological model are estimated empirically. The log-log functional form is chosen in the estimation. This assumes that the incremental increase (decrease) in the dependent variable with an incremental increase in the independent variable is at a decreasing (increasing) rate. This behavior is assumed to hold true for the concerned equations in the model. Yield is estimated as a function of the yield components[1]. These are the visible impacts of pest population on the crop. A log-log production function of the form

$$Y = e^{\alpha} X^{\beta} e^{\varepsilon} \qquad \ldots(2.1)$$

is used in the estimation where,

Y = corn yield in bushels per acre,

X = the yield component vector,

α = a parameter,

β = a vector of parameters and

ε is random error term assumed to be normally distributed with mean zero.

The yield components are estimated as functions of the estimated pest population. This can be represented by the following general equation,

$$X = f(\text{conventional inputs, weather, } \hat{Z}) \qquad \ldots(2.2)$$

where,

$\hat{Z}$ = estimated pest population (or damage index).

Pest population levels relate directly to the pest damage in a crop. Population levels can be predicted using insect counts of the previous period, egg counts at planting or larvae counts, depending on what is available. More formally, a general form for pest population levels may be represented by,

$$Z = g(\text{egg/larva/adult counts, damage counts}) \qquad \ldots(2.3)$$

where,

Z = pest population level (or some damage index).

In static models a *kill efficiency equation or control equation* (Osteen, Johnson and Dowler, 1982) is usually used in addition to the population prediction equation. This equation gives an estimate of the efficiency of an adopted control measure. Stated formally,

1 The term "yield component" (as used here) differs from the usual agronomic term applied to those factors used in estimating yield at harvest.

$$\hat{Z} = h(Z, M) \qquad \ldots(2.4)$$

where,

$\hat{Z}$ = estimated pest population (or damage) at harvest, and

M = the adopted control measure.

In this study, the control equation is embedded within the pest population prediction model where a given pest population is a function of earlier damage counts and control measures. The population prediction equation and the kill efficiency equation are combined to form a damage prediction equation wherein the effects of pest control measure are directly included along with the population dynamics.

Using the estimated parameters of the biological component, the bio-economic model can be simulated to obtain distributions of net revenue. Substituting equation 2.4 into 2.2 and 2.2 into 2.1, renders the yield equation to be a function of pest population levels and the adopted control measure. For a given level of initial pest population and each of the available pest control measures, simulation can then be used to obtain distributions of net revenue. The best pest control strategy can next be identified by comparing the distributions of net revenue.

2.3.2 The Economic Component

The economic component of the analysis deals with costs and returns associated with different decisions. Under the assumption that the only crop grown is corn, the per acre profit function of a farm is given by equation 2.6.

$$\pi = P_y Y - T C_o - P_m M \qquad \ldots(2.4)$$

where,

π = profit from corn in \$/acre,

Y = corn yield in bushels/acre,

P_y = price of corn in \$/bushel,

$T C_o$ = total cost of production, excluding the cost of pest control (in \$/acre), and

P_m = cost of control measure M in $/acre.

In order to maximize profit, an individual farmer must choose the optimal level of the control measure. If M is continuous, (under the assumptions of risk neutrality) this means operating at the point where $\partial \pi / \partial M = 0$, that is,

$$\frac{\partial \pi}{\partial M} = \frac{\partial (P_y Y - T C_o)}{\partial M} - P_m = 0 \qquad \ldots(2.5)$$

or,

$$\frac{\partial (P_y Y - T C_o)}{\partial M} = P_m \qquad \ldots(2.6)$$

i.e., marginal benefit from control = its marginal cost. The pest population level at which equation 2.6 holds is known as the economic threshold level (Headley, 1972).

To obtain the economic threshold level (in equation 2.4) yield is expressed as a function of pest population levels and control. When M is discrete, for a given initial level of pest population, potential pest damage is predicted considering two cases, with pest control and without pest control. The population level at which the two strategies yield the same revenue gives the economic threshold level of the pest. Simulating the model repeatedly for a range of management strategies over different initial pest conditions and sample states of nature results in distributions of net revenues. Comparison of the distributions of net revenues from different management strategies enables the identification of the optimal management strategy.

2.4 Brief Review on Estimating the Value of Information

There is a large literature concerned with the value of information. Reviewing all available literature is beyond the scope of this study, hence only a few selected works are briefly reviewed. The development of the theory of information has taken distinct dichotomous paths; one in the direction of measuring the *information content* of a given message (Theil, 1967; Shannon and Weaver, 1969) and the other in measuring the *value* of the message. The former path has been the primary focus of communications engineering while the latter is prevalent in economics literature.

Various approaches have been followed in economics to value information. One of these methods approximates the consumer surplus as the measure of value of information. This method was used by Hayami and Peterson (1972) in valuing the reporting of agricultural production statistics by USDA. This approach assumes that information changes perception and tastes of an individual leading to shifts in the demand curve. The value of information is then given by the difference between the consumer surpluses under the old and new demand curves. The value of information can also be estimated using bidding games to approximate an individual's willingness to pay for a particular information (Randall, Ives and Eastman, 1974) or by estimating the willingness to pay for a related commodity (Clawson, 1959). These methods have been typically used in valuation of outdoor recreation.

Lately, the expected utility approach has gained popularity in evaluating information. This approach was adopted by Chavas and Pope (1984) to develop a two period dynamic programing model in measuring the value of information. Their theoretical model was flexible and allowed both the cases of open loop (no feedback) and closed loop (feedback) solutions. However, no empirical application of the theoretical model was conducted. Empirical application of the expected utility approach was conducted by Byerlee and Anderson (1982) in their work of evaluating long-range rainfall forecasts in a decision to hold fodder reserves in livestock production. They used a Bayesian methodology wherein the value of information V_k satisfied the following equation.

$$E_k \left[U\left(\pi\ (x,\ \Theta) - V_k\right)\right] - E_k \left[U\left(\pi\ (x_o^*,\ \Theta)\right)\right] = 0 \qquad \ldots(2.7)$$

where,

x = input in the production process,

Θ = random event,

$E_k\left[U\left(\pi(x, \theta) - V_k\right)\right]$ = expected utility from optimal input choice under new (posterior) information, for which the individual is willing to pay V_k.

$E_k\left[U\left(\pi(x_o^*, \theta)\right)\right]$ = expected utility from optimal input choice without new information (under prior) given that the posterior prevails.

They estimated the value of rainfall prediction to Australian sheep producers using a quadratic utility function. The costs incurred in collecting and disseminating information were neither discussed nor justified.

Bosch and Eidman (1988) used simulation and generalized stochastic dominance to estimate the value of weather and soil water information in scheduling irrigation. Simulation was used to generate distributions of net income for various levels of information. Generalized stochastic dominance was used to select the rule that maximizes the value of a level of information and to estimate the margin of preference for a net return distribution generated with that decision rule and information level over the one generated without any information. The value of information estimated with generalized stochastic dominance is that amount by which each element of a net income distribution generated with information can be lowered before it no longer dominates a net income distribution generated without information. A decision rule i for allocating the variable input is selected and the value of information V_i calculated using this rule. The value of information V_i is the amount which simultaneously satisfies equations (2.8) and (2.9).

$$\int_0^1 \left(G(\pi) - F_i(\pi - V_i)\right) U'(\pi)\, d\pi > 0 \qquad \ldots(2.8)$$

$$\int_0^1 \left(G(\pi) - F_i(\pi - V_i - Y)\right) U'(\pi)\, d\pi \le 0 \qquad \ldots(2.9)$$

In equations (2.9) and (2.10) π is net income, U the Von-Neuman Morgenstern utility function and V_i the value of information that generates F_i using decision rule i. Y is a small positive amount If the net income is lowered by Y in addition to V_i the decision rule i generating F_i is no longer the preferred decision rule. The absolute risk aversion coefficient of the agents are restricted between some upper and lower boundaries by,

$$r_1(\pi) \geq -\frac{U''(\pi)}{U'(\pi)} \geq r_2(\pi). \qquad \ldots(2.10)$$

Except for the cost of providing Checkbook information (where the farmer keeps an account of soil water level), the cost of collecting and disseminating information was not mentioned in this study.

The study by King *et al.* (1986), already mentioned under 2.2, also introduces the concept of measuring the value of information under the expected utility framework. As they analyzed the risk neutral case, annualized net revenue was used as the performance criterion instead of expected utility. A bioeconomic model was used to evaluate weed management strategies under high and low initial weed conditions. The analysis was conducted for a 200 ha. farm assumed to have a continuous corn production system. The comparison of performance of the four weed management strategies indicated that the flexible strategy outperforms the fixed strategy. This difference between the expected annualized net returns of the flexible and fixed strategy can be considered as the value of information required to implement the flexible strategy. This value is sensitive to the relative changes in corn and herbicide prices. Given the cost of acquiring information it may not always be optimal to adopt a flexible control strategy. To obtain the optimal decision rule at planting requires information regarding weed seed numbers in the soil before planting, weed density estimates made prior to the time post-emergence herbicide would be applied, and the models and analysis required to implement the flexible threshold rule. The flexible strategy will be adopted over the fixed strategy only if the cost of the above information is less than the increase in expected annualized net return from this information. In comparison, the cost of adopting a mixed strategy is less, since this requires only the weed densities prior to post-emergence herbicide application and a simpler analysis. This strategy also outperformed the fixed strategies, and under low initial weed conditions was comparable to the flexible strategy.

Nyrop, Foster and Onstad (1986) calculate the value of sample information using decision theory. The estimated value is used as an objective criterion to evaluate and construct decision rules for use in pest management. The threshold estimated is termed "control decision threshold". This is believed to differ from the economic threshold in that it accounts for uncertainty in sampling and in cost of collecting sample information. They establish that the estimated threshold for pest control decision and sampling intensity are not independent.

Foster, Tollefson and Steffey (1986) estimated the value of adult CRW sample information and determined a decision making strategy for CRW in Iowa. Their estimation was based on the following definition (1986, p. 307),

> The value of sample information for a grower is the difference between the returns the grower can expect if he uses sample information to choose a control action and the returns the grower can expect for the best control action he could use had the sampling information not been available.

They estimated the value of adult CRW sample information to be zero and the best strategy for CRW management to be not to sample and always apply soil insecticide at planting. This result could be a consequence of the fact that damage levels below economic threshold were poorly predicted by adult CRW density estimates. With more data points below the threshold level a better prediction may have been achieved. This may have resulted in positive value of adult CRW sample information.

Chapters 5 and 6 deal with the methodology used in evaluating information. This methodology follows the expected utility framework as adopted by the studies mentioned above. Simulation and the compensation principle are the tools used in the analysis. According to the compensation principle, state B is preferred to state A if, in making the move from state A to state B, the gainers can compensate the losers such that everyone can be made better off (Just, Hueth and Schmitz, 1982, p. 34). As in the study by King *et al.* (1986) and Bosch and Eidman (1988), simulation will be used to generate distributions of net income under different levels of scouted information. The compensation principle will be used to select the most profitable level of information and to measure its value.

2.5 Summary

This chapter has reviewed the biology of CRW and ECB in relation with corn in Minnesota. The mobility of CRW beetles and the extent of dispersion of its pupae in soil hinders accurate CRW sampling. Moreover, the winter mortality of CRW eggs complicate the relation between egg counts in fall and the adult population the following spring. The emergence of second generation ECB larvae over an extended period creates difficulty in sampling. The indirect relationship between the overwintering second generation larvae and the damage due to first generation larvae the following crop season limits the prediction capability of any model based on second generation larvae.

Various studies dealing with modeling IPM have been reviewed in this chapter. In addition a bioeconomic model of CRW and ECB management in corn has also been described. This model is divided into two components; biological and economic. The biological component models pest dynamics and the effect of pest population on plant and subsequently its yield. The economic component models costs and returns associated with alternative CRW and ECB management strategies.

Finally, a brief review of literature dealing with estimating the value of information has been presented. The actual methodology used in evaluating information will be dealt with in chapters 5 and 6.

CHAPTER 3

MODEL SPECIFICATION AND ESTIMATION

The biological component of the model described in chapter 2 is specified and estimated in the following sections. First the data sources used for model building are described. Next the equations to be estimated are specified. Finally, parameter estimates are presented, followed by a brief summary.

3.1 Data Sources for Model Building

The data used for model building were collected from a RCB-split-split plot repeated measure design, replicated four times, planted to continuous corn on a field belonging to farmer Donald Nord in Goodhue, Minnesota. The data range over a three year period, 1985 through 1987. All the plots were at the same location, on the same field with similar soil and cropping history. This reduces the potential variations in yield due to extraneous factors not accounted for by the model. However, it also reduces the generality of the model. The pests considered in this study are mobile, and small experimental plots (of 95 sq. feet) lying next to each other may not be very efficient in studying different pest control strategies. Due to pest mobility, the pest population response to treatment on these plots may not appear as pronounced as they may otherwise have been on larger fields.

In the experimental design, the whole plots are three tillage systems; chisel plow, ridge till and no-till. These are divided into subplots for different pest management practices. The first subplots are two different management tactics for CRW: preplanting application of insecticide (1 lb. active ingredient per acre of Counter 15G), and no insecticide application. In 1985, the second tactic was application of .33 lb. active ingredient of Counter 15G instead of no insecticide application. This, however, showed results no different than the plots with no insecticide. Therefore, for the following analysis, this is grouped together with no-treatment tactics. The sub-sub-plot are three different levels of management for ECB: a prophylactic control, no control and a responsive IPM system. The IPM system was to apply insecticide if more than 50% plant injury was observed for either the first or the second generation. Over the three years experimental period, 1985-1987, ECB attack was so low that the IPM tactic was no application of any insecticide. Hence, for this analysis, the IPM treatment for ECB has been grouped together with no control. During all three years the same corn variety, Pioneer 3906, was grown on all the plots with the same seeding rate. All plots were treated with the same dosage of anhydrous ammonia and herbicides.

A representative plot design is depicted in Appendix 1. The means and variances of various variables used in the model are also presented in Appendix 1. These are given for the entire field, the different tillages, blocks and whole plots. As there are 24 sub-plots and 72 sub-sub-plots, the means and variances by sub-plots and sub-sub-plots are not given.

3.2 Model Specification

3.2.1 Yield Equation

The logarithmic form of the yield equation used in the empirical estimation is given by equation 3.1.

$$\ln Y = b_o + b_1 \ln S + b_2 \ln H2 + b_3 \ln E + b_4 D_{86} + b_5 D_{87} + b_6 D_{rid} + b_7 D_{min} + \varepsilon \qquad \ldots (3.1)$$

where,

Y = sample yield in bushels per acre,

S = number of plants per acre,

$H2$ = average plant height approximately 65 days after planting,

E = number of ears per plant, and

ε = the random error term assumed to be distributed normally with mean zero.

D_{86} and D_{87} are dummy variables set equal to one if year is 1986 and 1987 respectively, otherwise set equal to zero.

D_{rid} and D_{min} are dummy variables set equal to one if tillage is ridge and no-till respectively, otherwise set equal to zero.

The yield components chosen are the number of plants per acre (S), the number of ears per plant (E) and plant height approximately 65 days after planting (H2). There were no differences noted between the data on final plant height (H3) and the mid-season height H2. Therefore, although H2 is used in the analysis, the estimation can be considered equivalent to that of using H3. The yield components were chosen because they were expected to be good predictors of yield and, at the same time, are readily observed under diverse situations without demanding extremely detailed and costly data. The yield components chosen here are believed to reflect the effects of weather and pest populations on the crop, which ultimately affects corn yield. Since weather differed greatly over the three years, year dummy variables have been included in the estimation of all equations. Tillage was expected to influence the yield, yield components and the pest damage levels. Therefore tillage dummy variables were also included in all the estimations.

3.2.2 Yield Component Equations

Early plant stand (ES), and CRW and ECB damage were identified as predictors of the number of plants per acre (S) at harvest. Since ear drop is a typical symptom of ECB damage, the number of ears harvested depends on the severity of ECB infestation. Therefore, the number of ears per plant at harvest, E (excludes dropped ears), is estimated using ECB damage as the independent variable. Early plant height (H1) and CRW damage are used to estimate the midseason height (H2). Since weather differed greatly between the three years, year dummy variables were included in the estimation of these components. The functional forms chosen for these equations are again of the log-log form.

$$\ln S = b_{os} + b_{1s} \ln ES + b_{2s} CRW + b_{3s} \ln ECB + b_{4s} D_{86} + b_{5s} D_{87} + b_{6s} D_{rid} + b_{7s} D_{min} + u_s \quad \ldots(3.2)$$

$$\ln E = b_{oe} + b_{1e} \ln ECB + b_{2e} D_{86} + b_{3e} D_{87} + b_{4e} D_{rid} + b_{5e} D_{min} + u_e \quad \ldots(3.3)$$

$$\ln H2 = b_{oh} + b_{1h} \ln H1 + b_{2h} CRW + b_{3h} D_{86} + b_{4h} D_{87} + b_{5h} D_{rid} + b_{6h} D_{min} + u_h \quad \ldots(3.4)$$

The random error terms u_s, u_h and u_e are assumed to be normally distributed with mean zero.

CRW = estimate of damage caused by corn rootworm based on the scale developed in Iowa, which is approximately logarithmic,

ECB = ECB damage, which is represented by the total number of tunnels without live larvae present per 100 plants, and

D_{86}, D_{87}, D_{rid} and D_{min} are as defined earlier.

3.2.3 Pest Damage[1] Prediction Equations

CRW Damage

CRW damage is measured by a logarithmic index based on a scale developed at Iowa State University. CRW population levels determine the level of CRW damage. Two sources of information may be useful in predicting CRW population levels. First, counts of CRW eggs in the soil prior to planting are a logical basis for CRW population predictions. Making egg counts, however, is costly. Counts of CRW beetles in the previous growing season are a second source of information on the potential CRW population. This information is less

1 The term "damage" used in this study does not imply "potential loss". The term can instead be considered as meaning "plant injuries".

expensive than the egg counts. Both sources of information are considered in this analysis. Visual CRW beetle counts were taken several times during the crop season. This study utilizes the cumulative of visual counts taken approximately 67, 84 and 104 days after planting. The unit used in the analysis is total number of beetle counts per plant from three field visits.

The CRW population can be lowered by a pre-plant insecticide application. In this analysis, the reduction in CRW damage resulting from pre-plant application of Counter was estimated as a constant percentage of the potential damage. Three predictors were chosen for estimating CRW damage. The first predictor uses beetle counts. This is the cheapest form of available information and is considered to be the low level of CRW information. The second predictor uses the more expensive egg counts in forecasting CRW damage. This is considered to be the high level of CRW information. Finally, the third predictor uses both the beetle and egg counts. This is termed the combined level of CRW information. Since the predictors using low and combined levels of information require previous season's beetle counts, these two equations were estimated using two years of data. The functional forms for the three CRW damage prediction models considered in this analysis are given in equations 3.5, 3.6 and 3.7.

$$CRW^1 = (1 - k * \text{Control}) * (b^1_{oc} + b^1_{1c} * \text{CRWadult}) + b^1_{2c} D_{87} + b^1_{3c} D_{rid} + b^1_{4c} D_{min} + \varepsilon^1_c \quad \ldots(3.5)$$

$$CRW^2 = (1 - k * \text{Control}) * (b^2_{oc} + b^2_{1c} * \text{CRWegg}) + b^2_{2c} D_{86} + b^2_{3c} D_{87} + b_{4c}{}^2 D_{rid} + b^2_{5c} D_{min} + \varepsilon_c \quad \ldots(3.6)$$

$$CRW^3 = (1 - k * \text{Control}) * (b^3_{oc} + b^3_{1c} * \text{CRWadult} + b^3_{2c} * \text{CRWegg}) + b^3_{2c} D_{87} + b^3_{3c} D_{rid} + b^3_{4c} D_{min} + \varepsilon^3_c \quad \ldots(3.7)$$

where,

CRW = damage index of CRW,

CRWegg = egg counts (per pint of soil) of CRW before planting,

CRWadult = beetle counts (per plant) from previous season,

Control = dummy variable set equal to 1 if control is adopted and equal to 0 otherwise, and

ε_c^i = random error term assumed to be normally distributed with mean zero, i = 1, 2, 3.

D_{86}, D_{87}, D_{rid} and D_{min} are as defined earlier.

ECB Damage

Counts of empty (larvae free) ECB tunnels per one hundred plants are used as a measure of ECB damage. The number of ECB tunnels depends on first and second generation ECB population levels. Again, there are two sources of information for predicting potential ECB damage. First, early season counts of ECB shotholes are a commonly used indicator of the level of first generation ECB infestation and potential ECB damage. Second, counts of second generation ECB larvae in the preceding growing season may also be useful in predicting ECB damage. These second generation larvae overwinter in stubble. They lay eggs the following spring and produce the first generation ECB. Both these sources of information are considered in the analysis. It should be noted that neither measure is, itself, a good predictor of second generation ECB population levels. The first generation ECB population levels that these measures do help predict are, however, expected to be correlated with second generation ECB populations. There are some indications that the ovipositing moths, in spring, are attracted to taller plants (Andow and Ostlie, 1989). To account for this factor, early plant height, H1, was included in ECB damage estimation.

The ECB population can be lowered by an early season application of Dipel and later season application of pounce or asana. In this analysis, the reduction in ECB damage resulting from the insecticide application was estimated as a constant percentage of the potential damage. As with the CRW damage predictors, three different predictors were considered for ECB. The first predictor uses the inexpensive (low level) shothole counts in predicting potential ECB damage levels (equation 3.8). The second predictor uses the more expensive (high level) second generation larvae counts in the estimation of damage (equation 3.9). The third uses both the shothole and larvae counts i.e. uses the combined available information on ECB population (equation 3.10). The equations using previous season's second generation larvae counts were estimated using two years of data. The functional forms for the three ECB damage prediction models considered in this analysis are given in equations 3.8, 3.9 and 3.10.

$$ECB^1 = (1 - k * \text{control}) * (b^1_{oe} + b^1_{1e}\text{SHOTHOLE}) + b^1_{2e}H1 + b^1_{3e}D_{86} + b^1_{4e}D_{87} + b^1_{5e}D_{rid} + b^1_{6e}D_{min} + \varepsilon^1_e \qquad \ldots(3.8)$$

$$ECB^2 = (1 - k * \text{control}) * (b^2_{oe} + b^2_{1e}\text{LARVA2}^2_{-1}) + b^2_{2e}H1 + b^2_{3e}D_{87} + b^2_{4e}D_{rid} + b^2_{5e}D_{min} + \varepsilon^2_e \qquad \ldots(3.9)$$

$$ECB^3 = (1 - k * \text{control}) * (b^3_{oe} + b^3_{1e}\text{SHOTHOLE} + b^3_{2e}\text{LARVA2}_{-1}) \quad b^3_{3e}H1 + b^3_{3e}D_{87} + b^3_{4e}D_{rid} + b^3_{5e}D_{min} + \varepsilon^3_e \qquad \ldots(3.10)$$

where,

ECB = total ECB damage given by tunnels per 100 plants,

LARVA2_{-1} = previous season's second generation larvae per 100 plants,

SHOTHOLE = number of shotholes per 100 plants,

control = binary variable set equal to 1 for ECB control and zero otherwise,

ε^i_e = random error term assumed to normally distributed with mean zero, i = 1, 2, 3.

H1, D_{86}, D_{87}, D_{rid} and D_{min} are as defined earlier.

3.3 Parameter Estimates

Parameters of the yield and pest damage equations were estimated using data from the Nord farm experiment. These data, as already mentioned, originated from a split-split-plot experiment. A complete theoretical description of such an experimental design is presented by Montgomery (1984) and will not be given here. To account for the plot effects on variance components, generalized least squares (GLS) was adopted (Fuller and Battese, 1973). The parameter estimates obtained using OLS are unbiased, however, their standard errors may be biased. The estimators obtained using GLS are the best linear unbiased estimators (BLUE) (Johnston, 1984, p. 292). This procedure, in general, requires some nonsingular transformation matrix T, such that,

$$T\Omega T' = I \qquad \ldots(3.11)$$

where the variance matrix $V = \sigma^2\Omega$, and

I = identity matrix.

Given the number of observations, the variables in each equation and the experimental design, the variance matrix, V has a dimension of 216*216. Given the dimension, V cannot be directly estimated using most of the computer packages. Therefore, the method suggested by Fuller and Battese (1973) is adopted in estimating V. This procedure is fully outlined in Appendix 2. The estimators thus obtained have the same limiting distribution as the GLS estimators with known variance components (Fuller and Battese, 1973).

3.3.1 Yield Equation

Table 3.1 gives the estimated coefficients of the yield equation (equation 3.1). As indicated in Appendix 2 (A2.2.1) none of the variance components of the design effect on the yield equation is significantly different from zero at the five percent significance level. Therefore, ordinary least squares (OLS) was used in estimating the parameters of this equation. Coefficients on the yield components

TABLE 3.1 ESTIMATION OF YIELD EQUATION

Dependent variable = log (Yield in bushels per acre).

R-squared:	0.600	adjusted R-squared:	0.590
F(8,208):	90.544	Probability of F:	0.000

Variable	Estimate	Standard Error	t-value	Prob >¦t¦
Constant	-4.043480	0.713329	-5.668460*	0.000
log(# of plants/acre)	0.768522	0.071612	10.731796*	0.000
Log(# of ears/plant)	0.111659	0.091663	1.218146	0.223
Log(plant height)	0.303219	0.062155	4.878418*	0.000
D86	-0.138799	0.025666	-5.407962*	0.000
D87	0.051617	0.024031	2.147915+	0.032
DRID	0.016013	0.011725	1.365735	0.172
DMIN	0.012081	0.012586	0.959889	0.337

* implies significance at 1% level.

\+ implies significance at 5% level.

except for that of E are significant at the one percent significance level. Yield per acre increases as the number of plants per acre increases and plant height increases. The year effect is significant as indicated by the t-ratios corresponding to the year dummy variables. Weather conditions similar to that of 1987 lead to higher yields, and those similar to 1986 lead to lower yields when compared with that of 1985. However, no significant yield differences exist among the three tillage systems.

3.3.2 Yield Component Equations

Sub-plot effects are significant at the five percent level for equations 3.2 and 3.4 of the yield components. Therefore, the transformation approach suggested by Fuller and Battese (1973) was used in estimating these two equations. The transformation used is of the following form (Appendix 2),

$$Y_{ij} - \alpha \bar{Y}_i = \sum_{k=1}^{p} (X_{ijk} - \alpha \bar{X}_{ik}) \beta_k + U_{ij} \qquad \ldots(3.12)$$

where,

$$\alpha = 1 - \left(\frac{\sigma^2_{mse}}{\sigma^2_{mse} + \sigma^2_{SP}} \right)^{1/2} \qquad \ldots (3.13)$$

where,

$\bar{Y}_i$ = mean of the dependent variable for sub-plot i $\qquad i=1,\ldots,n$

$\bar{X}_{ik}$ = mean of independent variable k for sub-plot i $\qquad i=1,\ldots,n$; $k=1,\ldots,p$

σ^2_{mse} = mean square error of the equation

σ^2_{SP} = variance component due to sub-plots.

Since the tillage effect on number of plants per acre (equation 3.2) is insignificant at the five percent level (Appendix, A2.2.2), the equation was estimated restricting the coefficients on the tillage dummy variables to be zero. Since none of the variance components due to the experimental design was found to be significantly different from zero at the five percent level in equation 3.3, OLS was used in its estimation.

Parameter estimates for equations 3.2 through 3.4, the yield component equations, are given on Table 3.2. For all equations, except 3.3, the coefficients for most of the independent variables are significant at the one percent significance level. In all equations the signs of parameter estimates are as expected. The variable ECB, representing damage due to ECB, does not appear to significantly influence the yield components. This can be attributed to the fact that there were only small variations in ECB damage in the sample data. Nevertheless, the sign of the ECB coefficient is negative as expected in the equations estimating the number of plants and the number of ears. Greater damage due to CRW significantly reduces the crop stand and plant height. All yield components were significantly lower for 1986 than for 1985. Plant height was significantly lower for 1986 and 1987 compared with that of 1985. As it is not feasible

TABLE 3.2 ESTIMATION OF YIELD COMPONENT EQUATIONS

Dependent Variable = Log(Number of Plants per acre).

(GLS R-squared)	0.998	(GLS adjusted R-squared)	0.998
F(6,210):	22900.082	Probability of F:	0.000

Variable	Estimate	Standard Error	t-value	Prob >|t|
Constant	0.011284	0.004809	2.346610+	0.019
log(ECB damage)	-0.001997	0.001757	-1.136249	0.256
log(early plant stand)	0.993586	0.003076	322.982053*	0.000
CRW damage	-0.005075	0.002146	-2.365075*	0.018
D86	-0.028926	0.003681	-7.857805*	0.000
D87	-0.004534	0.003664	-1.237433	0.216

Dependent Variable = log(Number of Ears per Plant).

R-squared:	0.244	adjusted R-squared:	0.226
F(6,210):	13.532	Probability of F:	0.000

Variable	Estimate	Standard Error	t-value	Prob >|t|
Constant	-0.000901	0.007540	-0.119442	0.905
Log(ECB damage)	-0.006504	0.005523	-1.177694	0.239
D86	-0.051588	0.009678	-5.330474*	0.000
D87	0.008860	0.011575	0.765448	0.444
DRID	-0.006162	0.008189	-0.752562	0.452
DMIN	0.001810	0.008189	0.221020	0.825

Dependent Variable = log(Plant Height).

(GLS R-squared)	0.600	(GLS adjusted R-squared)	0.590
F(6,210):	1434.421	Probability of F:	0.000

Variable	Estimate	Standard Error	t-value	Prob >|t|
Constant	0.000000	-	-	-
CRW damage	-0.016491	0.010222	-1.61325	0.107
Log(midseason height)	1.248387	0.018450	67.66360*	0.000
D86	-0.501118	0.016313	-30.71848*	0.000
D87	-0.297427	0.014003	-21.23979*	0.000
DRID	0.062470	0.026480	2.35909+	0.018
DMIN	0.051925	0.026339	1.97143	0.049

* implies significance at 1% level.
+ implies significance at 5% level.

to obtain late season plant height without early plant height, the intercept in the equation estimating plant height was restricted to be zero. This equation had a better model fit than the equation which included an intercept for estimating plant height. Plant height was significantly higher for ridge-till at the 5 percent significance level. There was no significant difference in plant stand and the number of ears per plant between the three tillages.

3.3.3 Pest Damage Prediction Equations

CRW Damage

The estimated CRW damage prediction equations, equations 3.5 through 3.7, are presented in Table 3.3. Sub-plot effect was significant at the five percent level for equation 3.7. Therefore, the transformation approach suggested by Fuller and Battese (1973) was adopted in estimating this equation. The transformation is of the form given by equations 3.12 and 3.13 (Appendix, A2.2.3). As no variance component is significant at the 5% level for equations 3.5 and 3.6 both were estimated using OLS. In all three equations, the estimated coefficients on the control dummy variable and tillage dummy variables, and the variance component due to tillage were not significantly different from zero. Hence, these equations were re-estimated restricting these coefficients to be zero. The equations predicting CRW damage using previous season's adult beetle counts (equations 3.5 and 3.7) were estimated using two years' data.

Both the adult beetle counts and the egg counts perform reasonably well in predicting CRW damage. Equation 3.5, which uses previous season's beetle counts to predict damage, requires the least cost intensive information. More cost intensive egg count information does not necessarily strengthen predictive ability. The low t-ratio on equation 3.7 indicates that in the presence of adult beetle counts, the coefficient on egg and treatment interaction is not significantly different from zero. There was a significantly lower CRW damage in 1987 compared with 1986.

TABLE 3.3 ESTIMATION OF CRW DAMAGE PREDICTION EQUATIONS.

Dependent Variable = CRW Damage Ratings (Eq. 3.5)

R-squared: 0.493 Adjusted R-squared: 0.482
F(4,140): 45.335 Probability of F: 0.000

Variable	Estimate	Standard Error	t-value	Prob >|t|
Constant	3.277846	0.240620	13.622488*	0.000
Beetles/plant	0.100882	0.042193	2.390933+	0.018
Beetles * Control	-0.160855	0.022926	-7.016222*	0.000
D87	-0.869299	0.158006	-5.501673*	0.000

Dependent Variable = CRW Damage Ratings (Eq. 3.6)

R-squared: 0.475 Adjusted R-squared: 0.465
F(5,211): 47.669 Probability of F: 0.000

Variable	Estimate	Standard Error	t-value	Prob >|t|
Constant	2.257860	0.086624	26.06514*	0.000
Egg	0.047115	0.008788	5.36107*	0.000
Egg * Control	-0.043232	0.007417	-5.82868*	0.000
D86	0.915795	0.090499	10.11937*	0.000
D87	-0.025777	0.091506	-0.28170	0.778

Dependent Variable = CRW Damage Ratings (Eq. 3.7)

(GLS R-squared) 0.468 (Adjusted GLS R-squared) 0.449
F(6,138): 24.281 Probability of F: 0.000

Variable	Estimate	Standard Error	t-value	Prob >|t|
Constant	0.413648	0.063216	6.543428*	0.000
Beetles/plant	0.131402	0.042441	3.096121*	0.002
Egg	0.044609	0.014543	3.067437*	0.003
Egg * Control	-0.024031	0.018873	-1.273302	0.205
Beetles * Control	-0.145651	0.045084	-3.230633*	0.002
D87	-0.749583	0.146341	-5.122159*	0.000

* implies significance at 1% level.
\+ implies significance at 5% level.

ECB Damage

For the ECB damage prediction equations, equations 3.8 through 3.10, none of the components of the variance due to the experimental design was significantly different from zero at the five percent significance level. Therefore OLS was used in their estimation. The coefficients on the control variable were found not significantly different from zero. Similarly, in two of the three equations, coefficients on tillage and early height were found to be insignificant at the five percent level. In these equations, the variance components due to tillage and early plant height were also insignificant. Therefore, as in the estimation of CRW damage, these equations have been re-estimated restricting these coefficients to be zero. Equations using previous season's second generation larvae counts were estimated with two years' data.

Parameter estimates for the ECB damage prediction equations are presented in Table 3.4. Both the variables representing the shotholes and the second generation ECB larvae perform reasonably well in predicting potential ECB damage. In all three years over which the data were collected, however, the ECB population was low so that it was never necessary to adopt a control. Due to this low incidence of ECB, the relationship between control and damage levels is not clear from this study. The data points contain several zero entries on shothole and larvae counts. Adopting a control on such a plot with zero counts cannot result in a decrease in observed pest population. This helps explain the positive (insignificant) coefficients for treatment interactions with shothole in equation 3.10 and the insignificant coefficient in equation 3.8.

3.3.4 Correlation and Standard Deviation of Regression Residuals

To introduce random behavior into the simulation model which is used to generate distributions of net revenues, sample states of nature need to be specified. It is desirable to define these sample

TABLE 3.4 ECB DAMAGE PREDICTION EQUATIONS.

Dependent Variable = ECB Damage (Eq. 3.8)

R-squared:	0.657	Adjusted R-squared:	0.645
F(8,208):	56.896	Probability of F:	0.000

Variable	Estimate	Standard Error	t-value	Prob >|t|
Constant	-0.465573	4.129203	-0.11275	0.910
Shotholes/100 plants	0.282485	0.048824	5.78583*	0.000
Midseason plant height	0.057782	0.067211	0.85971	0.390
Shotholes * Control	-0.162247	0.154194	-1.05222	0.293
D86	7.484527	1.881611	3.97772*	0.000
D87	14.383405	1.745059	8.24236*	0.000
DRID	1.988587	0.948330	2.09693+	0.036
DMIN	2.126481	1.040057	2.04458+	0.041

Dependent Variable = ECB Damage (Eq. 3.9)

R-squared:	0.525	Adjusted R-squared:	0.515
F(4,140):	51.669	Probability of F:	0.000

Variable	Estimate	Standard Error	t-value	Prob >|t|
Constant	13.187667	0.690287	19.104608*	0.000
Lag Larvae2	0.035917	0.014340	2.504730+	0.013
Lag Larvae2 * Control	-0.079612	0.012392	-6.424408*	0.000
D87	7.986962	1.669539	4.783932*	0.000

Dependent Variable = ECB Damage (Eq. 3.10)

R-squared:	0.556	Adjusted R-squared:	0.539
F(6,138):	34.495	Probability of F:	0.000

Variable	Estimate	Standard Error	t-value	Prob >|t|
Constant	12.575547	0.703008	17.888192*	0.000
Shotholes/100 plants	0.193990	0.065274	2.971918*	0.003
Lag Larvae2	0.040188	0.014284	2.813431*	0.006
Shotholes * Control	0.082365	0.257378	0.320015	0.749
Lag Larvae * Control	-0.060904	0.015457	-3.940297*	0.000
D87	5.284273	1.855010	2.848650*	0.005

* implies significance at 1% level.

+ implies significance at 5% level.

states of nature such that they are representative of the pattern of randomness prevalent the system. Hence, the sample states of nature are defined considering the correlation among the residuals of each equation in the model and their standard deviations. For those equations estimated using GLS, the heteroskedastic error term is considered in drawing the sample states of nature. For example if the estimated equation is given by 3.14,

$$\tilde{Y} = \hat{\beta}\,\tilde{X} + \tilde{e} \qquad \ldots(3.14)$$

$\tilde{Y}$, $\tilde{X}$ and $\tilde{e}$ give the weighted dependent and independent variables and the homoskedastic error term respectively. The estimated GLS parameters are given by $\hat{\beta}$. In estimating the model parameters and their standard deviation, the corrected homoskedastic error terms are considered. However, since the actual system comprises of heteroskedastic random disturbances, these heteroskedastic disturbances are considered in simulation. The residual used in drawing the sample states of nature is given by equation 3.15.

$$e = Y - \hat{\beta}\,X \qquad \ldots(3.15)$$

where,

Y, X and e give the unweighted original dependent and independent variables and the heteroskedastic error term respectively. The procedure by which the sample states are generated and incorporated into the simulation model is dealt with in chapter 5.

The correlations between the the residuals of each of the equations in the model are given in Table 3.5. As evident from the table, the error terms of the three CRW damage prediction equations are correlated. This implies that if one of the damage predictions is incorrect, the other two may also be incorrect. Likewise, the residuals of the three ECB damage prediction equations are correlated. In addition, the residuals between the ECB damage prediction equations and the number of ears per plant are correlated. Therefore, if one of the ECB damage predictions is incorrect, it is likely that the rest

TABLE 3.5 CORRELATION MATRIX OF THE REGRESSION RESIDUALS

Equation	ECB^3	ECB^2	ECB^1	CRW^3	CRW^1	CRW^2	Ht	Ear	Stand	Yield
ECB^3	1.00	.968	.910	.010	-.014	.039	.063	-.176	-.056	.076
ECB^2	.968	1.00	.869	.014	-.014	.033	.063	-.160	-.066	.054
ECB^1	.910	.869	1.00	.050	.060	.095	.060	-.170	-.074	-.025
CRW^3	.010	.014	.050	1.00	.889	.839	-.168	-.014	-.081	-.059
CRW^1	-.014	-.014	.059	.889	1.00	.895	-.145	-.047	-.083	-.113
CRW^2	.039	.033	.095	.839	.895	1.00	-.158	-.017	-.073	-.115
Ht	.063	.063	.060	-.168	-.145	-.158	1.00	.007	.075	.137
Ear	-.176	-.160	-.170	-.014	-.047	-.017	.007	1.00	.205	-.023
Stand	-.056	-.066	-.074	-.081	-.083	-.073	.075	.205	1.00	.125
Yield	.076	.054	-.025	-.059	-.113	-.115	.137	-.023	.125	1.00

of the ECB damage predictions and the predicted number of ears per plant are incorrect. The residuals for the number of ears per plant and the number of plants per acre are also correlated.

The variance of the error term is assumed to be influenced by the pest control strategy adopted, the year variable and the tillage variable. Accordingly regression is run on these variables using the absolute regression residual as the dependent variable. For those equations where GLS is used in the estimation process, the absolute heteroskedastic error term (equation 3.15) is the dependent variable. As evident from Table 3.6, controlling for CRW reduces uncertainty regarding the potential damage levels due to this pest. Controlling for ECB on the other hand does not reduce the prediction uncertainty. The positive coefficients estimated, however are not significant at the five percent significance level.

TABLE 3.6 STANDARD DEVIATION OF THE DISTURBANCE TERM

Dependent Variable = |Residual|

Equation	Intercept	Control	D_{86}	D_{87}	D_{rid}	D_{min}
ECB^3	3.9499*	0.0577	-	-0.9087*	0.9230	0.7008
ECB^2	4.0958*	0.3827	-	-0.7843	0.7640	0.4776
ECB^1	1.9104*	0.4257	2.1237*	1.7080*	0.8196*	0.9117*
CRW^3	0.5560*	-0.1419*	-	-0.1248*	-	-
CRW^2	0.2426*	-0.1248*	0.4714	0.1520	-	-
CRW^1	0.6455*	-0.2008*	-	-0.2096*	-	-
Height	0.0561*	-	0.0092	0.0031	-0.0252	-0.0170
Ear	0.0031	-	0.0328	0.0022	0.0104	0.0016
Stand	0.0094*	-	0.0143	0.0042*	-	-
Yield	0.0528	-	0.0040	-0.0038	-0.0081	-0.0030

* = significant at 5% level.

3.4 Summary

This chapter has specified and estimated the biological component of the model used in this study. The yield equation is specified as a function of yield components; number of plants per acre, plant height and number of ears per plant. The yield components in turn are estimated as functions of CRW and ECB damage. Early plant stand is also used in estimating number of plants per acre and early plant height is used in estimating plant height. CRW damage is specified as a function of adult beetle counts and egg counts. ECB damage is specified as a function of shothole counts and previous season's second generation larvae counts. In estimating pest damage, the reduction in damage resulting from the application of pesticide is estimated as a constant percentage of potential damage. In all these equations tillage and year dummy variables are used to capture the weather variations between each year and the differences due to tillage.

Parameters were estimated using data collected from a RCB-split-split plot design. The estimation technique took into consideration the experimental design effects on the variance components of the model. Generalized least squares procedure as suggested by Fuller and Battese (1973) was used to estimate those equations in which the variance components resulting from the experimental design were significant at the five percent significance level.

CHAPTER 4

MODEL VALIDATION

The model specified and estimated in chapters 2 and 3 is validated in this chapter. Due to data constraints, the model cannot be validated as a whole. Therefore, the validation is carried out in two distinct stages. First, the yield component of the biological model is validated with one set of data. Next the pest dynamics component of the model is validated with another set of data. In the following pages the data used for validation are described and a brief review of validation methodology presented. Finally, the actual validation is presented followed by a brief discussion and summary.

4.1 Data Sources for Model Validation

The model developed and estimated in chapter 3 is validated using two separate data sets. The first set is the 1987 and 1988 experimental plot data from Waseca, Minnesota. The second set is the 1987-88 data from a field in Goodhue, Minnesota adjacent to the one from which the model building data were collected.

The yield component of the model is validated using the Waseca data. The Waseca experiment was designed to test the effects of various pest damages on corn. The experimental design was a RCB-split-split-split-split plot replicated 8 times. The whole plots were four tillage systems: fall moldboard plow, fall chisel plow, ridge-till and no till. The first subplot was two control tactics for CRW, 1 lb. a.i. Counter 15G/acre and no insecticide application. The second subplot was three treatments of first generation ECB attack, natural population, an additional one egg/mass above natural levels, and application of Dipel to reduce populations of ECB. The third subplot level was two treatments of stalk rot attack, natural and an artificial inoculation with *F. graminearum* infested toothpicks. The fourth subplot was three treatments of second generation ECB, natural, artificial infestation of an additional one egg mass per plant above natural levels and application of Dipel. As the individual pest treatments varied from that of the data used in modeling, these data may not be suitable for validating pest dynamics, and therefore are used only to validate the yield components of the model.

Yield, final plant stand, final plant height and the number of ears per plant are available for 718 observations. However, other observations prior to harvest are available for a smaller number of plots. These plots were chosen at random. Unfortunately, the plots chosen for CRW damage and ECB damage assessment or early plant height measurement do not overlap. Hence the average level of CRW damage was used in forecasting equations involving these variables. Data from moldboard plowed plots were removed before validation.

The 1987-88 Goodhue data were used to validate the pest dynamics component of the model. These data are from the first two years of an ongoing study initiated to evaluate the effects of tillage, and rate and frequency of injected liquid swine manure on corn (Joshi *et al.*, 1989). The experimental design was a RCB-split-split plot replicated four times. The whole plots were two tillage systems, ridge-till and chisel plow. The first subplot was 8 fertilization treatments of anhydrous ammonia and liquid swine manure. In 1988 the second subplot comprised of 2 treatments for CRW; application of 1 lb. a.i. Counter 15G at planting and no application. In 1987 this subplot was omitted. Therefore, the validation of CRW damage equations was done considering only those plots where no Counter was applied. Similarly, as ECB treatment plots were not included in the design, ECB damage equations are validated considering only the no treatment strategy. Since fertilizer treatments greatly influence the yield, these data were deemed unsuitable for validating the yield component of the model. They should, however, be suitable for validating the pest dynamics. The same corn variety, Pioneer 3906, was grown both the years in all the plots in Waseca. In Goodhue, Pioneer 3906 was used in 1987, however, in 1988 a different variety, Pioneer 3737 was used.

4.2 Methodology of Model Validation

A simulation model is validated to determine whether it accurately represents the actual system being studied. Since a model is only an approximation of a complex real-world system, it is difficult to use exact statistical tests for validation. Hence the rules applied in validation are generally subjective. A model may not be validated in an absolute sense (with objective statistical tests) but may be validated in terms of the degree to which it agrees with the actual system. For this purpose, it is preferable to validate a model relative to a specified set of criteria; ie. those criteria that will be used for decision making. Pindyck and Rubinfeld (1976, p. 333-48) point out that models designed for forecasting should have as small a standard error of forecast as possible. Those designed to test a specific hypothesis should have high t-statistics.

Various techniques of validation have been outlined by Law and Kelton (1982, p. 333-48), Anderson (1974), and Pindyck and Rubinfeld (1976, p. 314-20). The first two works make a distinction between validation and verification. Verification, which Law and Kelton (1982, p. 333) define as "determining whether a simulation model performs as intended, ie. debugging the computer program" is generally considered as a component of validation. They define validation (1982, p. 334) as "determining whether a simulation model is an accurate representation of the real-world system under study". Only validation and not verification is the focus of this chapter.

Validation techniques can be summarized under the following three groups (Law and Kelton, 1982, p. 338).

1. Testing the face validity of a model.
2. Testing the underlying theoretical assumptions of a model.
3. Testing how closely a given model resembles the actual system.

The first technique involves consultation with experts in the area to judge whether the outcomes of a model appear reasonable (Law and Kelton, 1982). The second deals with testing if the assumptions made during modeling are justified. For example, in economic models, sensitivity analysis with output and factor price changes can indicate whether a model is consistent with fundamental demand and supply theories of economics. If acute (unexpected) output sensitivity to changes in certain input parameter is noticed, it may imply that the model is flawed and requires re-estimation. The final group of techniques deal with establishing how closely the model outputs resemble those which may be expected from the actual system. Most of the techniques involved are subjective. One of the tests which Law and Kelton (1982, p. 341) mention is known as the Turing test. This requires that people knowledgeable about the system compare one or more sets of actual system data and one or more sets of the model outcomes. If the data from the two sources can be differentiated, then the model needs to be further improved.

Statistical tests can also be placed under the final group of techniques used in model validation. Pindyck and Rubinfeld (1976, p. 316) outline a few of these by which a model may be statistically validated. None of the tests, however, is completely objective. All involve a certain degree of subjectivity. A model with a system of equations can either be validated as a whole or equation by equation. Often, individual equations may do a good job of predicting a particular component of the system; however, the model as a whole may be a bad representation of the actual system. Thus the validation of the system as a whole is preferred. When individual equations are validated, the choice of the validation technique should be based on the purpose for which the model is constructed. Models designed for forecasting purposes should have small forecast errors, whereas, those designed to test a specific hypothesis should have high t statistics.

A measure of validation used to validate multi-equation models is the Root-Mean-Square (RMS) simulation error. This gives a measure of the "fit" of the individual variables in a simulation context. The simulated values of an endogeneous variable are compared to those of the actual system. The values may be obtained either through the simulation of a system as a whole or through the simulation of one of the equations of a system.

$$\text{RMS} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(Y_t^s - Y_t^a)^2} \qquad \ldots(4.1)$$

where,

Y_t^s = the simulated value of Y_t,

Y_t^a = the actual value of Y_t,

T = the number of periods (observations) in the simulation.

The magnitude of this error can be evaluated only by comparison with the average size of the variable in question. Therefore the percentage RMS is a better measure of evaluation (equation 4.2). In general, low RMS indicates a good fit and large RMS a poor fit. Various modifications of the RMS error measure frequently applied in validation are presented in equations 4.2 through 4.4.

$$\text{RMS \% error} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\frac{Y_t^s - Y_t^a}{Y_t^a}\right)^2} \qquad \ldots(4.2)$$

$$\text{Mean Error} = \frac{1}{T}\sum_{t=1}^{T}(Y_t^s - Y_t^a) \qquad \ldots(4.3)$$

$$\text{Mean \% error} = \frac{1}{T}\sum^{T}\left(\frac{Y_t^s - Y_t^a}{Y_t^a}\right) \qquad \ldots(4.4)$$

When mean error is used as the validation technique, large positive simulation errors may cancel out large negative errors resulting in near 0 mean error. Therefore, RMS is a better measure of the simulation error. The mean error test can, however, be modified to define a confidence interval for $(Y_t^s - Y_t^a)$. This is done by defining forecast errors Z_t (Law and Kelton, 1982, p. 319) by,

$$Z_t = (Y_t^s - Y_t^a) \qquad \ldots(4.5)$$

$$\bar{Z}_T = \frac{1}{T}\sum Z_t \quad \text{(mean error)} \qquad \ldots(4.6)$$

$$\hat{\sigma}^2(\bar{Z}_T) = \frac{\sum(Z_t - \bar{Z}_T)^2}{T(T-1)} \qquad \ldots(4.7)$$

and the 100(1-α) percent confidence interval around mean error,

$$\bar{Z}_T \pm t_{T-1,\ 1-\alpha/2}\sqrt{\hat{\sigma}^2(\bar{Z}_T)} \qquad \ldots(4.9)$$

This procedure does not require that Y_t^s and Y_t^a be independent. If the Z_t's are normally distributed, the confidence interval around mean forecast error is exact, otherwise it holds with probability (1-α) for large samples. Again the decision as to whether the simulation model fit is appropriate is entirely subjective. This judgment is based on the size of the interval and its proximity to zero.

The purpose of the simulation model designed in this study is to forecast potential pest damages and associated levels of corn yield. Based on these forecasts a producer decides on the appropriate method of pest control. Therefore, the forecast errors of this model should be small. To check the validity of the model both percentage RMS measure and 95% confidence interval around mean forecast errors are calculated. Small percentage RMS errors and mean forecast errors close to zero with a narrow confidence interval indicate high model validity.

4.3 IPM Model Validation

The face validity of the model was checked by consulting "experts" in the area, namely entomologists Dave Andow and Ken Ostlie. Both indicated that the model gives a relatively accurate description of the dynamics involved given the particular patterns of weather and pest population occurring during the data period. The ECB population pattern is believed to resemble a sine curve and the data period of 1985-87 appeared to be at a trough of the curve. The estimated model is consistent with this belief. The trend of the curve is rising with the lowest ECB occurrence in 1985, and the highest in 1988. Predicting damages beyond these three years, however, is difficult with this model.

The underlying theoretical assumptions of the bioeconomic model are not tested in this chapter. Sensitivity analysis of the model to relative changes in corn and pesticide prices are dealt with in chapter 6. In addition, the sensitivity of the model to different levels of producer risk preferences and errors in the estimated pest damage-yield loss relationship are also presented in chapter 6. In the following section statistical validation of the model is given. Both the percentage RMS and the confidence interval methods are utilized in validating the IPM model. Only an equation by equation method of validation is possible due to data limitations. The forecast errors from validation are compared to the forecast errors present in the estimated equations.

4.3.1 Yield Equation

Except for the equation measuring the number of ears per plant, the yield and the yield component equations' estimated parameters from chapter three appear to be reasonably valid for the Waseca data. The estimated yield equation from chapter 3 is given by equation 4.10.

$$\ln Y = -4.043 + .768 \ln S + .303 \ln H2 + .112 \ln E - .139 D_{86} + .052 D_{87} + .016 D_{rid} + .012 D_{min} \quad \ldots(4.10)$$

Using equation 4.10, the logarithmic form of yield is first simulated with the original data used for modeling. The forecast errors from this simulation are presented in Table 4.1. The equation is next simulated using the validation data from Waseca. These results are given in Table 4.2. As evident from Table 4.2 the yield equation has low percentage RMS and a narrow 95% confidence interval close to zero. The calculated percentage RMS from validation is close to that of the original equation, indicating that the equation performs just as well with a different data set as with that used for model building. However, the 95% confidence interval from validation indicates a

TABLE 4.1 FORECAST ERRORS OF THE ESTIMATED EQUATIONS

Equation	T	%RMS	Mean Error	Standard Error	95% Confidence Interval for $\bar{Z}_T$	
Yield	216	0.0126	0.0000	0.0043	-0.0084,	0.0084
<u>Yield Component</u>						
Stand	216	0.0066	-0.0658	0.0011	-0.0680,	-0.0636
Ear	216	0.0625	-0.0000	0.0033	-0.0065,	0.0065
Height	216	0.0183	-0.0506	0.0054	-0.0612,	-0.0400
<u>CRW Damage Equation</u>						
Equation 4.14	216	0.1826	0.0000	0.0364	0.0713,	-0.0713
Equation 4.15	216	0.3862	-0.0000	0.0492	0.0964,	-0.0964
Equation 4.16	216	0.2188	-0.1635	0.0504	-0.2623,	-0.0647
<u>ECB Damage Equation</u>						
Equation 4.17	216	0.5537	-0.0000	4.9617	-9.7224,	9.7224
Equation 4.18	216	1.2717	0.0000	0.4410	-0.8644,	0.8644
Equation 4.19	216	1.2541	0.0000	0.4259	-0.8348,	0.8348

slight positive bias in forecasting yield. Since the number of observations is large, ranging from 576 to 718, the estimated confidence interval for $\bar{Z}_T$ is reliable. Validation is first carried out assuming the 1988 weather pattern to be similar to that of 1985. Validation is next carried out using only the 1987 data.

4.3.2 Yield Component Equations

For the yield component equations, validation is first carried out assuming the 1988 weather pattern to be similar to that of 1985. Next, validation is carried out assuming the 1988 weather pattern to be similar to that of 1987. In both the cases, the estimated

TABLE 4.2 MODEL VALIDATION RESULTS

Equation	T	%RMS	Mean Error	Standard Error	95% Confidence Interval for $\bar{Z}_T$
Yield					
1988 as 1985	718	.06705	.21954	.01050	.19896, .24013
1987 only	576	.00323	.18901	.00955	.17028, .20774
Yield Component					
Stand					
1988 as 1985	219	.02829	.16725	.01204	.14364, .19086
1988 as 1987	219	.02803	.16489	.01198	.14140, .17241
Ear					
1988 as 1985	219	.02011	-.02013	.00049	-.02109, -.01918
1988 as 1987	219	.02010	-.01552	.00048	-.01648, -.01456
Height					
1988 as 1985	142	.05359	-.05681	.02045	-.09689, -.01672
1988 as 1987	142	.12568	-.08879	.03981	-.46682, -.31077
CRW Damage Equation					
Equation 4.14					
1988 as 1987	24	.66770	1.05034	.16297	.71315, 1.38753
Equation 4.15					
1988 as 1987	24	.47753	.73302	.12993	.46219, 1.00185
Equation 4.16					
1988 as 1987	24	.34805	-.70819	.16779	-1.05536, -.36103
ECB Damage Equation					
Equation 4.17					
1988 as 1987	24	0.6891	-20.4718	4.99383	-30.79405, -10.1495
Equation 4.18					
1988 as 1987	24	1.1140	-14.4787	4.92004	-24.65827, -4.29913
Equation 4.19					
1988 as 1987	24	1.0413	-16.6405	4.97058	-26.92463, -6.35636

parameters performed reasonably well in predicting the yield components. The estimated equations used for validation are given by 4.11 to 4.13.

$$\ln S = .011 + .993 \ln ES - .005\, CRW - .002 \ln ECB - .029\, D_{86} - .004\, D_{87} \qquad \ldots(4.11)$$

$$\ln E = -.001 - .006 \ln ECB - .052\, D_{86} + .009\, D_{87} - .006\, D_{rid} + .002\, D_{min} \qquad \ldots(4.12)$$

$$\ln H2 = -.016\, CRW + 1.248 \ln H1 - .501\, D_{86} + .297\, D_{87} + .062\, D_{rid} + .052\, D_{min} \qquad \ldots(4.13)$$

For equation 4.11, the calculated percentage RMS from validation (Table 4.2) is slightly larger than that from the estimated equation (Table 4.1). For the ear equation, 4.12, the percentage RMS from validation is surprisingly lower than that from the actual estimated equation. For the height equation, 4.13, the forecast errors given by percentage RMS are higher than those from the actual equation. As the errors are not too large the estimated equation (4.13) can, however, be considered valid. The estimated confidence interval for $\bar{Z}_T$ is small for all three equations and (in Table 4.2) indicates a slight over-estimation of plant stand and an under-estimation of plant height and number of ears. In the original estimation (Table 4.1) plant height and stand were under-estimated, and the estimation of the number of ears per plant was unbiased.

4.3.3 Pest Damage Prediction Equations

The data available for validating pest dynamics have several limitations. Unlike the data used for model estimation, here only the scenario of no pest control is possible. In addition, only twenty-four observations exist for each equation. The plots from which these data are collected were treated with liquid swine manure instead of chemical fertilizer. It is likely that this influenced the pest population dynamics. The corn variety for the year 1988 also differed on these plots from those used for model estimation. The validation of yield and yield component equations indicates that the assumption of 1988 weather being similar to 1987 is reasonable. Moreover, field samplings also indicate that the pest levels in 1988 were closer to 1987 than to either 1985 or 1986. Therefore, pest damage equations (equations 4.14 to 4.19) are validated assuming 1988 weather pattern to be the same as that of 1987.

CRW Damage Equation

The equations estimated in chapter 3 used for validation are given by 4.14 to 4.16.

$$CRW^1 = 2.256 + .047\ CRWegg - .043\ CRWegg*Control + .916\ D_{86} - .026\ D_{87} \quad \ldots(4.14)$$

$$CRW^2 = 3.278 + .101\ Beetle - .161\ Beetle*Control - .869\ D \quad \ldots(4.15)$$

$$CRW^3 = .414 + .044\ CRWegg + .131\ Beetle - .024\ CRWegg*Control - .146\ Beetle*Control - .750\ D_{87} \quad \ldots(4.16)$$

From Table 4.1, it is evident that the forecast errors of the actual estimated equations are rather high, ranging from 18% to 39%, indicating poor prediction power. The percentage RMS calculated using the validation data set (Table 4.2) are higher than those calculated from the estimated equations (Table 4.1). This may partly have resulted due to validation data limitations and partly due to poor prediction capability of the model. Except for equation 4.16, the 95% confidence interval for mean forecast error indicate that the predictions using model building data are unbiased (Table 4.1). For equation 4.16, the actual estimation under-estimates the damage (Table 4.1). In Table 4.2, the first two CRW damage prediction equations (4.14 and 4.15) over-estimate the damage while the third equation (equation 4.16) under-estimates it.

ECB Damage Equation

The estimated ECB damage prediction equations from chapter 3 are given by equations 4.17 through 4.19.

$$ECB^1 = -.466 + .282\ \text{Shothole} + .058\ \text{H1} - .162\ \text{Shothole*Control} - 7.48\ D_{86} + 14.4\ D_{87} + 1.99\ D_{rid} + 2.13\ D_{min} \quad \ldots(4.17)$$

$$ECB^2 = 13.19 + .036\ \text{Larva2}_{-1} - .080\ \text{Larva2}_{-1}\text{*Control} + 7.99\ D_{87} \quad \ldots(4.18)$$

$$ECB^3 = 12.58 + .194\ \text{Shothole} + .040\ \text{Larva2}_{-1} + 5.28\ D_{87} -.082\ \text{Shothole*Control} - .061\ \text{Larva2}_{-1}\text{*Control} \quad \ldots(4.19)$$

The forecast errors of the actual fitted equations are high ranging from 55% to 127% (Table 4.1). As in the case of CRW damage, this indicates poor prediction capability of the model. The mean forecast error, however, is approximately equal to zero. The forecast errors from validation, on the other hand, indicate a significant under-estimation of ECB damage by the estimated equations (Table 4.2). It should be noted that the damages estimated here are 1988 ECB damages using shotholes for the same year and the 1987 second generation larvae. As mentioned earlier, ECB pest infestation levels increase significantly from year to year starting with 1985. Thus in 1988, the pest levels were much higher than in any of the former three years. The average number of tunnels per hundred plants are 40.5 in 1988 compared with 6.85 in 1985, 13.5 in 1986 and 22.68 in 1987. The model developed, using 1985-87 data, clearly does not capture the dynamics of ECB population.

4.4 Summary

The model specified and estimated in chapter 2 has been validated in this chapter. Two different sources of data were used for the validation. The first source, a RCB-split-split-split-split plot experimental data from Waseca, was used to validate the yield and yield component equations of the model. The second source, a RCB-split-split plot data from Goodhue, was used to validate the pest dynamics component of the model. Since all necessary data were not available from one source, an equation by equation approach was adopted for validation rather than validating the complete model as a whole. The results from validation are compared to the forecast errors present in the actual estimated equations.

Validation indicates that the estimated parameters of yield and yield component equations of the model more or less agree with the data from Waseca. However, the estimated parameters of the pest dynamics component of the model do not perform as well with the Goodhue data. This may partly be due to the inherent problems existing within the Goodhue data and partly due to the poor predictive capability of the damage prediction equations. Thus the weakness of the model developed in this study appears to be in predicting pest damages. In all the three years over which the data is collected, pest infestation levels were low that accurate estimation of pest damage prediction equations is not possible.

CHAPTER 5

THE SIMULATION MODEL

In this chapter a simulation model that combines economic components with the biological model designed and estimated in chapters 2 and 3 is described[1]. Simulation experiments designed to evaluate alternative pest management strategies are also described, and the methodology used in calculating the value of information is explained.

The purpose of the simulation is to characterize distributions of net revenue under different management strategies and economic conditions. To incorporate stochastic behavior into the model, the performance of each strategy is simulated under many random states of nature. The strategies under consideration include a choice of tillage, choice of information on which to base CRW and ECB control decisions and a choice of a rule for determining when pesticides should be applied. By evaluating a wide range of strategies, the model can be used to identify preferred pest management strategies for CRW and ECB. Inputs to the model include: the estimated parameters from chapter 3, initial pest population conditions, information defining random states of nature, production costs and output prices, and levels of absolute risk aversion.

In the sections that follow, the model structure is first described, strategies to be evaluated are defined, and inputs to the model are identified. Next, the methodology for measuring the value of information is identified. Finally, estimates of the cost of

---

1 A listing of the computer program is given in Appendix 3.

providing scouting information are presented.

5.1 The Bioeconomic Model

The biological model estimated in chapter 3 is combined with economic components to develop a bioeconomic simulation model. Repeated runs of a deterministic model are used for generating distributions of net revenue. Net revenue per acre is the response of the system as a function of model inputs. The model is represented by equation 5.1

$$\pi = P_y Y - TC_o - P_m M \qquad \ldots(5.1)$$

where,

π = net revenue from corn in \$/acre,

Y = corn yield in bushels/acre,

P_y = price of corn in \$/bushel,

TC_o = total cost of production, excluding the cost of pest control, and

P_m = cost of pest control measure M in \$/acre.

For a given management strategy, corn price and initial pest conditions, the level of net revenue is simulated repeatedly each time adding a new set of random disturbances. In this study there is no uncertainty associated with corn price. Pest control costs, on the other hand, depend on control decisions of a corn producer and can therefore vary. Simulation is conducted for a single enterprise (corn per acre) and a single crop year.

The model begins with a decision facing the corn producer in spring. As indicated by Figure 2.1, the decision regarding CRW control is made at planting. The available information at this time (assuming a farmer has chosen to acquire them) are the CRW spring egg counts, previous season's beetle counts and the ECB second generation larvae counts from the previous season. No current shothole estimates are available at this point. These are taken 6-7 weeks after planting (Figure 2.1). At planting, however, the long run average of ECB shothole counts is assumed to be available under strategies that base

ECB control decisions on shothole counts. Using this information, the expected level of CRW damage is predicted, and, using the available ECB information, ECB damage is predicted. These estimated CRW and ECB damages are in turn used to predict the yield components, the number of plants per acre, the number of ears per plant and plant height. The expected yield per acre is next estimated using the predicted levels of yield components. Finally, revenue per acre is calculated using the yield estimates.

Simulation is carried out for two different CRW and ECB damage predictions: the first assuming that no pesticide is used, and the second where pesticide is used. The simulated levels of revenue obtained from the two ECB damage predictions are compared. The ECB decision rule is then used to identify the preferred ECB control action. Using this as the chosen strategy for ECB, revenues obtained with and without CRW control are compared. The CRW decision rule is then used to determine the preferred CRW control action. This CRW control action is the one that a producer adopts at planting.

With the CRW control decision made, the producer is next faced with decisions regarding the control strategies for ECB. This decision is made after the shothole counts are taken (Figure 2.1). Hence, for strategies that use shothole information, the long run average shothole count is replaced by its observed level. Here, simulation is carried out for two ECB control strategies; using pesticide and without using pesticide. Using these strategies, the available pest information and the CRW control action, damage levels of CRW and ECB are estimated. The damage levels are substituted into the yield component equations. The estimated yield components are next used to estimate the yield. Again revenues obtained with and without ECB control are compared, and the ECB decision rule is used to identify the preferred ECB control action.

The producer has now made all the necessary control decisions based on the available information and the selected damage predictor. Simulation is finally conducted to obtain the level of net revenues given these choices of CRW and ECB control. Randomly generated disturbance terms are added to each equation as the model is solved. Once crop yield is determined, net revenue is calculated. This procedure is repeated for each of a large number of "states of nature", with each state of nature being defined by a set of random disturbances to the model equations. The resulting set of net revenue define a net revenue distribution for the strategy being evaluated.

5.1.1 Strategies

The strategies considered in the model are defined by a choice of tillage, choice of information on which to base CRW and ECB control decisions and a choice of a rule for determining when pesticides should be applied.

Tillage

The tillage systems considered are chisel plow, ridge till and no-til. The choice of a tillage is a long term decision made by a farmer and not subject to changes on a year to year basis. Therefore, the choice of tillage is exogenously determined in the model.

Pest Information

As mentioned in chapter 3, three levels of information are used in predicting CRW and ECB damages. These are,

CRW^1 = f(CRWadult, X) using low level of information,

CRW^2 = f(CRWegg, X) using high level of information,

CRW^3 = f(CRWegg, CRWadult, X) using combined information,

ECB^1 = f(SHOTHOLE, X) using low level of information,

ECB^2 = f($LARVA2_{-1}$, X) using high level of information, and

ECB^3 = f(SHOTHOLE, $LARVA2_{-1}$, X) using combined information,

where,

X = other exogenous factors and control.

The various strategies available to a farmer in managing CRW and ECB infestation levels are the following.

1. Always adopt CRW and ECB control measures.
2. Never control for either pests.
3. Routinely control for one pest and base the control decision of the other on one of the damage predictors. (6 choices)
4. Never control for one pest and base the control decision of the other on one of the damage predictors. (6 choices)
5. Base control decisions on combined CRW and ECB information, i.e. using CRW^3 and ECB^3.
6. Base control decisions on combined CRW information and "high level" ECB information, i.e. using CRW^3 and ECB^2.
7. Base control decisions on combined CRW information and "low level" ECB information, i.e. using CRW^3 and ECB^1.
8. Base control decisions on "high level" CRW and combined ECB information, i.e. using CRW^2 and ECB^3.
9. Base control decisions on "high level" CRW and ECB information, i.e. using CRW^2 and ECB^2.
10. Base control decisions on "high level" CRW and "low level" ECB information, i.e. using CRW^2 and ECB^1.
11. Base control decisions on "low level" CRW and combined ECB information, i.e. using CRW^1 and ECB^3.
12. Base control decisions on "low level" CRW and "high level" ECB information, i.e. using CRW^1 and ECB^2.
13. Base control decisions on "low level" CRW and ECB information, i.e. using CRW^1 and ECB^1.

Hence there are 23 possible (6 choices of 3 and 4) strategies for controlling CRW and ECB. The majority of farmers growing continuous corn in Minnesota routinely adopt chemical control for CRW. For ECB, however, routine control is never adopted. Nevertheless, for heuristic purpose all the above strategies are considered in the analysis.

Decision Rule

Three types of decision rules are used for determining the management strategies for CRW and ECB. The first is a fixed rule which involves routine control or routine no-control for both the pests. The second is a flexible rule, which bases pest control decisions on the observed levels of pest population. The third is a mixed rule which routinely controls or never controls one of the two pests and bases the control decisions of the other on the observed levels of pest population.

The fixed rule is simple. For each pest both the scenarios routine control and routine no-control are considered. In Minnesota, the general rule followed by farmers is routine control for CRW and routine no-control for ECB.

The flexible rule depends on the scouted pest information. As explained in 5.1, for a given pest information revenues with and without pest control are estimated. These revenues are evaluated at a specified level of benefit-cost ratio of pest control. For each pest, a level of benefit-cost ratio at which the model is evaluated is specified before running the simulation. Given a specified benefit-cost ratio, x, control is adopted for a particular pest based on the following rule.

$$\frac{E\text{ [Revenue with control] - E [Revenue without control]}}{\text{Cost of control}} \geq x.$$

The use of benefit-cost ratio reduces the number of simulations required to identify threshold levels of pest population. In addition, benefit-cost ratios are generally invariant to changes in relative corn and pesticide prices.

The mixed rule routinely (or never) controls for one pest and adopts the rule based on benefit-cost ratio for control of the second pest.

5.1.2 Model Inputs for the Simulation Experiment

The following section describes the various inputs used in the simulation experiment. Management choices for a particular strategy, such as tillage and benefit-cost ratios are entered interactively into the program. However, the following inputs used in the model are read in as computer files.

Model Parameters

The estimated model parameters (Chapter 3) are entered into a computer file which is read into the simulation model. For a given pest information, using these parameters, pest damage level is predicted. This is next substituted recursively (using the corresponding model parameters) into the yield component equations and subsequently the yield equation.

Initial levels of Pest Population

The pest counts in the experimental data used to estimate model parameters represent a small segment of a typical population distribution for a given pest. In a real setting, CRW beetles are known to range from a low count of no beetles to a high count of 10-15 beetles per plant. Similarly ECB shotholes are known to range from 0 to 95 shotholes per 100 plants. In the experimental data, CRW beetles ranged from 1-9 per plants (total of three counts) and ECB shotholes ranged from 0-45 per 100 plants. To account for the different possible levels of pest population, ten initial conditions were chosen for each pest information required by the model, namely CRW egg and beetle counts and the ECB second generation larvae and shothole counts. A probability distribution was initially generated for each of the above counts. The distribution was next divided into ten equally likely intervals with 0.1 probability of an observation falling within the range of the interval. To obtain the ten initial conditions, one observation was randomly chosen from each interval. Observations for CRW and ECB were arranged randomly in the computer file. This was done as no significant relationship was found between the different population levels of CRW and ECB. However, for counts within the same pest, i.e. for CRW egg and beetle counts, the observations were matched in magnitude. For instance, if the first observation for CRW eggs in the file was from the fifth interval, the beetle counts from the fifth interval was also chosen for the first observation of this count. Likewise the ECB larvae and shothole counts were matched in magnitude. The list of the initial conditions used in the simulation model is given in Table 5.1.

TABLE 5.1 INITIAL LEVELS OF PEST COUNTS

CRW eggs/ pint soil	CRW beetles per plant	ECB larvae/ 100 plants	ECB shothole/ 100 plants
0.0	0.3	0.0	2.0
1.0	0.9	12.0	3.0
3.0	2.1	28.0	5.0
4.0	4.5	47.0	8.0
13.0	5.1	89.0	13.0
18.0	7.2	127.0	25.0
19.0	9.0	167.0	35.0
22.0	11.4	177.0	47.0
28.0	14.5	229.0	59.0
69.0	15.6	269.0	90.0

The data used to generate three of the four distributions of pest counts were obtained from the Minnesota Pest Survey (Department of Agriculture) through Bruce Potter at the Department of Plant Pathology, University of Minnesota. The CRW beetle count distribution was generated from the counts on all Minnesota corn on corn fields during the years 1985 through 1989. The ECB initial counts were obtained from distributions generated using the data from counties in S.E. Minnesota during the years 1987 and 1988. Unfortunately, no such survey data were present for the CRW egg counts. Therefore, this population distribution was generated using the 1987-88 University of Minnesota manure experimental plot data on Donald Nord's farm in Goodhue, Minnesota.

Sample States of Nature

Stochastic behavior is introduced into the model through many sample states of nature and a set of random variables characterizing random weather pattern. It is desirable to define these sample states of nature such that they are representative of the pattern of randomness prevalent in the actual system. Hence, the sample states of nature are defined considering the correlation between the residuals of each equation in the model and their standard deviations (Tables 3.5 and 3.6). For those equations estimated using GLS, the uncorrected heteroskedastic error term is considered in drawing the sample states of nature.

The simulation experiment is carried out for 25 random sample states of nature which are read into the program from a file. Each state is defined by a set of disturbance terms one for each equation in the model. The program written by Robert P. King (King, 1979), based on the procedure described by Naylor *et al.* (1966, p. 97), is used to generate these random terms. This program takes into consideration the correlation of the disturbance terms of different equations in the model. These correlations are specified (Table 3.5) and read into the program. The disturbance terms are drawn at random from their multivariate normal distribution with mean zero and a correlation matrix equal to the one specified (Table 3.5). As strategy performance is simulated, these are then multiplied by the conditional standard deviation of the respective disturbance terms (Table 3.6) in the estimated model.

Stochastic behavior is also introduced into the simulation model through disturbances representing random annual weather pattern. Each of the three years occurring in the model, 1985-87, is considered to be an equally likely random event with .33 probability of occurring. Three random variables are generated from their underlying uniform distribution. To obtain the probability of an individual year, a random variable is divided by the sum of the three random variables.

In those equations containing the year variables, the estimated parameters on the year dummy variables are multiplied by these corresponding probabilities.

Corn Price and Variable Input Cost

Corn price and input cost information are entered into the simulation program through a file. Corn price was set at three levels, $1.80, 1.98 and 2.25 per bushel. The production costs for each of the three tillage systems (chisel, ridge and minimum till) were estimated for a representative farmer (Table 5.2). Equipment and operating costs for each tillage were estimated based on 1987 prices, using the estimates developed by Fuller and Dornbush (1987). Equipment assumptions for these cost estimates were based on the information provided by the farmer, Donald Nord. The estimated costs per acre include labor cost.

TABLE 5.2 ESTIMATED COSTS FOR DIFFERENT TILLAGE SYSTEMS ($/Acre)

Tillage	Equipment	Cost/acre	Total Cost/acre
Chisel	Disk Chisel 120 HP	5.74	
	Field disk 20ft 100 HP	3.45	
	Corn planter 4-36 40 HP	8.54	17.73
Ridge	Ridge cultivator 4-36 75 HP	4.95	
	Corn planter 4-36 40 HP	8.54	13.49
No-till	Min-til planter 60 HP	11.91	11.91

All plots were treated with anhydrous ammonia and herbicides. The same corn variety, Pioneer 3906, was grown on all plots, therefore, this cost was not considered in the analysis. The treatments used for CRW and ECB control are given in Table 5.3. Costs for these chemicals were based on 1987 prices from the Goodhue elevator. In the table, total costs per acre give the purchase and application cost of the inputs. An estimated application cost of $3.50 per acre was added to the purchase cost of ECB treatment. Since Counter is applied at planting (for CRW treatment) no additional cost of application was added. In 1985 there were two CRW treatments, a low rate of Counter at .33 lb active ingredient per acre and a high of 1 lb active ingredient per acre. Since no difference was observed between low rate of Counter and no treatment the two are grouped together for the following analysis.

TABLE 5.3 ESTIMATED COSTS OF TREATMENTS ($/Acre)

Year	Treatment	Cost/acre	Total Cost/acre
	CRW treatment		
1985	Counter 15G .33 lb.a.i./acre	3.17	3.17
	Counter 15G 1 lb.a.i./acre	9.60	9.60
1986	Counter 15G 1 lb.a.i./acre	9.60	9.60
1987	Counter 15G 1 lb.a.i./acre	9.60	9.60
	ECB treatment		
1985	Dipel 10G 1 lb. a.i./acre	13.00	
	Pounce 3.2E .15 a.i./acre	10.56	23.56
1986	Dipel 10G 1 lb. a.i./acre	13.00	
	Pounce 3.2E .15 a.i./acre	10.56	23.56
1987	Dipel 10G 1 lb. a.i./acre	13.00	
	Asana .05 lb. a.i./acre	7.70	20.70

Producer Risk Preferences

Risk has been defined by Robison and Barry (1987, p. 13) as "those uncertain events whose outcomes alter the decision maker's well being". A major tool used in analyzing problems under risk is the expected utility method. This has been defined by Anderson, Dillon and Hardaker (1977, p. 66) as "a device for assigning numerical utility values to consequences in such a way as that a decision maker should act to maximize subjective expected utility if he is consistent with his expressed preferences." For the preferences to be stated in the expected utility framework, certain assumptions have to be made regarding an individual's preferences among risky prospects. If preferences can be ordered, are transitive, continuous, and independent, then the utility function, U, associates a single real number (utility value) with any risky prospect. This utility function has the following properties.

1. If a risky prospect a is preferred over another risky prospect b, then the utility of a, $U(a) > U(b)$.
2. The utility of a risky prospect is given by its expected utility.
3. The properties of a utility function regarding choice are not changed by any positive linear transformations, i.e. expected utility rankings are unique only upto a positive linear transformations.

Individual decision makers' risk preferences can be compared by measures that categorize them as risk preferring, risk neutral and risk averse (Keeny and Raiffa, 1976). An agent is said to be *risk preferring* if he/she prefers the risky prospect to the expected consequence of the risky prospect. Conversely, an agent is said to be *risk averse* if he/she prefers the expected consequence of the risky prospect to the risky prospect.

Theorem 1

An agent is risk averse if and only if the agent's utility

function is concave. (Keeny and Raiffa, 1976, p. 149).
This indicates a decreasing marginal utility of income for a risk averse agent. Therefore, the value of information is greatest for a risk averse agent if information improves the worst outcome.

Theorem 2

An agent is risk preferring if and only if the agent's utility function is convex. (Keeny and Raiffa, 1976, p. 151).
This indicates an increasing marginal utility of income for a risk preferring agent. Therefore, the value of information is greatest for a risk preferring agent if information improves the most favorable outcome.

By properties one and two, comparisons between utilities of outcomes based on different information levels should give the relative value of one information compared to the other. However, by property three, utility is unique only up to a positive linear transformation, and comparisons of the relative value of information from different sources and to different decision makers cannot be made. Hence a money measure of welfare, *certainty equivalent*, is used to compare the value of information. The *certainty equivalent* of a risky prospect has been defined as an amount π_{ce} such that the individual is indifferent between the risky prospect and the amount π_{ce} for certain (Keeney and Raiffa, 1976, p. 143).

A numerical measure of the risk attitudes of decision makers is given by the absolute risk aversion function introduced by Pratt (1964) and Arrow (undated). For a utility function $U(\pi)$, the absolute risk aversion function, $r(\pi)$, is given by the following equation.

$$r(\pi) = - \frac{U''(\pi)}{U'(\pi)} \qquad \ldots(5.2)$$

where $U'(\pi)$ and $U''(\pi)$ are the first and second derivatives of the utility function $U(\pi)$. Thus for an agent with a concave utility function (risk averse agent) $r(\pi)$ is positive, and for an agent with a convex utility function (risk preferring agent) $r(\pi)$ is negative.

Raskin and Cochran (1986) show that the absolute risk aversion coefficient can be interpreted as the percentage change in marginal utility per unit of outcome space. A change in the temporal or spatial dimension of outcome can therefore change an individual's risk attitude. Differences in certainty equivalents generally change when fixed costs are excluded from the analysis. However, when a constant absolute risk aversion utility function (equation 5.3) is used in the estimation, differences in certainty equivalents are invariant to parallel shifts in the outcome distributions. Hence this study has chosen a constant absolute risk aversion utility function of the form given by equation 5.3.

$$U(\pi) = -e^{-\lambda \pi} \qquad \ldots(5.3)$$

where,

π = profit function as given by equation 5.1,

$\lambda = \frac{-U''(\pi)}{U'(\pi)}$ is the absolute risk aversion function.

Another advantage of this form of utility representation is in its calculation of the certainty equivalent which is given by equation 5.4 (Robison & Barry 1987 pp. 38).

$$\pi_{ce} = \frac{-\ln E\,[-U(\pi)\,]}{\lambda} \qquad \ldots(5.4)$$

The five levels of risk attitudes chosen in this study are the following; -.01 (risk preferring), 0 (risk neutral) and three levels of risk aversion, .01, .05 and .1. This range of risk aversion coefficient was established to ensure a wide range of risk attitudes. No direct measurements of risk preferences were made. Previous studies (Knowles, 1980; Wilson and Eidman, 1983) indicated that the majority of farmers in Minnesota fall into the risk neutral and risk averse category. Wilson and Eidman note that 78% of the swine producers in Minnesota fall within the risk aversion coefficient range of (-0.0002, 0.0003), 11% within (-0.0002, $-\infty$) and 13% within (0.0003, ∞). As these studies were conducted on a whole farm basis the coefficients are not directly applicable to this study. Raskin and

Cochran (1986) have pointed out the absolute risk aversion coefficient varies with the scale of outcome space. When the scale is small (enterprise) it is reasonable to have a wider range of risk attitudes than when the scale is large (whole farm).

5.1.3 Simulation Experiments

As mentioned in section 5.1.1, the bioeconomic model is simulated for 25 random states of nature and 10 initial levels of pest population. Each of the initial pest levels used in the simulation experiment is treated as an equally likely random event. The experiment therefore results in a net revenue distribution consisting of 250 equally likely outcomes. Hence a distribution of net revenues consisting of 250 outcomes is obtained for each strategy. From this distribution, average net revenue and the probability of a control being adopted are calculated.

The strategies used in the experiment are three tillages, 23 pest control strategies and five flexible decision rules (0.8 to 1.2). For a given tillage, the experiment is conducted separately for each decision rule; flexible, fixed and mixed. For the flexible rule, for each pest information strategy, a distribution of net revenue is obtained for each of the benefit-cost ratios. Therefore, for one pest information strategy there are five distributions of net revenue. The expected is calculated for each distribution and the benefit-cost ratio associated with the highest expected utility is identified.

For the fixed rule, for each of the possible cases, routine control of both the pests, routine no-control of both the pests and routine control of one pest and routine no-control of the second pest, distributions of net revenues are generated.

The results of the earlier simulations indicated that the optimal control of ECB was routine no-control. Hence the only mixed rule considered in the experiment is routine no-control of ECB and an information based control strategy for CRW.

5.2 Calculating the Value of Information

In agriculture, there is always some uncertainty regarding the level of future production. This production risk has to be incorporated into the bioeconomic model. In this study, two sources of risk exist. First, there is uncertainty in the expected levels of yield. Second, when pest control decisions are based on information, there is uncertainty regarding the expected levels of pest control costs. Corn price at harvest is not known early in the season when pest control decisions are made. However, the risk associated with corn price is not considered in this study.

The uncertainty regarding the level of expected yield can be partly attributed to the uncertainty regarding potential pest infestations. The use of information in deciding a suitable pest control strategy can be considered as another input in the production technology. The problem facing the producer is then to maximize his/her expected utility by choosing the best combination of pest information and damage predictor in basing control decisions.

The changes in producer welfare associated with different pest management strategies are evaluated using the compensation principle (Just, Hueth and Schmitz, 1982, p. 34). According to this principle, a particular strategy A is preferred to strategy B if, in moving from strategy B to A, the gainers can compensate the losers such that everyone can be made better off. In the context of a single producer, this definition reduces to, strategy A is preferred to strategy B if, in moving from strategy B to strategy A, the firm is as well off or better off than with strategy B. The measure used in determining just how well off (or worse off) a producer is, are the compensating and equivalent variations. The *compensating variation* (Just, Hueth and Schmitz, 1982, p. 52) associated with a change in production input is the sum of money that when taken away from the producer, leaves the producer as well off as if the input did not change, given the producer is free to adjust the level of output to profit maximizing quantities. On the other hand, *equivalent variation* is the sum of money which, when given to a producer, leaves the producer as well off without the input change as if the change occurred (assuming freedom of output adjustment). Under uncertainty these welfare changes are measured by changes in producer surplus. Given the form of the utility function specified by equation 5.3, both these measures are equal and are given by the change in the level of the certainty equivalents (Just, Hueth and Schmitz, 1982, p. 348-356). For a producer considering two strategies A and B, strategy A will be chosen over strategy B if and only if

$$\pi^{a}_{ce} \geq \pi^{b}_{ce}.$$

In this study, the value of information is estimated under the expected utility framework. As mentioned by Byerlee and Anderson (1982) the value of information can be categorized into two groups; the value of individual predictions and the value of a predictor. Suppose, a farmer purchases scouting services and obtains information about the random pest incidence θ, which has a probability density $h(\theta)$. With the help of this information and a predictor, a damage prediction P_k is made. Based on this information, the optimal strategy x^*_k is chosen. Then assuming that the farmer maximizes expected utility of profits, the value of this prediction, V_k is given by the difference between the certainty equivalents obtained and that which would be obtained, if the optimal action was based without the knowledge of P_k. In terms of compensation principle, this can be defined as the "sum of money that the producer could pay for the information and remain as well off as would be without this information".

The value of a prediction varies depending on the information. It tends to be higher for extreme and unexpected predictions. Since the value of a prediction depends on the individual initial conditions used in simulating, an invariant measure which evaluates the value of the type of pest information used as a whole is not possible. This can, however, be obtained by calculating the value of a predictor. To estimate the value of a predictor, predictions from each of the initial pest population levels are considered. As the initial pest counts used in the simulation model are drawn with equal probability, the value of a predictor in this study is given by the difference between the certainty equivalents between the two optimal actions. In other words, instead of considering the certainty equivalent for each of the initial conditions separately, for a given strategy, certainty equivalent is calculated for all ten initial conditions.

Scouting for pest information is economically justified if the value of information is greater than the cost of acquiring information. In the following section, an outline of the costs involved in scouting for pest information is presented.

5.3 Cost of Acquiring Information

Scouting cost estimates were obtained from a survey sent out to 13 crop consultants in Minnesota. Ten of the consultants responded. The non-respondents were not pursued further as it was not known whether those firms continued to operate. The survey questionnaire and a summary of the results are presented in Appendix 4. Scouting cost estimates are given in Table 5.4. For cost estimates on factors that are generally not scouted, such as ECB second generation larvae and CRW egg counts, entomologist Ken Ostlie of the University of Minnesota was consulted.

Sequential sampling is the most common approach followed in monitoring CRW beetle. Scouting is started one week after the adult beetles emerge (about 1 August) (Ostlie and Noetzel, 1987). If the population is low, scouting is stopped and started again one week later. If the beetle population is high, pesticide application or crop rotation may be suggested the following season. In case of continued low population, scouting is continued at one week intervals uptil mid September. Given this method of sampling, scouting costs for CRW depend on the number of visits per season. In addition, all the consultants that answered the mailed questionaire noted that their services are generally offered as a "package" for crop protection whereby insect pests, diseases and weeds are all scouted for simultaneously. Therefore, an arbitrary CRW scouting cost per acre is used in the following analysis, based on the facts obtained from the survey questionaires. The average size of a field being scouted is about 60 acres, and the average pay of hired scouts $6.00 per hour. In general, 5-10 locations in the shape of an inverted U are selected at random and 5-10 plants inspected per location for CRW beetles. The average time required for scouting (with one scout) is about 30 minutes. Assuming that CRW is scouted for 3 times, the cost per acre is 15 cents. Adding 15 cents per acre for other costs (time and material involved in travel and scouting), a total cost of $0.30 per acre is used as the scouting cost for CRW beetles. This is less than the $0.44 per acre estimated by Foster, Tollefson and Steffey (1986). The difference is mainly due to the higher overhead cost per acre used by them.

CRW eggs, in general, are not scouted by commercial crop consultants. The cost estimated here is based on information obtained from entomologist Ken Ostlie. Egg density in a given field can vary greatly with locations. Taking this fact into consideration, the recommended sample is 15 locations per field with five core samples at each location. The contents of five cores in a location are mixed, sifted and one sample drawn out from it. This is assumed to take an average of 15 minutes. Processing time for each of the 15 samples is about 8 minutes, and examining the soil another fifteen minutes. The total is 38 minutes per sample per person. Assuming an average sized field of 60 acres and $6.00 per hour pay for the hired scout, scouting costs for CRW egg is $0.95 per acre. This has not considered equipment, supplies and travel cost. The equipement required for egg processing and counting are expensive, but they can be considered as fixed costs since the same equipement is used year after year. Given the form of the utility fuction used in the estimation (see 5.1.2), producer risk preferences are not sensitive to scalings of outcome space. Hence the results from this study are not affected by excluding fixed costs from the analysis. Considering only the variable costs involved, travel and related cost is added based on the 15 cents that was arbitrarily added to CRW beetle cost. CRW beetle cost is estimated assuming three trips are made for scouting. Therefore, for one trip the travel related cost is $0.05. The total scouting cost for CRW egg is $1.00.

The ECB shothole scouting cost estimates is based on information obtained from crop consultants. Again, scouting is not conducted specifically for ECB, but ECB is monitored together with other pests as a package offered to the farmer by crop consultants. On an average 20 plants are inspected per location, and 5-10 locations are taken per field. This requires approximately 30 minutes per field. Assuming a field of 60 acres and $6.00 per hour as the pay for the hired scout, scouting for ECB shotholes costs 5 cents per acre. Adding travel related cost of 5 cents, total cost for ECB scouting is $0.10 per acre.

As with the CRW eggs, ECB second generation larvae are generally not scouted. The scouting costs are estimated based on information obtained from entomologist Ken Ostlie. It is assumed that five locations, each with 10 plants are chosen per field. Time required for uprooting and dissecting plants at each location is approximately 30 minutes. For a 60 acre field, at $6.00 per hour pay for scouts, this sums to $0.25 per acre. With $0.05 added travel related cost, ECB second generation larvae scouting cost is $0.30 per acre.

The costs as given by Table 5.4, do not reflect the costs that may actually be charged by consultants to the farmer. Travel costs depend on the distance of individual farms from the consultant's office. These may be higher than what is actually used in the above

TABLE 5.4 ESTIMATED SCOUTING COSTS IN $/ACRE

Sampling Unit	Number of visits	Total Cost/acre
CRW eggs	1	$1.00
CRW beetles	3	0.30
ECB shotholes	1	0.10
ECB second generation larvae	1	0.30

estimates. But it is very rare (if at all) that a crop consultant travels to a farm to solely scout for CRW beetles or for any other one particular insect. The package offered for field scouting cost on an average $3.50 per acre (see Appendix 4), but this does not include CRW egg sampling or ECB second generation larvae sampling.

5.4 Summary

In this chapter an overview of the bioeconomic simulation model is presented. The strategies considered in the simulation experiment and the decision rule used in chosing a control action are described. The strategies considered are defined by a choice of tillage, choice of information on which to base CRW and ECB control decisions and a choice of a rule for determining when pesticides should be applied.

The inputs used in the simulation model are also described in this chapter. The model inputs include the estimated parameters from chapter 3, initial levels of pest population, random sample states of nature, corn price and input costs and five different levels of producer risk aversion coefficients. These inputs are read into the simulation program through computer files.

The operational procedure of the simulation model consists of three steps. First, based on all available pest information the CRW control strategy is selected. Next, given the CRW control strategy, the control strategy for ECB is selected. Finally, given the CRW and ECB control strategies, yield is simulated and net revenue is calculated.

The methodology used in calculating the value of information is presented. An expected utility framework is adopted in the analysis. The producer welfare changes associated with different strategies are measured by the changes in the level of certainty equivalents. The value of information for a particular pest damage predictor compared to another damage predictor is calculated by the difference between the levels of certainty equivalents associated with each predictors. Scouting for pest information is economically justified if the estimated value of information is greater than the cost of acquiring information. Hence a description of the costs involved in scouting are also described.

CHAPTER 6

VALUE OF INFORMATION AND THE ECONOMIC THRESHOLD

From net revenue distributions generated by the bio-economic model, the value of information and the economic thresholds can be estimated for an individual corn producer. Management strategies are defined by choice of tillage, choice of pest damage predictor and the choice of a pest control decision rule. Three tillage systems are considered in the model: chisel plow, ridge till and no-till. For each pest (CRW and ECB), three different damage predictors are considered based on low, high and combined pest information. Three types of decision rules are used for CRW and ECB control: a flexible rule which bases pest control decisions on information, a fixed rule which routinely controls or never controls CRW and ECB, and a mixed rule which adopts flexible rule for one pest and fixed rule for the second pest. With a flexible decision rule, pest control is adopted if and only if the resulting benefit cost ratio (BC) from pest control is greater than the specified benefit-cost ratio.

For a given management strategy, a distribution of net revenue is generated through repeated simulation. From, this certainty equivalents (CE) are calculated for each of the five levels of absolute risk aversion coefficients. The value of moving from one information level to another level is given by the difference between the certainty equivalents associated with each level.

In this chapter value of information results are presented first for CRW and then for ECB. Sensitivity analysis is then conducted to check the sensitivity of the estimated value of information to errors in relating the pest damage to yield loss. Finally, economic threshold levels of CRW beetle and egg counts are estimated.

6.1 The Estimated Value of Pest Information

In this section, preferred decision rules are identified for each tillage system and information level. The highest attainable level of certainty equivalent is presented along with the probability of adopting a pest control. First, the results obtained from CRW flexible decision rules are discussed. This is followed by a discussion of the results obtained from CRW fixed and mixed decision rules. Next the results obtained from different decision rules for ECB are presented.

6.1.1 Value of CRW Information

Flexible Decision Rule

For the flexible decision rule, preferred levels of certainty equivalents are calculated for the three tillages, chisel plow, ridge till and no-till at three levels of corn price; $1.80, 1.98 and 2.25 per bushel. For each information level, the preferred benefit-cost ratio (BC) is reported along with its certainty equivalent (CE) and the probability of CRW control being adopted (%CRW control).

Simulation results for chisel plow are presented in Table 6.1. At corn price of $1.80 per bushel, there is no change in the level of certainty equivalent when moving from one CRW damage predictor to the next. It should be borne in mind, however, that these certainty equivalents do not account for the cost of acquiring information. When this is taken into consideration, at corn price of $1.80, the low level of information, i.e. beetle counts, performs the best. The cost of acquiring this information is $0.30 per acre in comparison with $1.00 for the high level and $1.30 for the combined information.

At a higher corn price of $1.98 the value of moving from a low or high information based strategy to a combined information based strategy ranges from zero for risk preferring and risk neutral to $0.24 per acre for the most risk averse agent. The value increases with the degree of risk aversion. This behavior is consistent with

TABLE 6.1 CERTAINTY EQUIVALENTS FOR CHISEL PLOW IN $/ACRE

Info. State		Certainty Equivalent for r.a. coefficient				
		-.01	.00	.01	.05	.10
Corn Price = $ 1.80 per bushel.						
Combined	CE	343.57	339.86	336.00	320.01	304.26
	BC	1.00	1.00	1.00	1.00	1.00
%CRW control		10.00	10.00	10.00	10.00	10.00
High	CE	343.57	339.86	336.00	320.01	304.26
	BC	0.90	0.90	0.90	0.90	0.90
%CRW control		10.00	10.00	10.00	10.00	10.00
Low	CE	343.57	339.86	336.00	320.01	304.26
	BC	0.80	0.80	0.80	0.80	0.80
%CRW control		10.00	10.00	10.00	10.00	10.00
Corn Price = $ 1.98 per bushel.						
Combined	CE	380.23	375.74	371.04	351.85	334.16
	BC	0.90	0.90	1.00	1.00	1.00
%CRW control		20.00	20.00	10.00	10.00	10.00
High	CE	380.23	375.74	371.03	351.72	333.92
	BC	0.80	0.80	0.80	0.80	0.80
%CRW control		10.00	10.00	10.00	10.00	10.00
Low	CE	380.23	375.74	371.03	351.72	333.92
	BC	0.70	0.70	0.70	0.70	0.70
%CRW control		20.00	20.00	20.00	20.00	20.00
Corn Price = $ 2.25 per bushel.						
Combined	CE	435.41	429.65	423.58	399.06	378.76
	BC	1.00	1.00	1.00	1.20	1.20
%CRW control		20.00	20.00	20.00	30.00	30.00
High	CE	435.24	429.50	423.50	399.06	378.76
	BC	1.00	1.00	1.00	0.90	0.90
%CRW control		10.00	10.00	10.00	10.00	10.00
Low	CE	435.41	429.65	423.58	399.06	378.76
	BC	0.80	0.80	0.80	1.00	1.00
%CRW control		20.00	20.00	20.00	10.00	10.00

the usual theoretical belief that risk averse producers are willing to pay more for an input (information) which reduces risk (assuming information reduces risk) than risk preferring and risk neutral agents.

At corn price of $2.25, the value of moving from a high information based strategy to a low and combined information based strategy is $0.08 per acre for the agent with the absolute risk aversion coefficient of 0.01, and $0.15 and $0.17 for the risk neutral and risk preferring agents respectively. There is no change in certainty equivalents among the three information based strategies for the more risk averse agents. This may be due to the fact that, as the level of net revenue increases its associated variance also increases. After considering the cost of each information, the most profitable predictor is the one using the low level of pest information.

Similar results occur under ridge till (Table 6.2). At a corn price of $1.80, there is no change in the levels of certainty equivalent among all three information based strategies. At a corn price of $1.98 per bushel, for the risk preferring, risk neutral and the least risk averse agents, the value of the predictors using combined information and low levels of information compared with the predictor using high levels of information ranges from $0.06 to $0.03 respectively. The predictor using high levels of information has a value over the other two for the two extremely risk averse agents. This again may be due to increasing variance of net revenue as its mean increases. When the cost of information is considered, the predictor using low levels of information performs best.

At corn price of $2.25 per bushel, the value of the predictors using combined information and low levels of information compared with the predictor using high levels of information ranges from $0.21 to $0.17 per acre for agents with risk aversion coefficients of 0.01, 0.0 and -0.01. Only extremely risk averse agents prefer the high level

TABLE 6.2 CERTAINTY EQUIVALENT FOR RIDGE TILL IN $/ACRE

Info. State		Certainty Equivalent for r.a. coefficient				
		-.01	.00	.01	.05	.10
Corn Price = $ 1.80 per bushel.						
Combined	CE	358.78	355.64	352.38	338.56	323.85
	BC	1.00	1.00	1.00	1.00	1.00
%CRW control		10.00	10.00	10.00	10.00	10.00
High	CE	358.78	355.64	352.38	338.56	323.85
	BC	0.90	0.90	0.90	0.90	0.90
%CRW control		10.00	10.00	10.00	10.00	10.00
Low	CE	358.78	355.64	352.38	338.56	323.85
	BC	0.80	0.80	0.80	0.80	0.80
%CRW control		10.00	10.00	10.00	10.00	10.00
Corn Price = $ 1.98 per bushel.						
Combined	CE	396.49	392.70	388.73	371.97	355.18
	BC	1.00	1.00	1.00	1.00	1.00
%CRW control		20.00	20.00	20.00	20.00	20.00
High	CE	396.43	392.65	388.70	372.05	355.36
	BC	1.00	1.00	1.00	1.00	1.00
%CRW control		10.00	10.00	10.00	10.00	10.00
Low	CE	396.49	392.70	388.73	372.05	355.36
	BC	0.80	0.80	0.80	0.90	0.90
%CRW control		20.00	20.00	20.00	10.00	10.00
Corn Price = $ 2.25 per bushel.						
Combined	CE	453.22	448.36	443.23	421.79	402.31
	BC	1.00	1.00	1.00	1.00	1.00
%CRW control		20.00	20.00	20.00	20.00	20.00
High	CE	453.01	448.17	443.06	421.73	402.33
	BC	0.90	0.90	0.90	0.90	0.90
%CRW control		10.00	10.00	10.00	10.00	10.00
Low	CE	453.22	448.36	443.23	421.79	402.31
	BC	0.90	0.90	0.90	0.90	0.90
%CRW control		20.00	20.00	20.00	20.00	20.00

of information over the other two information levels. As with the earlier cases, when the cost of acquiring information is considered, low levels of information (CRW beetle counts) perform the best.

For no-till, the results are similar to those for chisel plow and ridge till (Table 6.3). At a corn price of $1.80 there is no change in the levels of certainty equivalents among any of the three predictors. However, as corn price increases, the risk preferring, risk neutral and the least risk averse agents have higher certainty equivalents for the predictors using combined and low levels of pest information compared to the high levels of information. This value is highest for the risk preferring agent and lowest for the risk averse agent with risk aversion coefficient of 0.01.

From the simulation results (Tables 6.1 to 6.3), three main characteristics of the CRW flexible decision rule are evident. First, for all levels of producer risk preferences, for a given management strategy, the decision rule used in controlling CRW generally does not change. In other words, the highest level of certainty equivalents occur for all producers when pest control is adopted at the same benefit-cost ratio. Second, the value of information depends on producer risk attitudes and outcome levels. As explained earlier (refer 5.1.2), risk averse agents are characterized by a decreasing marginal utility of income. Hence, the value of information is greatest for a risk averse agent when it improves the worst outcome. Accordingly, the highest gain in certainty equivalent, to an extremely risk averse agents, from moving to higher levels of information occurs under low levels of certainty equivalent. In contrast, risk preferring agents are characterized by an increasing marginal utility of income. Therefore, their value of information is greatest when it improves the most favorable outcome. Finally, for all three tillages, after considering the cost of acquiring information, the economically optimal CRW information is the low level using beetle counts.

TABLE 6.3 CERTAINTY EQUIVALENT FOR NO-TILL IN $/ACRE

Info. State		Certainty Equivalent for r.a. coefficient				
		-.01	.00	.01	.05	.10
Corn Price = $ 1.80 per bushel.						
Combined	CE	358.87	355.33	351.65	336.33	320.88
	BC	1.00	1.00	1.00	1.00	1.00
%CRW control		10.00	10.00	10.00	10.00	10.00
High	CE	358.87	355.33	351.65	336.33	320.88
	BC	0.90	0.90	0.90	0.90	0.90
%CRW control		10.00	10.00	10.00	10.00	10.00
Low	CE	358.87	355.33	351.65	336.33	320.88
	BC	0.80	0.80	0.80	0.80	0.80
%CRW control		10.00	10.00	10.00	10.00	10.00
Corn Price = $ 1.98 per bushel.						
Combined	CE	396.48	392.20	387.72	369.28	351.89
	BC	1.00	1.00	1.00	1.10	1.10
%CRW control		20.00	20.00	20.00	10.00	10.00
High	CE	396.41	392.15	387.70	369.28	351.89
	BC	1.00	1.00	1.00	1.00	1.00
%CRW control		10.00	10.00	10.00	10.00	10.00
Low	CE	396.48	392.20	387.72	369.28	351.89
	BC	0.80	0.80	0.80	0.90	0.90
%CRW control		20.00	20.00	20.00	10.00	10.00
Corn Price = $ 2.25 per bushel.						
Combined	CE	453.06	447.56	441.79	418.19	398.08
	BC	1.00	1.00	1.00	1.00	1.00
%CRW control		20.00	20.00	20.00	20.00	20.00
High	CE	452.85	447.38	441.63	418.16	398.13
	BC	1.00	1.00	1.00	1.00	1.08
%CRW control		10.00	10.00	10.00	10.00	10.00
Low	CE	453.06	447.56	441.79	418.19	398.08
	BC	0.90	0.90	0.90	0.90	0.90
%CRW control		20.00	20.00	20.00	20.00	20.00

Fixed Decision Rule

Certainty equivalents obtained using the flexible decision rules are compared to the case where a producer bases control decisions on fixed decision rules. Table 6.4 presents the case of routine pest control for CRW. These results indicate that an IPM system using any of the three CRW damage predictors is always superior to the case of routine control. The value of the predictors ranges from $4.21 to $5.29 per acre. These are far above the cost of acquiring even the most expensive information of $1.30 for the combined information predictor. It is interesting to note that the value is greater at lower corn prices. This is consistent with expectations, as adopting a control becomes more profitable at higher levels of corn price. The value of information decreases with increases in the degree of risk aversion. Again this can be explained by the decreasing (increasing) marginal utility of income for risk averse (preferring) agents, and the fact that the variance of net income increases as its value increases. The values are higher for chisel plow which is associated with lower levels of certainty equivalents and are the lowest for ridge till which is associated with the highest certainty equivalents.

When control is never adopted (Table 6.5) for both CRW and ECB, the increase in certainty equivalent associated with basing control decisions on any of the predictors ranges from $0.14 to $0.88 per acre. For all three tillages, the value increases as corn price increases. It is highest for ridge till, and the lowest for chisel plow. At low corn price levels the value of scouting information is not as large as the cost of acquiring it. At higher price levels, however, the value of the low level of scouting information does exceed its cost. It is possible that the value of scouting information is under-estimated. Corn rootworm is routinely controlled by farmers in S.E. Minnesota and a model built using three years of experimental plot data may fail to capture the actual potential for yield loss when control is never used.

TABLE 6.4 ROUTINE CONTROL FOR CRW

Corn Price Per Bushel	Certainty Equivalent for r.a. coefficient					%CRW control
	-.01	.00	.01	.05	.10	
Tillage = Chisel						
$ 1.80	338.36 (5.21)	334.65 (5.21)	330.77 (5.23)	314.71 (5.29)	299.08 (5.18)	100
$ 1.98	375.32 (4.94)	370.85 (4.89)	366.15 (4.89)	346.83 (5.02)	329.27 (4.89)	100
$ 2.25	430.90 (4.51)	425.14 (4.48)	419.06 (4.52)	394.45 (4.61)	374.31 (4.45)	100
Tillage = Ridge till						
$ 1.80	353.66 (5.12)	350.54 (5.10)	347.28 (5.10)	333.43 (5.13)	318.84 (5.01)	100
$ 1.98	391.67 (4.82)	387.90 (4.80)	383.95 (4.78)	367.21 (4.84)	350.66 (4.70)	100
$ 2.25	448.80 (4.42)	443.95 (4.41)	438.80 (4.43)	417.33 (4.46)	398.10 (4.21)	100
Tillage = No-till						
$ 1.80	353.74 (5.13)	350.21 (5.12)	346.52 (5.13)	331.14 (5.19)	315.82 (5.06)	100
$ 1.98	391.65 (4.83)	387.38 (4.82)	382.91 (4.81)	364.38 (4.90)	347.13 (4.76)	100
$ 2.25	448.63 (4.37)	443.14 (4.42)	437.35 (4.44)	413.69 (4.50)	393.83 (4.25)	100

The figures in parentheses give the comparative benefit in $/acre from using the flexible decision rule.

TABLE 6.5 ROUTINE NO-CONTROL FOR CRW AND ECB

Corn Price Per Bushel	Certainty Equivalent for r.a. coefficient -.01	.00	.01	.05	.10	%CRW control
Tillage = Chisel						
$ 1.80	343.30 (0.27)	339.58 (0.28)	335.72 (0.28)	319.80 (0.21)	304.12 (0.14)	0
$ 1.98	379.80 (0.46)	375.32 (0.42)	370.63 (0.41)	351.48 (0.37)	333.81 (0.35)	0
$ 2.25	434.68 (0.73)	428.91 (0.71)	422.85 (0.73)	398.44 (0.62)	378.04 (0.72)	0
Tillage = Ridge till						
$ 1.80	358.47 (0.31)	355.33 (0.31)	352.05 (0.33)	338.26 (0.30)	323.59 (0.26)	0
$ 1.98	396.00 (0.49)	392.21 (0.49)	388.24 (0.49)	371.57 (0.48)	354.86 (0.50)	0
$ 2.25	452.42 (0.80)	447.53 (0.83)	442.40 (0.83)	420.99 (0.80)	401.43 (0.88)	0
Tillage = No-till						
$ 1.80	358.56 (0.31)	355.02 (0.31)	351.34 (0.31)	336.05 (0.28)	320.66 (0.22)	0
$ 1.98	395.99 (0.49)	391.71 (0.49)	387.25 (0.47)	368.84 (0.44)	351.43 (0.46)	0
$ 2.25	452.26 (0.74)	446.75 (0.81)	440.97 (0.82)	417.46 (0.73)	397.28 (0.80)	0

The figures in parentheses give the comparative benefit in $/acre from using the flexible decision rule.

When control is adopted for both CRW and ECB the value of the predictor is high, ranging around $27 per acre (Table 6.6). Since adopting a control is more profitable at higher corn price, this value decreases with increasing corn price. It is interesting to note the changes in the magnitude of the value of information with changes in producer risk preferences. The value of scouted information is the

TABLE 6.6 ROUTINE CONTROL FOR CRW AND ECB

Corn Price Per Bushel	Certainty Equivalent for r.a. coefficient -.01	.00	.01	.05	.10	%CRW, ECB control
Tillage = Chisel						
$ 1.80	315.62 (27.95)	311.92 (27.94)	308.04 (27.96)	291.99 (28.02)	276.37 (27.89)	100
$ 1.98	352.58 (27.68)	348.10 (27.64)	343.41 (27.63)	324.10 (27.75)	306.56 (27.60)	100
$ 2.25	408.14 (27.27)	402.38 (27.24)	396.30 (27.28)	371.71 (27.35)	351.58 (27.18)	100
Tillage = Ridge till						
$ 1.80	330.93 (27.87)	327.80 (27.84)	324.54 (27.84)	310.71 (27.85)	296.13 (27.72)	100
$ 1.98	368.92 (27.59)	365.15 (27.55)	361.20 (27.53)	344.48 (27.57)	327.94 (27.42)	100
$ 2.25	426.03 (27.19)	421.18 (27.18)	416.06 (27.17)	394.59 (27.20)	375.37 (26.94)	100
Tillage = No-till						
$ 1.80	331.00 (28.87)	327.47 (31.40)	323.79 (27.86)	308.42 (27.91)	293.11 (27.77)	100
$ 1.98	368.90 (27.58)	364.63 (27.57)	360.17 (27.55)	341.65 (27.63)	324.41 (27.48)	100
$ 2.25	425.86 (27.14)	420.37 (27.19)	414.59 (27.20)	390.95 (27.24)	371.10 (26.98)	100

The figures in parentheses give the comparative benefit in $/acre from using the flexible decision rule.

lowest for the highly risk averse producer with an absolute risk aversion coefficient of 0.1. Among all risk averse agents, the value of scouted information is the highest for the moderately risk averse agent (absolute risk aversion coefficient of 0.05). This value decreases as the degree of risk aversion decreases, but it again increases for the risk preferring agent (absolute risk aversion coefficient of -0.01).

The simulated results obtained from fixed decision rules indicate that CRW scouting is economically justified compared to the case of routine control. When the cost of scouting is considered, CRW beetle counts perform better than egg counts and combined CRW information. Therefore, based on this study, there is no reason to recommend scouting for CRW egg counts. Assuming that the yield loss potential from CRW damages are under-estimated, scouting may also be economically justifiable when compared to the case of routine no-control. As the social costs of using pesticides are excluded from this study, the calculated value of information may be under-estimated. However, it has to be borne in mind that the predicting capabilities are relatively low for the estimated equations.

Mixed Rule

For all the flexible decision rules, the optimal strategy for ECB management was routine no-control. Hence the case where a flexible rule is used for CRW management and ECB is never controlled yield the same results as when both the pests are managed using the flexible rule (Tables 6.1 to 6.3). As routine control for ECB is generally not adopted by farmers in Minnesota, the case where flexible rule is adopted for CRW and ECB is routinely controlled was not explored.

6.1.2 Value of ECB Information

Flexible Rule

As it has already been pointed out, all flexible rules used for ECB management indicate that the optimal strategy for ECB is routine no-control. This may be due to the following reasons. For ECB, the cost of adopting a control is relatively high with an average of $22.61 per acre compared with $9.60 per acre for CRW. This is due, in part, to the higher pesticide cost for ECB control and the cost of its application. In contrast, as CRW control is adopted at planting, no extra application cost is incurred. In addition, as indicated by Table 3.6, the variability in ECB damage prediction increases with the adoption of pest control. Hence in all of the simulation experiments conducted, it was never profitable to adopt ECB control. Therefore, the results from flexible rule for ECB management are the same as that for the fixed rule of routine no-control.

Fixed rule

The cases where both ECB and CRW are routinely controlled and never controlled has been dealt with in 6.1.1 (Tables 6.5 and 6.6). Thus the only new case considered here is where CRW is not controlled and ECB is always controlled. This is presented in Table 6.7. Compared to this strategy, the value of information ranges around $22 to $23 per acre, which is about the cost of controlling ECB. The value increases as the relative price of corn increases. ECB is rarely (if ever) routinely controlled. Thus scouting cannot be recommended based on this value of information. Given the poor performance of ECB damage predictors in this study, it is doubtful if any conclusions can be drawn regarding the usefulness of scouting in ECB management.

Mixed Rule

This has already been dealt with under 6.1.1.

6.2 Sensitivity of the Value of Information to Errors in Relating Pest Damage to Yield Loss

The weakest component of the model is that which predicts pest damage given a certain level of pest information. This is due to the fact that the data used in model building contained very few incidences where the pest population exceeded economic threshold levels. It is also assumed that the low pest incidence has distorted the damage-yield loss relations which in turn have lead to relatively higher levels of threshold populations. Assuming that the damage predictors do indeed correctly relate the pest population counts to damage levels, it is interesting to examine what would be the value of

TABLE 6.7 ROUTINE CONTROL FOR ECB ALONE

Corn Price Per Bushel	Certainty Equivalent for r.a. coefficient					%ECB control
	-.01	.00	.01	.05	.10	
Tillage = Chisel						
$ 1.80	320.56 (23.01)	316.85 (23.01)	312.99 (23.01)	297.08 (22.92)	281.42 (22.84)	100
$ 1.98	357.05 (23.21)	352.57 (23.17)	347.89 (23.15)	328.76 (23.09)	311.09 (23.07)	100
$ 2.25	411.91 (23.50)	406.15 (23.47)	400.10 (23.48)	375.71 (23.35)	355.31 (23.45)	100
Tillage = Ridge till						
$ 1.80	335.73 (23.05)	332.59 (23.05)	329.32 (23.06)	315.54 (23.02)	300.89 (23.85)	100
$ 1.98	373.25 (23.24)	369.46 (23.24)	365.50 (23.23)	348.84 (23.21)	332.14 (23.22)	100
$ 2.25	429.65 (23.57)	424.76 (23.60)	419.63 (23.60)	398.25 (23.09)	378.70 (23.61)	100
Tillage = No-till						
$ 1.80	335.83 (23.04)	332.29 (23.04)	328.61 (23.04)	313.34 (22.99)	297.96 (22.92)	100
$ 1.98	373.24 (23.24)	368.97 (23.23)	364.51 (23.21)	346.11 (23.17)	328.72 (23.17)	100
$ 2.25	429.49 (23.51)	423.99 (23.57)	418.21 (23.58)	394.72 (23.47)	374.55 (23.50)	100

The figures in parentheses give the comparative benefit in $/acre from using the flexible decision rule.

information if the damage loss manifested in yield components were actually greater. To test the sensitivity of the model, the yield component equation coefficients on the damage variables were raised by one standard deviation (equations 6.3 to 6.5). The resulting relationships used in the simulation are given as follows.

$$\ln S = .011 - .004 \ln ECB + .99\ ES - .007\ CRW - .029\ D_{86} - .004\ D_{87} \qquad \ldots(6.3)$$

$$\ln E = -.001 - .012 \ln ECB - .05\ D_{86} + .009\ D_{87} - .006\ D_{rid} - .002\ D_{min} \qquad \ldots(6.4)$$

$$\ln H = 1.25 \ln H1 - .016\ CRW - .5\ D_{86} - .3\ D_{87} - .06\ D_{rid} - .52\ D_{min} \qquad \ldots(6.5)$$

Flexible Rule

The results from simulation using the flexible decision rule are presented in Tables 6.8-6.13. The best strategy for ECB is still to never adopt any control measures. For CRW, under all of the three tillages (Tables 6.8-6.13), combined and low levels of information perform better than high levels of information at all corn price levels. Differences in certainty equivalents range from $0.21 to $1.35 per acre, which are considerably higher than $0.01 to 0.24 observed in section 6.1. As before, after the cost of acquiring information is accounted for, the most profitable strategy is to use the low level of pest information. The value is highest for the risk preferring agent and decreases as the level of risk aversion increases. This, as explained before, is due to the decreasing (increasing) marginal utility of income for the risk averse (preferring) agent and the fact that the variance increases as the reference amount of certainty equivalent increases. Generally, the value of information increases as the corn price increases.

TABLE 6.8 CERTAINTY EQUIVALENT FOR CHISEL PLOW WITH DAMAGE PARAMETERS RAISED BY ONE S.D.

Info. State		Certainty Equivalent for r.a. coefficient				
		-.01	.00	.01	.05	.10
Corn Price = $ 1.80 per bushel.						
Combined	NR	339.00	335.33	331.51	315.79	300.25
	BC	0.90	0.90	0.90	1.10	1.10
%CRW control		30.00	30.00	30.00	20.00	20.00
High	NR	338.49	334.84	331.05	315.50	300.04
	BC	1.00	1.00	1.00	1.00	1.00
%CRW control		10.00	10.00	10.00	10.00	10.00
Low	NR	339.00	335.33	331.51	315.79	300.25
	BC	0.90	0.90	0.90	1.00	1.00
%CRW control		30.00	30.00	30.00	20.00	20.00
Corn Price = $ 1.98 per bushel.						
Combined	NR	375.35	370.92	366.31	347.43	329.89
	BC	0.90	1.00	1.00	1.00	1.10
%CRW control		40.00	30.00	30.00	30.00	20.00
High	NR	374.59	370.19	365.61	346.95	329.54
	BC	0.80	0.80	0.80	0.80	0.80
%CRW control		10.00	10.00	10.00	10.00	10.00
Low	NR	375.35	370.92	366.31	347.43	329.89
	BC	0.80	0.90	0.90	0.90	1.00
%CRW control		40.00	30.00	30.00	30.00	20.00
Corn Price = $ 2.25 per bushel.						
Combined	NR	430.11	424.43	418.45	394.33	374.22
	BC	1.00	1.00	1.00	1.00	1.10
%CRW control		40.00	40.00	40.00	40.00	30.00
High	NR	428.87	423.22	417.31	393.56	373.50
	BC	1.00	1.00	1.00	1.00	1.00
%CRW control		10.00	10.00	10.00	10.00	10.00
Low	NR	430.11	424.43	418.45	394.33	374.22
	BC	0.80	0.80	0.80	0.80	1.00
%CRW control		40.00	40.00	40.00	40.00	30.00

TABLE 6.9 CERTAINTY EQUIVALENT FOR RIDGE TILL WITH DAMAGE PARAMETERS RAISED ONE S.D.

Info. State		Certainty Equivalent for r.a. coefficient				
		-.01	.00	.01	.05	.10
Corn Price = $ 1.80 per bushel.						
Combined	NR	354.13	351.02	347.80	334.19	319.67
	BC	1.00	1.00	1.00	1.00	1.10
%CRW control		30.00	30.00	30.00	30.00	20.00
High	NR	353.55	350.46	347.25	333.80	319.38
	BC	1.00	1.00	1.00	1.00	1.00
%CRW control		10.00	10.00	10.00	10.00	10.00
Low	NR	354.13	351.02	347.80	334.19	319.67
	BC	0.90	0.90	0.90	0.90	1.00
%CRW control		30.00	30.00	30.00	30.00	20.00
Corn Price = $ 1.98 per bushel.						
Combined	NR	391.53	387.76	383.87	367.49	350.94
	BC	0.90	0.90	1.00	1.00	1.00
%CRW control		40.00	40.00	30.00	30.00	30.00
High	NR	390.67	386.95	383.07	366.85	350.45
	BC	0.80	0.80	0.80	0.80	0.80
%CRW control		10.00	10.00	10.00	10.00	10.00
Low	NR	391.53	387.76	383.87	367.49	350.94
	BC	0.80	0.80	1.00	1.00	1.00
%CRW control		40.00	40.00	30.00	30.00	30.00
Corn Price = $ 2.25 per bushel.						
Combined	NR	447.82	443.02	437.98	416.91	397.65
	BC	1.00	1.00	1.00	1.00	1.10
%CRW control		40.00	40.00	40.00	40.00	30.00
High	NR	446.47	441.68	436.68	415.91	396.74
	BC	1.00	1.00	1.00	1.00	1.00
%CRW control		10.00	10.00	10.00	10.00	10.00
Low	NR	447.82	443.02	437.98	416.91	397.65
	BC	0.90	0.90	0.90	0.90	1.00
%CRW control		40.00	40.00	40.00	40.00	30.00

TABLE 6.10 CERTAINTY EQUIVALENT FOR NO-TILL WITH DAMAGE PARAMETERS RAISED BY ONE S.D.

Info. State		Certainty Equivalent for r.a. coefficient				
		-.01	.00	.01	.05	.10
Corn Price = $ 1.80 per bushel.						
Combined	NR	354.23	350.73	347.09	331.99	316.75
	BC	1.00	1.00	1.00	1.00	1.20
%CRW control		30.00	30.00	30.00	30.00	20.00
High	NR	353.66	350.17	346.56	331.65	316.49
	BC	1.00	1.00	1.00	1.00	1.00
%CRW control		10.00	10.00	10.00	10.00	10.00
Low	NR	354.23	350.73	347.09	331.99	316.75
	BC	1.00	1.00	1.00	1.00	1.00
%CRW control		30.00	30.00	30.00	30.00	20.00
Corn Price = $ 1.98 per bushel.						
Combined	NR	391.52	387.29	382.89	364.77	347.51
	BC	0.90	0.90	1.00	1.00	1.00
%CRW control		40.00	40.00	30.00	30.00	30.00
High	NR	390.68	386.48	382.11	364.18	347.06
	BC	1.00	1.00	1.00	1.00	1.00
%CRW control		10.00	10.00	10.00	10.00	10.00
Low	NR	391.52	387.29	382.89	364.77	347.51
	BC	0.80	0.80	0.90	0.90	0.90
%CRW control		40.00	40.00	30.00	30.00	30.00
Corn Price = $ 2.25 per bushel.						
Combined	NR	447.67	442.25	436.56	413.37	393.49
	BC	1.00	1.00	1.00	1.00	1.10
%CRW control		40.00	40.00	40.00	40.00	30.00
High	NR	446.33	440.93	435.30	412.44	392.63
	BC	1.00	1.00	1.00	1.00	1.00
%CRW control		10.00	10.00	10.00	10.00	10.00
Low	NR	447.67	442.25	436.56	413.37	393.49
	BC	0.80	0.80	0.80	0.80	1.00
%CRW control		40.00	40.00	40.00	40.00	30.00

Fixed Rule

Table 6.11 gives the certainty equivalents for the case where CRW and ECB are routinely controlled. Compared with the case of using the optimal strategy based on information provided through a predictor, both routine strategies have lower certainty equivalents. The loss in

TABLE 6.11 ROUTINE CONTROL FOR CRW AND ECB WITH DAMAGE PARAMETERS RAISED BY ONE STANDARD DEVIATION.

Corn Price Per Bushel	Certainty Equivalent for r.a. coefficient -.01	.00	.01	.05	.10	%CRW, ECB control
Tillage = Chisel						
$ 1.80	312.46 (26.54)	308.83 (26.50)	305.04 (26.47)	289.36 (26.43)	273.98 (26.27)	100
$ 1.98	349.09 (26.26)	344.71 (26.21)	340.11 (26.20)	321.25 (26.18)	303.94 (25.95)	100
$ 2.25	404.17 (25.94)	398.52 (25.91)	392.57 (25.88)	368.53 (25.80)	348.63 (25.59)	100
Tillage = Ridge till						
$ 1.80	327.68 (26.45)	324.62 (26.40)	321.43 (26.37)	307.92 (26.27)	293.59 (26.08)	100
$ 1.98	365.34 (26.19)	361.65 (26.11)	357.78 (26.09)	341.45 (25.40)	325.16 (25.29)	100
$ 2.25	421.95 (25.89)	417.19 (25.83)	412.19 (25.29)	391.22 (25.69)	372.22 (25.43)	100
Tillage = No-till						
$ 1.80	327.77 (26.46)	324.30 (26.43)	320.70 (26.39)	305.68 (26.31)	290.61 (26.14)	100
$ 1.98	365.33 (26.19)	361.14 (26.15)	356.78 (26.11)	338.68 (26.09)	321.66 (25.85)	100
$ 2.25	421.79 (25.88)	416.41 (25.84)	410.75 (25.81)	387.64 (25.73)	368.01 (25.48)	100

The figures in parentheses give the comparative benefit in $/acre from using the flexible decision rule.

certainty equivalent associated with routine use of pesticide is about $26 per acre. This loss decreases with corn price and is the highest for chisel plow and the lowest for ridge till. The value of scouted information is the highest for risk prone producers and decreases with the degree of risk aversion. All these results are similar to those presented earlier in Table 6.6.

When CRW and ECB control is never adopted, the loss in certainty equivalent ranges from $1.42 to $4.06 per acre (Table 6.12). Given the cost of a CRW predictor at $0.30 to $1.30, any of the strategies using a predictor is preferable to routine no-control of CRW. The value of information increases with corn price and with the degree of producer risk aversion. The latter result differs from those presented earlier in Table 6.5. When crop losses are more sensitive to pest damage, the value of scouted information compared to routine no-control increases for risk averse producers. When crop losses are more sensitive to pest damage, risk averse producers will prefer to adopt pest control measures. The probability that a flexible decision rule will lead to the adoption of CRW control is 10 to 40 percent. Hence, compared to the decision of routine CRW control, highly risk averse producers will not prefer a flexible decision rule. However, compared to the fixed decision rule of never controlling, all producers prefer the flexible decision rule.

Table 6.13 presents the certainty equivalents for the case where routine control is adopted only for CRW. The benefits from adopting an optimal strategy based on a predictor range from $3.98 per acre for corn price at $1.80 to $2.92 per acre for corn price at $2.25. These values are lower than those estimated earlier. When crop losses are more sensitive to pest damages, the benefits of adopting a control are expected to be higher, hence these results are reasonable. Similarly as corn price (relative to control cost) increases, the benefits of adopting a control are greater. The gains in certainty equivalent are the greatest for risk preferring agents and decrease with the degree

TABLE 6.12 ROUTINE NO-CONTROL FOR CRW AND ECB WITH DAMAGE PARAMETERS RAISED BY ONE STANDARD DEVIATION

Corn Price Per Bushel	Certainty Equivalent for r.a. coefficient -.01	.00	.01	.05	.10	%CRW, ECB control
Tillage = Chisel						
$ 1.80	337.67 (1.73)	333.95 (1.38)	330.09 (1.42)	314.30 (1.49)	298.51 (1.74)	0
$ 1.98	373.61 (1.74)	369.11 (1.81)	364.44 (1.87)	345.45 (1.98)	327.54 (2.35)	0
$ 2.25	427.66 (2.45)	421.87 (2.56)	415.82 (2.63)	391.60 (2.73)	370.73 (3.49)	0
Tillage = Ridge till						
$ 1.80	352.69 (1.44)	349.50 (1.52)	346.21 (1.59)	332.43 (1.76)	317.58 (2.09)	0
$ 1.98	389.65 (1.88)	385.80 (1.96)	381.81 (2.06)	365.17 (1.68)	348.14 (2.31)	0
$ 2.25	445.20 (2.62)	440.25 (2.77)	435.09 (2.89)	413.71 (3.20)	393.59 (4.06)	0
Tillage = No-till						
$ 1.80	352.80 (1.43)	349.23 (1.50)	345.54 (1.55)	330.34 (1.65)	314.78 (1.97)	0
$ 1.98	389.66 (1.86)	385.34 (1.95)	380.87 (2.02)	362.56 (2.21)	344.85 (2.66)	0
$ 2.25	445.07 (2.60)	439.51 (2.74)	433.73 (2.83)	410.32 (3.05)	389.60 (3.89)	0

The figures in parentheses give the comparative benefit in $/acre from using the flexible decision rule.

of risk aversion. This as already explained is reasonable, since flexible decision rules only lead to CRW control measures being adopted 10 to 40 percent of the times and risk averse agents may prefer to control CRW more often.

TABLE 6.13 ROUTINE CONTROL FOR CRW ALONE WITH DAMAGE PARAMETERS RAISED BY ONE STANDARD DEVIATION

Corn Price Per Bushel	Certainty Equivalent for r.a. coefficient					%CRW control
	-.01	.00	.01	.05	.10	
Tillage = Chisel						
$ 1.80	335.02 (3.98)	331.38 (3.95)	327.60 (3.91)	311.92 (3.87)	296.55 (3.70)	100
$ 1.98	371.64 (3.71)	367.26 (3.66)	362.66 (3.65)	343.81 (3.62)	326.51 (3.38)	100
$ 2.25	426.71 (3.40)	421.06 (3.37)	415.12 (3.33)	391.08 (3.25)	371.19 (3.03)	100
Tillage = Ridge till						
$ 1.80	350.23 (3.90)	347.17 (3.85)	343.98 (3.82)	330.48 (3.71)	316.15 (3.52)	100
$ 1.98	387.89 (3.64)	384.20 (3.56)	380.33 (3.43)	364.01 (3.48)	347.72 (3.22)	100
$ 2.25	444.49 (3.42)	439.73 (3.29)	434.73 (3.25)	413.77 (3.14)	394.78 (2.87)	100
Tillage = No-till						
$ 1.80	350.32 (3.91)	346.86 (3.87)	343.25 (3.84)	328.24 (3.75)	313.18 (3.57)	100
$ 1.98	387.87 (3.65)	383.69 (3.60)	379.33 (3.56)	361.24 (3.53)	344.24 (3.27)	100
$ 2.25	444.33 (3.34)	438.95 (3.30)	433.29 (3.27)	410.19 (3.18)	390.57 (2.92)	100

The figures in parentheses give the comparative benefit in $/acre from using the flexible decision rule.

Table 6.14 presents the certainty equivalents when ECB control is routinely adopted. The benefits from using an optimal strategy based on information ranges from $23.89 to $26.62 per acre for the low and high corn prices respectively. This, again, as in the case of CRW is lower than the value obtained earlier. The value of information

TABLE 6.14 ROUTINE CONTROL FOR ECB ALONE WITH DAMAGE PARAMETERS RAISED BY ONE STANDARD DEVIATION

Corn Price Per Bushel	Certainty Equivalent for r.a. coefficient					%ECB control
	-.01	.00	.01	.05	.10	
Tillage = Chisel						
$ 1.80	315.11 (23.89)	311.39 (23.94)	307.53 (23.98)	291.74 (24.05)	275.95 (24.30)	100
$ 1.98	351.06 (24.29)	346.56 (24.36)	341.89 (24.42)	322.89 (24.54)	304.98 (24.91)	100
$ 2.25	405.11 (25.00)	399.32 (25.11)	393.27 (25.18)	369.05 (25.26)	348.18 (26.04)	100
Tillage = Ridge till						
$ 1.80	330.13 (24.00)	326.95 (24.07)	323.65 (24.15)	309.87 (24.32)	295.02 (24.65)	100
$ 1.98	367.10 (24.42)	363.25 (24.51)	359.26 (24.61)	342.61 (24.88)	325.58 (25.36)	100
$ 2.25	422.66 (25.16)	417.71 (25.31)	412.54 (25.44)	391.16 (25.38)	371.03 (26.62)	100
Tillage = No-till						
$ 1.80	330.25 (23.98)	326.67 (24.06)	322.98 (24.11)	307.77 (24.22)	292.21 (24.54)	100
$ 1.98	367.11 (24.41)	362.79 (23.69)	358.32 (23.99)	340.00 (24.18)	322.29 (24.77)	100
$ 2.25	422.53 (25.14)	416.97 (25.28)	411.18 (25.38)	387.77 (25.60)	367.05 (26.44)	100

The figures in parentheses give the comparative benefit in $/acre from using the flexible decision rule.

increases with corn price and with the degree of producer risk aversion. It is the highest for ridge till and the lowest for chisel plow. As already mentioned under 6.1.2, ECB is generally never routinely controlled by farmers in Minnesota. Hence, scouting cannot be recommended based on this result.

6.3 Estimating the Economic Threshold

As mentioned in the earlier section, simulation experiments were carried out to identify the benefit-cost ratios that yield the highest level of certainty equivalents. The results of these experiments have been given on Tables 6.1 through 6.13. In this section, the threshold pest population level which yields the certainty equivalent maximizing value of benefit-cost ratio is identified. Since it was never profitable to control for ECB, thresholds are identified only for CRW. Tables 6.1 through 6.13 indicate that for a given management strategy the optimal control action is the same for all producers. Therefore, the pest population thresholds are insensitive to producer risk preferences.

Economic threshold levels of CRW egg and beetle counts are given in Table 6.14. In the case where a decision maker chooses to use the combined CRW information (both beetles and eggs) the threshold levels of egg and beetle counts vary depending on their relative numbers. When egg (beetle) counts are very high, the threshold level of beetle (egg) counts will be low. Similarly, when egg (beetle) counts are very low, the threshold level of beetle (egg) counts will be high. Therefore for this predictor, the threshold level of an index given by the sum of beetle and egg counts weighted by their respective regression coefficients is provided.

Thresholds for beetles are given as the cumulative number of beetles per plant obtained from three field visits taken approximately 67, 84 and 104 days after planting. The general norm suggested by Ostlie and Noetzel (1987) is to consider the highest number of beetles observed in one visit. In addition they calculate the threshold number of beetles considering the Northern rootworms as 0.5 of the Westerns. The data used in building the IPM model in this study contained approximately 40% northern corn rootworms. Rough approximations can, therefore, be obtained to compare these results

TABLE 6.15 THE CRW ECONOMIC THRESHOLD LEVELS

Info. State	Corn Price in $ per bushel 1.80	1.98	2.25
Tillage = chisel			
Full	3.00*	2.70*	2.50*
High	27 eggs/pint	25 eggs/pint	22 eggs/pint
Low	12 beetles/plant (3.2)	9 beetles/plant (2.4)	9 beetles/plant (2.4)
Tillage = ridge			
Full	3.10*	2.80*	2.60*
High	32 eggs/pint	30 eggs/pint	26 eggs/pint
Low	12 beetles/plant (3.2)	10 beetles/plant (2.7)	10 beetles/plant (2.7)
Tillage = no-till			
Full	2.80*	2.70*	2.30*
High	27 eggs/pint	25 eggs/pint	22 eggs/pint
Low	12 beetles/plant (3.2)	11 beetles/plant (2.9)	10 beetles/plant (2.7)

* This figure is obtained by summing the product of beetle and egg counts with their respective regression coefficients.

The numbers in parentheses give the equivalent threshold according to Ostlie and Noetzel.

with the threshold of 1.8 beetles per plant (when ten plants are sampled) recommended by Ostlie and Noetzel. In doing so one has to assume that the number of beetles are equally distributed between the three visits.

The estimated thresholds behave in a fashion consistent with expectations. They fall as the corn price increases (cost of control is set constant). The thresholds for CRW eggs are generally higher for ridge till, otherwise no major differences are noted between the three tillages. The threshold levels of CRW beetles are generally higher than the rate of 1.8 per plant recommended by Ostlie and Noetzel (1987), or the 1 per plant recommended by Foster, Tollefson and Steffey (1986). There are no published threshold guidelines for the egg counts or the egg and the beetle counts together for comparison, but observing the high threshold numbers of egg counts per pint of soil, it is fair to assume that these may be higher than the actual threshold levels.

6.4 Sensitivity of the Estimated Economic Thresholds to Errors in Damage-Yield Loss Relationship

The estimated economic thresholds appear to be generally high. Due to the low levels of pest infestations present in the data used in modeling, the relationship expressed by the estimated model may be lower than the true relationship. Accordingly new thresholds (Table 6.16) were identified using equations 6.3 through 6.5, where the estimated parameters on the damage variables of the yield component equations are raised by one standard deviation.

The resulting estimated economic thresholds are presented in Table 6.16 As expected these are lower than the ones given by Table 6.15. The threshold levels of beetles per plant are closer to the ones obtained by Foster, Tollefson and Steffey, and Ostlie and Noetzel. The thresholds fall with the increase in price of corn relative to the cost of control.

6.5 Summary

This chapter has presented the results obtained from the simulation experiments of the model built and estimated in chapters 2 and 3 respectively. For both CRW and ECB, a positive value of information is noted when a flexible decision rule is compared with a fixed decision rule. In moving from a fixed rule of never controlling ECB to a flexible ECB rule, there is no gain in the level of certainty

TABLE 6.16 CRW ECONOMIC THRESHOLD LEVELS WITH DAMAGE PARAMETERS RAISED BY ONE STANDARD DEVIATIONS

Info. State	Corn Price in $ per bushel		
	1.80	1.98	2.25
Tillage = chisel			
Full	1.90*	1.80*	1.60*
High	20 eggs/pint	18 eggs/pint	16 eggs/pint
Low	10 beetles/plant (2.7)	9 beetles/plant (2.4)	8 beetles/plant (2.1)
Tillage = ridge			
Full	1.90*	1.80*	1.60*
High	20 eggs/pint	18 eggs/pint	16 eggs/pint
Low	9 beetles/plant (2.4)	8 beetles/plant (2.1)	7 beetles/plant (1.9)
Tillage = no-till			
Full	1.90*	1.80*	1.60*
High	20 eggs/pint	18 eggs/pint	16 eggs/pint
Low	11 beetles/plant (2.9)	8 beetles/plant (2.1)	7 beetles/plant (1.9)

* This figure is obtained by summing the product of beetle and egg counts with their respective regression coefficients.

The numbers in parentheses give the equivalent threshold according to Ostlie and Noetzel.

equivalent. However, there are gains in certainty equivalent levels, in moving from high levels of information based strategy to low levels and combined information based CRW control strategies. These gains are noted at corn prices of $1.98 per bushel or higher. When the cost of acquiring information is taken into consideration, the most profitable information is the low level of CRW beetle counts. Therefore, based on this study, scouting for CRW beetle counts are economically justifiable.

Assuming that the yield loss due to pest damage is understated by the model, simulation was conducted using yield component equations which have the parameters on damage variables increased by one standard deviation. Results indicate that routine no-control is still the best strategy for ECB. For CRW, positive value of information is obtained for the combined and low levels of information at all three price levels. Taking into consideration the cost of acquiring information, as before, beetle counts appear to be the most profitable level of CRW information. For all predictors, positive value is noted when compared to the cases of no CRW control and routine CRW control. The value of scouted information increases with the degree of producer risk aversion when producers move from routine no-control for CRW to a flexible control rule. In contrast, the value of scouted information decreases with the degree of producer risk aversion when producers move from routine CRW control to a flexible control rule.

Economic threshold levels of CRW egg and beetle counts were identified. Since it was never optimal to control for ECB, thresholds were not obtained for ECB. CRW thresholds were obtained for all three tillages and corn prices. These thresholds do not differ with producer risk preferences. Thresholds obtained from the simulation where parameters on damage variables are raised by one standard deviation are lower. No major differences is noted between the three tillages. Thresholds decrease with increase in the relative price of corn.

CHAPTER 7

SUMMARY AND CONCLUSIONS

The objective of this study was to estimate the value of information in integrated pest management of CRW and ECB in continuous corn. More specific objectives can be summarized as follows.

1. To develop a bioeconomic model for corn considering the two pests, CRW and ECB,
2. To estimate the value of monitored pest data to individual farmers, considering their risk preferences,
3. To estimate economic threshold levels for each pest and to analyze its sensitivity to relative corn and pesticide price changes.
4. To examine the economic justification of scouting data collection methods.

In the following sections, a discussion on the specification, estimation and validation of the biological model is presented first. Next, the method used in estimating the value of information and its results are briefly described. This is followed by a discussion of the estimated pest threshold levels. Finally, based on this study, the economic justification of CRW and ECB scouting data collection methods are examined.

Model Specification, Estimation and Validation

This study has presented a bioeconomic model for continuous corn considering the two pests, CRW and ECB. This model is divided into two components, biological and economic. The biological component models pest dynamics and the effect of pest population on plant and subsequently its yield. The economic component models costs and returns associated with alternative CRW and ECB management strategies.

The biological component of the model is recursive in nature. It consists of a yield equation, yield component equations and the pest damage prediction equations. The yield and yield component equations have a log-log form. The pest damage prediction equations are linear. Yield is specified as a function of yield components. These are the number of plants at harvest, the number of ears per plant and the mid-season plant height. The yield components in turn are specified as functions of pest damage predictions. Pest damage is predicted using scouted pest information. The reduction in pest damage from the use of pesticide is estimated as a constant percentage of the potential damage.

In this study, CRW damage is given by the root rating index developed at Iowa. CRW damage levels are predicted using three different equations. The first considers low levels of information, i.e. beetle counts per plant. The second uses high levels of information, i.e. egg counts per pint of soil. Finally, the third equation uses combined information, i.e. both the beetle counts and the egg counts. The low level of information is defined by the cumulative beetle counts per plant from three field visits, taken approximately 67, 84 and 104 days after planting.

ECB damage is given by the number of empty tunnels due to the first and second generation larvae per 100 plants. Three equations are considered for ECB damage prediction. The first uses low levels of information, i.e. first generation shothole counts per 100 plants. The second equation uses high levels of information, i.e. second generation larvae counts per 100 plants. The third uses full information, i.e. both the larvae and the shothole counts.

The specified model was estimated using RCB-split-split plot experimental data from Goodhue, Minnesota. This data ranges over a three year period, 1985-87 and were collected under three tillage systems, chisel plow, ridge till and no-till. Year effects and tillage effects were considered in the model by the use of dummy variables. To account for the effects of experimental design on the variance components of the model, the generalized least squares procedure suggested by Fuller and Battese (1973) was followed.

The estimated model was validated using two sets of data. The first set was the 1987-88 experimental plot data from Waseca, Minnesota. The second was the 1987-88 data from a field in Goodhue, Minnesota adjacent to the one from which the model building data was collected.

The Waseca experiment was designed to test the effects of various levels of pest damage on corn. This involved artificial augmentation of pest population levels. Therefore validating the pest dynamics component of the model was deemed inappropriate. The data set was, however, suitable for validating the yield component of the model.

The Goodhue experiment was designed to evaluate the effects of tillage and the rate and frequency of injected liquid swine manure on corn. Although several limitations existed, this data set was used for validating the pest dynamics component of the model. Pest data were available only for the case where no control was adopted both for CRW and ECB. For each pest only 24 observations were taken. In addition, the corn variety for 1988 was different from that of 1987 and from the plots used for model building.

The percentage root mean square error (%RMS) method (Pindyck and Rubinfeld, 1976, p. 316) is used as a criteria for model validation. Given the data limitations, validation was carried out on an equation by equation basis. Validation results indicate that the yield and the yield component equations perform reasonably well. However, the pest damage prediction equations perform poorly. This could be due partly to the inherent problems existing in the data used for validation and partly to the poor predictive capability of the estimated damage equations.

Estimating the Value of Information

To estimate the value of information, the estimated biological model was combined with economic components to develop a bio-economic simulation model. The simulation model characterizes distributions of net revenue under different management strategies and economic conditions. To incorporate stochastic behavior into the model, the performance of each strategy is simulated under many random states of nature. By evaluating a wide range of strategies, the model is used to identify preferred pest management strategies for CRW and ECB. Inputs to the model include: the estimated model parameters, initial pest population conditions, information defining random states of nature, production costs and output prices, and levels of absolute risk aversion.

The strategies considered in the model are defined by a choice of tillage, choice of information on which to base CRW and ECB control decisions and a choice of a rule for determining when pesticides should be applied. The tillage systems considered are chisel plow, ridge till and no-til. The various strategies available to a farmer in managing CRW and ECB infestation levels are the following.

1. Always adopt CRW and ECB control measures.
2. Never control for either pests.
3. Routinely control for one pest and base the control decision of the other on one of the damage predictors. (6 choices)
4. Never control for one pest and base the control decision of the other on one of the damage predictors. (6 choices)
5. Base control decisions on combined CRW and ECB information.
6. Base control decisions on combined CRW information and "high level" ECB information.
7. Base control decisions on combined CRW information and "low level" ECB information.
8. Base control decisions on "high level" CRW and combined ECB information.
9. Base control decisions on "high level" CRW and ECB information.
10. Base control decisions on "high level" CRW and "low level" ECB information.
11. Base control decisions on "low level" CRW and combined ECB information.

12. Base control decisions on "low level" CRW and "high level" ECB information.
13. Base control decisions on "low level" CRW and ECB information.

Three types of decision rules are used to determine control action for CRW and ECB. The first is a fixed rule which involves routine control or routine no-control for both the pests. The second is a flexible rule, which bases pest control decisions on observed levels of pest population. The third is a mixed rule which routinely controls or never controls one of the two pests and bases control decisions for the other on observed levels of pest population.

The flexible rule depends on scouted pest information. For a given pest information level, revenues with and without pest control are estimated. These revenues are evaluated at a specified level of benefit-cost ratio of pest control. Given a specified benefit-cost ratio, x, control is adopted for a particular pest based on the following rule.

$$\frac{\text{E [Revenue with control] - E [Revenue without control]}}{\text{Cost of control}} \geq x.$$

Each management strategy was simulated for 25 random states of nature and 10 initial levels of pest population. Each of the initial pest levels used in the simulation experiment was treated as an equally likely random event. The experiment therefore resulted in a net revenue distributions consisting of equally likely 250 outcomes. From these distributions, expected utility levels and the probability of a control being adopted were calculated.

Changes in producer welfare associated with different pest management strategies were evaluated using the compensation principle (Just, Hueth and Schmitz, 1982, p. 34). According to the compensation principle, under uncertainty welfare changes are measured by changes in producer surplus. Given the form of the utility function used in the estimation, this was estimated by the change in the level of the certainty equivalents (Just, Hueth and Schmitz, 1982, p. 348-356) between the optimal actions.

From the simulation results, the following characteristics of the CRW flexible decision rule are evident. First, for a given information level and tillage, the decision rule used in controlling CRW is generally not sensitive to risk preferences. Second, the value of information depends on producer risk attitudes and outcome levels. Risk averse agents are characterized by a decreasing marginal utility of income. Hence the value of information is greatest for a risk averse agent when it improves the worst outcome. In contrast, risk preferring agents are characterized by an increasing marginal utility of income. Therefore, their value of information is greatest when it improves the most favorable outcome.

Certainty equivalents obtained using the flexible decision rule were compared to the case where a producer bases control decisions on the fixed decision rule of routine control. The results indicate that an IPM system using any of the three CRW damage predictors is always superior to the case of routine control. The value of the predictors ranges from $4.21 to $5.29 per acre. These are far above the cost of acquiring even the most expensive information of $1.30 for the combined information predictor. The value is greater at lower corn prices. This is consistent with expectations, as adopting a control becomes more profitable at higher levels of corn price. The value of information decreases with the increase in the degree of risk aversion. The values are higher for chisel plow which is associated with lower levels of certainty equivalents and are the lowest for ridge till which is associated with the highest certainty equivalents.

When compared to the case of routine no-control, for both CRW and ECB, the value of a CRW damage predictor ranges from $0.14 to $0.88 per acre. For all three tillages, the value increases as corn price increases. It is highest for ridge till, and lowest for chisel plow. At low corn price levels the value of information is not as large as the cost of acquiring it. At higher price levels, however, the value of low levels of scouting information does exceed its cost. It is possible that the value was under-estimated. Corn rootworm is routinely controlled by farmers in S.E. Minnesota and a model built using three years of experimental plot data may fail to capture the actual potential for yield loss when control is never used.

When control is adopted for both CRW and ECB the value of the predictor is high, ranging around $27 per acre. Since adopting a control is more profitable at a higher corn price, this value decreases with increasing corn price.

All flexible rules used for ECB management indicate that the optimal strategy for ECB is routine no-control. This may be due to the following reasons. For ECB, the cost of adopting a control is relatively high with an average of $22.61 per acre compared with $9.6 per acre for CRW. This is due, in part, to the higher pesticide cost for ECB control and the cost of its application. In contrast, as CRW control is adopted at planting, no extra application cost is incurred. In addition, in this study the variability in ECB damage prediction increases with the adoption of pest control. Hence in all of the simulation experiments conducted, it was never profitable to adopt ECB control. Therefore, the results from flexible rule for ECB management are the same as that for the fixed rule of routine no-control.

Compared to the case where CRW is not controlled and ECB is always controlled, the value of information ranges around $22 to $23 per acre, which is about the cost of controlling ECB. The value increases as the relative price of corn increases. ECB is rarely (if ever) routinely controlled by farmers in Minnesota. Thus scouting cannot be recommended based on this value of information. Given the poor performance of ECB damage predictors in this study, however, it is doubtful that any conclusions can be drawn regarding the usefulness of scouting in ECB management.

To check the sensitivity of the value of information to errors in relating pest damage to yield loss, the yield component equation coefficients on the damage variables were raised by one standard deviation. The simulation results thus obtained indicate that the best management strategy for ECB is to never adopt any control measures. For CRW a positive value of information is noticed at all levels of corn price. When crop losses are more sensitive to pest damage, values of information compared to routine pest control decreases from those estimated earlier, and the value of information compared to routine no-control increases. In addition, the value of scouted information compared to routine no-control increases with the degree of producer risk aversion. In contrast, the value of scouted information compared to routine control decreases with the degree of producer risk aversion. This phenomenon may be due to the fact that when crop losses are more sensitive to pest damages, risk averse producers prefer to adopt pest control measures.

Estimating Economic Thresholds

The estimated pest population thresholds are insensitive to producer risk preferences. The estimated thresholds behave in a fashion consistent with expectations. They decrease as the corn price increases (cost of control is set constant). The thresholds for CRW eggs, are generally higher for ridge till (26 to 30 per pint of soil), otherwise no major differences are noted between the three tillages. The threshold levels of CRW beetles are generally higher[1] than the rate of 1.8 per plant recommended by Ostlie and Noetzel (1987), or the 1 per plant recommended by Foster, Tollefson and Steffey (1986). There are no published threshold guidelines for the egg counts or the egg and the beetle counts together for comparison. But observing the high threshold numbers of egg counts per pint of soil, it is fair to assume that these may be higher than the actual threshold levels.

To check the sensitivity of the estimated thresholds to errors in damage-yield relationship, the parameters of the damage variables of

---

[1] These ranged from a total of 9 to 12 per plant from three field trips. This is approximately equivalent to 2.4 to 3.2 per plant according to Ostlie and Noetzel's method.

the yield component equations were raised by one standard deviation. The resulting estimated thresholds are lower than the ones obtained earlier. The threshold levels of beetles per plant are closer to the ones obtained by Foster, Tollefson and Steffey, and by Ostlie and Noetzel. The thresholds fall with the increase in price of corn relative to the cost of control.

Economic Justification of Scouting for CRW and ECB

Comparing the results obtained from flexible and fixed decision rules, CRW scouting is economically preferable to routine control. When the cost of scouting is considered, CRW beetle counts perform better than CRW egg counts and combined CRW information. Scouting cost for CRW beetles is approximately $0.30 per acre, while scouting cost for CRW eggs is about $1.00 per acre. Therefore, based on this study, there is no reason to recommend scouting for CRW egg counts. However, based on this study, scouting for CRW beetles is economically justifiable. Assuming that the yield loss potential from CRW damage is under-estimated, scouting may also be economically justifiable when compared to the case of routine no-control. As the social costs of using pesticides are excluded from this study, the calculated value of information may be under-estimated. Moreover, it has to be borne in mind that the predicting capabilities are relatively low for the estimated equations.

Farmers in Minnesota do not routinely control ECB. All flexible rules used for ECB control decisions indicate that the best strategy for ECB control is routine no-control. Comparing the certainty equivalents obtained from flexible decision rules and the fixed rule of routine no-control, scouting for ECB information cannot be economically justified. Based on this study, the optimal control strategy for a corn producer is to neither purchase ECB scouting services nor to adopt any ECB control measures. It has to be borne in mind that the weakest component of the estimated model is in predicting ECB damages from the scouted pest information. Therefore, this conclusion has to be accepted with some caution.

Implications for Further Research

This study has constructed a bio-economic model for continuous corn and estimated the value of CRW and ECB population information in their optimal management. The findings of this research include two unexpected results. No differences in CRW and ECB control behavior exist between producers with different risk preferences. At all pest population levels, the best strategy for ECB is no-control. Future research can be directed to confirm the above findings. In addition, the methodology used here can be extended to cover issues not covered in this study.

The methodology developed in this study can be adopted for future research. Use of better data covering a period of 7-10 years may lead to more reliable pest damage parameter estimates. This may enable estimation of the value of ECB information. In such a scenario, the value of information can be estimated for different levels of pest information and for different intensity of scouting.

A possible extension of this study is in analyzing the social cost of pesticide use and the social gains from the adoption of scouting. Using the methodology outlined here, the value of scouted information for individual farmers can be estimated. These can then be compared with its social value estimated by incorporating an environmental externality into the model. This may be done by following the method outlined by Moffitt (1988) in which a utility maximization problem is solved subject to a minimum environmental quality constraint.

The common property nature of pests and their information is another avenue that can be explored. The common property nature of pests has been analyzed by Lazarus and Dixon (1984). The externality considered by them is the pest resistance to insecticides. For mobile insect pests a decision made by a farmer has effects on the neighboring fields. There are possible free rider problems associated with the common property nature of information. A farmer may base his/her control decisions by observing or talking with a neighbor who purchases scouting services.

Some of the possible extensions to the methodology used in this study have been presented above. Although the focus of this research has been specific, the model developed may provide a general guideline in optimal management and use of information on any crop and for any pest.

APPENDIX 1

EXPERIMENTAL DESIGN

A1.1 A Representative Plot Design

A representative design of the experimental plots at Donald Nord's farm in Goodhue Minnesota during 1985 through 1987 is given on the following page. As shown, the entire field is divided into four blocks. These are then divided into three whole plots for each of the three tillages. The whole plots are divided into two sub-plots and the sub-plots to three sub-sub-plots. The codes used in the figure are as follows.

Tillages (Whole plots)

C = Chisel plow (1)
R = Ridge-till (2)
N = No-till (3)

Treatments

The two digits are for CRW treatment and ECB treatment respectively.

CRW Treatment (Sub-plot)

1 = Pre-planting insecticide application
2 = No insecticide application

ECB Treatment (Sub-sub-plot)

1 = No insecticide application
2 = Insecticide application
3 = IPM strategy

Figure A1.1 A Representative Plot Design

Blocks						
	N		C		R	
	12	21	13	22	21	13
1	13	23	12	21	23	12
	11	22	11	23	22	11
	R		C		N	
	12	23	13	23	11	23
2	11	21	12	21	13	21
	13	22	11	22	12	22
	N		R		C	
	21	11	21	13	21	12
3	22	12	22	11	22	11
	23	13	23	12	23	13
	C		N		R	
	12	22	13	22	12	21
4	13	21	12	21	13	22
	11	23	11	23	11	23

Source: David Andow, Department of Entomology, University of Minnesota.

A1.2 Mean and Standard Deviation of Variables

List of Variables Used

YR	Year, 1 = 1985, 2 = 1986, 3 = 1987
BL	Block, 1-4
TIL	Tillage, 1 = chisel, 2 = ridge, 3 = minimum till
CRW	CRW treatment, 1 = preplant application of Counter 2 = no control
ECB	ECB treatment, 1 = no control 2 = pesticide application 3 = adoption of IPM
TUN	Percentage ECB damage
LTUN	Log(percentage ECB damage)
LSTDA	Log(number of plants/acre at harvest)
LEARPS	Log(number of ears per plant)
LEMERA	Log(number of plants/acre at early crop stage)
LYLDA	Log(yield in bushels/acre)
CRATE	CRW damage rate
LHT	Log(Mid-season plant height)
LHTI	Log(Early plant height)
EGG	CRW egg counts
TMTEG	Interaction of CRW egg counts and treatment
ADLT	CRW beetle counts
TMTADLT	Interaction of CRW beetle counts and treatment
SHOT	ECB first generation shothole counts
TMTSHOT	Interaction between shotholes and treatment
LGLAR2	ECB second generation larva counts
TMTLGLR2	Interaction between ECB second generation larva counts and treatment

A1.2.1 Overall Mean and Standard Deviation of Variables

VARIABLE	MEAN	STANDARD DEVIATION
YLDA	163.3085107	20.81109992
STDA	28188.6432646	2538.98249086
EARPS	0.9808720	0.04523094
HT	175.7772859	18.98580422
CRATE	2.7813426	0.73870632
EMERA	28654.3776708	2950.81658144
CRWEGG	8.68541667	4.83578067
ADLT	4.05698296	1.89472231
TUN	14.34807861	8.47098147
SHOT	8.07589583	8.73799477
HTI	69.65416667	12.73385457

A1.2.2 Mean and Standard Deviation By Block

VARIABLE	MEAN	STANDARD DEVIATION
---------------- BL=1 ----------------		
YLDA	161.2430328	24.64786329
STDA	28139.6256946	2732.93065384
EARPS	0.9862709	0.03183363
HT	175.3463443	18.65420342
CRATE	2.6966667	0.60686015
EMERA	28491.4973387	2950.44541850
CRWEGG	9.13055556	5.89248335
ADLT	3.54320964	1.38676751
TUN	13.27161333	8.68118845
SHOT	8.00966667	8.56228001
HTI	69.36481481	14.48067232
LGLAR2	6.47444444	4.44065983
---------------- BL=2 ----------------		
YLDA	161.4847512	19.23380525
STDA	27858.8268668	2263.91178833
EARPS	0.9772089	0.03548812
HT	172.9399784	19.76059547
CRATE	2.8407407	0.87878959
EMERA	28454.0957474	2921.45063035
CRWEGG	9.95555556	5.39605610
ADLT	3.89691358	1.61008159
TUN	13.27162556	7.84889295
SHOT	7.94800926	8.10986476
HTI	69.12037037	12.51164559
LGLAR2	9.84683333	7.61841805

VARIABLE	MEAN	STANDARD DEVIATION
---------------- BL=3 ----------------		
YLDA	162.2735749	17.80749841
STDA	28122.9169292	2470.44253594
EARPS	0.9860171	0.03171842
HT	176.4375824	19.29456860
CRATE	2.8305556	0.72414013
EMERA	28598.7587092	2908.12194569
CRWEGG	7.41851852	3.35704408
ADLT	4.16280867	2.11768142
TUN	15.15436000	7.62231888
SHOT	8.39220370	7.69336962
HTI	69.69629630	12.45406599
LGLAR2	12.69388889	9.46603561
---------------- BL=4 ----------------		
YLDA	168.2326840	20.70814958
STDA	28633.2035679	2671.00809859
EARPS	0.9739911	0.07001235
HT	178.3852387	18.32321712
CRATE	2.7574074	0.73126973
EMERA	29073.1588880	3061.89925513
CRWEGG	8.23703704	4.00855436
ADLT	4.62499994	2.24194138
TUN	15.69471556	9.54739225
SHOT	7.95370370	10.55098516
HTI	70.43518519	11.63824465
LGLAR2	15.17777778	12.44919392

A1.2.3 Mean and Standard Deviation By Tillage

VARIABLE	MEAN	STANDARD DEVIATION
--------------- TIL=1 ---------------		
YLDA	166.5119294	18.29332640
STDA	28657.5326806	2532.02271123
EARPS	0.9815745	0.03426414
HT	185.6065962	13.51734865
CRATE	2.7763889	0.79545240
EMERA	29188.6804863	2977.04054557
CRWEGG	6.60277778	3.10249660
ADLT	3.99016198	2.09114376
TUN	14.15508750	8.14755024
SHOT	11.58011111	10.39852290
HTI	73.82638889	12.80381758
LGLAR2	10.11666667	8.97021533
--------------- TIL=2 ---------------		
YLDA	162.7353902	20.42175497
STDA	28007.4285302	2679.35809425
EARPS	0.9777934	0.06328485
HT	172.5479488	18.17742755
CRATE	2.7402778	0.57596452
EMERA	28434.5875328	3063.76001245
CRWEGG	9.23402778	4.98610623
ADLT	4.12326392	1.85539869
TUN	14.65301167	8.32445261
SHOT	7.07184028	7.39308481
HTI	68.73055556	12.58623929
LGLAR2	12.24575000	9.92595338
--------------- TIL=3 ---------------		
YLDA	160.6782125	23.28210461
STDA	27900.9685831	2364.44700125
EARPS	0.9832481	0.03162754
HT	169.1773128	20.63186227
CRATE	2.8273611	0.82708549
EMERA	28339.8649933	2771.10742754
CRWEGG	10.21944444	5.40705431
CRATE	2.82666667	0.82768300
ADLT	4.05752298	1.76018440
TUN	14.23613667	9.02607680
SHOT	5.57573611	6.97193030
HTI	66.40555556	11.80888766
LGLAR2	10.78229167	9.53411640

A1.2.4 Mean and Standard Deviation By Whole Plot

VARIABLE	MEAN	STANDARD DEVIATION
--------------- WP=11 ---------------		
YLDA	174.0417920	24.92417582
STDA	29421.2103797	3112.66681854
EARPS	0.9842363	0.03720273
HT	186.2174308	11.38556573
CRATE	2.7472222	0.78730221
EMERA	29739.8025250	3383.39851175
CRWEGG	7.19444444	3.45512786
ADLT	3.42592575	1.68384815
TUN	13.14812000	8.38490550
SHOT	8.52627778	6.34904022
HTI	75.25555556	14.69218369
LGLAR2	5.32666667	3.89992852
--------------- WP=12 ---------------		
YLDA	164.1686012	14.49888975
STDA	28605.9702803	1950.26633707
EARPS	0.9868659	0.02833547
HT	173.9458245	17.35262638
CRATE	2.6916667	0.51428134
EMERA	28998.3362232	2386.96938275
CRWEGG	9.85555556	6.86709736
ADLT	3.72685158	1.01916491
TUN	14.02779667	8.34925195
SHOT	8.23922222	9.17078336
HTI	70.11111111	14.27683805
LGLAR2	8.82000000	5.10512399
--------------- WP=13 ---------------		
YLDA	145.5187052	24.86536673
STDA	26391.6964239	2142.16463539
EARPS	0.9877104	0.03107195
HT	165.8757775	20.78353053
CRATE	2.6511111	0.50882667
EMERA	26736.3532679	2193.36394526
CRWEGG	10.34166667	6.56318274
ADLT	3.47685158	1.47932068
TUN	12.63892333	9.68985287
SHOT	7.26350000	10.15979611
HTI	62.72777778	12.25060890
LGLAR2	5.27666667	3.53100123

VARIABLE	MEAN	STANDARD DEVIATION
	WP=21	
YLDA	167.0801788	13.25222881
STDA	28708.7052275	2048.31945641
EARPS	0.9759701	0.03811049
HT	184.9027831	12.16718742
CRATE	2.7916667	0.80918441
EMERA	29498.2695871	3017.93384248
CRWEGG	7.82500000	3.95705810
ADLT	3.90046292	1.71165979
TUN	13.51854333	7.16602257
SHOT	11.02666667	9.42562714
HTI	73.42777778	12.55902795
LGLAR2	9.44083333	7.39770414
	WP=22	
YLDA	152.2498012	23.53780293
STDA	26541.2762206	2335.37826958
EARPS	0.9806675	0.02350840
HT	163.1688440	16.45088145
CRATE	2.6722222	0.56962894
EMERA	26925.6956525	2598.81149131
CRWEGG	10.68611111	4.78796916
ADLT	3.22453733	1.00080352
TUN	12.54631667	7.66151377
SHOT	7.44458333	8.19759552
HTI	65.78333333	11.66514416
LGLAR2	8.85216667	7.31239533
	WP=23	
YLDA	165.1242736	16.91784524
STDA	28326.4991521	1869.45008035
EARPS	0.9749891	0.04360989
HT	170.7483079	23.25954278
CRATE	3.0583333	1.16002662
EMERA	28938.3220025	2621.23202563
CRWEGG	11.35555556	6.68940974
ADLT	4.56574050	1.82642864
TUN	13.75001667	9.00824381
SHOT	5.37277778	5.62835657
HTI	68.15000000	12.72016694
LGLAR2	11.24750000	8.54851835

VARIABLE	MEAN	STANDARD DEVIATION
--------------- WP=31 ---------------		
YLDA	163.5771104	14.11511768
STDA	28225.7858101	2529.51677196
EARPS	0.9892544	0.03095116
HT	190.9278698	13.50102655
CRATE	2.8694444	0.79338050
EMERA	28695.5213850	2850.72296276
CRWEGG	5.83611111	2.25171866
ADLT	4.53009250	2.46030379
TUN	14.62965667	6.84343530
SHOT	11.54527778	9.27932497
HTI	75.53888889	13.49906920
LGLAR2	12.08833333	10.22214693
--------------- WP=32 ---------------		
YLDA	164.0772852	17.76902592
STDA	28223.5037697	2633.04275632
EARPS	0.9836809	0.03496353
HT	172.5997172	16.11943418
CRATE	2.9555556	0.75340187
EMERA	28773.3039161	3169.62251219
CRWEGG	7.64722222	4.03089073
ADLT	4.40046308	2.30804756
TUN	15.41672333	6.75343672
SHOT	7.27022222	6.58826501
HTI	67.71666667	11.52053154
LGLAR2	14.15666667	10.04962535
--------------- WP=33 ---------------		
YLDA	159.1663291	21.40528101
STDA	27919.4612077	2372.79441474
EARPS	0.9851160	0.03063292
HT	165.7851601	18.98580396
CRATE	2.6666667	0.62544102
EMERA	28327.4508265	2841.34532475
CRWEGG	8.77222222	3.02816301
ADLT	3.55787042	1.51027454
TUN	15.41670000	9.39445167
SHOT	6.36111111	6.22803329
HTI	65.83333333	10.60743358
LGLAR2	11.83666667	8.72274595

VARIABLE	MEAN	STANDARD DEVIATION
--------------- WP=41 ---------------		
YLDA	161.3486365	17.43106611
STDA	28274.4293050	2349.49286082
EARPS	0.9768371	0.03133543
HT	180.3783012	15.59890679
CRATE	2.6972222	0.84947600
EMERA	28821.1284483	2740.35204548
CRWEGG	5.55555556	1.94889779
ADLT	4.10416675	2.48548322
TUN	15.32403000	10.27452304
SHOT	15.22222222	14.56347387
HTI	71.08333333	10.74540942
LGLAR2	13.61083333	11.23779456
--------------- WP=42 ---------------		
YLDA	170.4458732	21.87143031
STDA	28658.9638501	3261.59324530
EARPS	0.9599592	0.11695850
HT	180.4774092	19.66251359
CRATE	2.6416667	0.40265662
EMERA	29041.0143392	3667.00990258
CRWEGG	8.74722222	3.45600382
ADLT	5.14120367	2.25270980
TUN	16.62121000	10.27447185
SHOT	5.33333333	5.36053114
HTI	71.31111111	13.02413546
LGLAR2	17.15416667	13.59440290
--------------- WP=43 ---------------		
YLDA	172.9035423	21.82353711
STDA	28966.2175485	2414.46849293
EARPS	0.9851770	0.01646583
HT	174.3000057	19.75519977
CRATE	2.9333333	0.85594805
EMERA	29357.3338765	2849.26350213
CRWEGG	10.40833333	4.63389843
ADLT	4.62962942	2.03808890
TUN	15.13890667	8.46580627
SHOT	3.30555556	4.48900254
HTI	68.91111111	11.55304334
LGLAR2	14.76833333	13.22525878

APPENDIX 2

DERIVATION OF GLS TRANSFORMATIONS

A2.1 Methodology

The procedure given by Fuller and Battese (1973) for a two-fold nested-error model is described with a few minor changes.

For data from a split-split-plot experiment, a linear model may be expressed as,

$$Y_{ijk} = \sum_{m=1}^{n} X_{ijkm} \beta_m + u_{ijk} \qquad \text{...(i)}$$

where,

$k = 1,\dots,K_i$,

$j = 1,\dots,n_i$,

$i = 1,\dots,t$.

Y_{ijk} = the value of the variable obtained at the $k^{th.}$ split-split-plot of the $j^{th.}$ split-plot on the $i^{th.}$ whole-plot.

X_{ijkm}, $m = 1,\dots,p$ denote the levels of p control variables at which the observation Y_{ijk} is obtained.

β_m, $m = 1,\dots,p$ denote the unknown parameters to be estimated.

u_{ijk} = the random error associated with the observation Y_{ijk}. This is assumed to be the sum of the random effects associated with the $i^{th.}$ whole-plot (v_i), $j^{th.}$ split-plot on the $i^{th.}$ whole-plot (e_{ij}), and the $k^{th.}$ split-split-plot of the $j^{th.}$ split-plot on the $i^{th.}$ whole-plot (ε_{ijk}).

Then,

$$u_{ijk} = v_i + e_{ij} + \varepsilon_{ijk}. \qquad \text{...(ii)}$$

Assume that the three components of u_{ijk} are independently distributed with zero mean and respective variances σ_v^2, σ_e^2 and σ_ε^2 where σ_v^2, $\sigma_e^2 \geq 0$ and $\sigma_\varepsilon^2 > 0$. The covariance structure can be expressed by,

$$E(u_{ijk}\, u_{i'j'k'}) = \sigma_v^2 + \sigma_e^2 + \sigma_\varepsilon^2 \quad \text{if } i = i',\ j = j' \text{ and } k = k'$$
$$= \sigma_v^2 + \sigma_e^2 \quad \text{if } i = i',\ j = j' \text{ and } k \neq k'$$
$$= \sigma_v^2 \quad \text{if } i = i',\ j \neq j';$$
$$= 0 \quad \text{if } i \neq i'.$$

Transformation

The transformation suggested is of the following form.

$$(Y_{ijk} - \alpha_1 \bar{Y}_{ij} - \alpha_2 \bar{Y}_{i..}) = \sum_{m=1}^{p} (X_{ikm} - \alpha_{1i} \bar{X}_{ij.m} - \alpha_{2i} \bar{X}_{i..m})\, \beta_m + u^{*}_{ijk} \qquad \ldots(iii)$$

where,

$k = 1, \ldots, K_i$,

$j = 1, \ldots, n_i$,

$i = 1, \ldots, t.$

$$\alpha_{1i} = 1 - \left[\sigma_\varepsilon^2 / (\sigma_\varepsilon^2 + K_i\, \sigma_e^2)\right]^{1/2}, \text{ and} \qquad \ldots(iv)$$

$$\alpha_{2i} = \left[\sigma_\varepsilon^2 / (\sigma_\varepsilon^2 + K_i\, \sigma_e^2)\right]^{1/2} - \left[\sigma_\varepsilon^2 / (\sigma_\varepsilon^2 + K_i\, \sigma_e^2 + n_i K_i \sigma_v^2)\right]^{1/2} \qquad \ldots(v)$$

$\bar{Y}_{ij}$, $\bar{X}_{ij.m}$ $m = 1,2,\ldots,p$ denote the split-split-plot averages of the Y and X for the the $j^{th.}$ split-plot on the $i^{th.}$ whole-plot.

These variance components can be approximately estimated with appropriate computer packages such as SAS. The following section outlines the estimation procedure followed in this study.

A2.2 Estimation of Variance Components

The experimental design of the data source in this study differs slightly from the hypothetical one presented under the discussion of the methodology. The design comprises of the following,

4 blocks (BL),

12 whole plots (3 tillages per block) (WP),

24 sub-plots (2 CRW treatments per whole plot) (SP), and

72 sub-sub-plots (3 ECB treatments per sub-plot) (SSP).

Hence the variance covariance matrix (matrix V described in 3.3 pp. 32) is of the form,

$V_{ij} = \sigma^2_{BL} + \sigma^2_{WP} + \sigma^2_{SP} + \sigma^2_{error}$	if observations i and j are in the same SSP.
$V_{ij} = \sigma^2_{BL} + \sigma^2_{WP} + \sigma^2_{SP}$	if observations i and j are in the same SP but not the same SSP.
$V_{ij} = \sigma^2_{BL} + \sigma^2_{WP}$	if observations i and j are in the same WP but not the same SP.
$V_{ij} = \sigma^2_{BL}$	if observations i and j are in the same BL but not the same WP.
$V_{ij} = 0$	otherwise.

With the help of the GLM procedure in SAS all the above variance components are estimated. The mean square error (MSE) of the model gives an estimate of σ^2_{error}. The other variance components are estimated as follows.

$$\sigma^2_{SP} = \frac{MS_{SP} - MSE}{\text{\# SSP per SP}} \qquad \text{...(vi)}$$

$$\sigma^2_{WP} = \frac{MS_{WP} - MS_{SP}}{(\text{\# SSP per SP})\ (\text{\# SP per WP})} \qquad \text{...(vii)}$$

$$\sigma^2_{BL} = \frac{MS_{BL} - MS_{WP}}{(\text{\# SSP per SP})\ (\text{\# SP per WP})\ (\text{\# WP per BL})} \qquad \text{...(viii)}$$

where,

MS = mean square.

A2.2.1 Yield Equation

DEPENDENT VARIABLE: YLDA
NUMBER OF OBSERVATIONS IN DATA SET = 216

GENERAL LINEAR MODELS PROCEDURE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE
MODEL	28	2.83874577	0.10138378	27.56
ERROR	187	0.68793620	0.00367880	PR > F
CORRECTED TOTAL	215	3.52668197		0.0001

R-SQUARE	C.V.	ROOT MSE	YLDA MEAN
0.804934	1.1922	0.06065314	5.08752546

SOURCE	DF	TYPE I SS	F VALUE	PR > F
LSTDA	1	1.01947582	277.12	0.0001
LEARPS	1	0.19799637	53.82	0.0001
LHT	1	1.12469712	305.72	0.0001
BL	3	0.02402959	2.18	0.0922
TIL	2	0.12223909	16.61	0.0001
TIL(BL)	6	0.05363543	2.43	0.0276
CRW(BL*TIL)	12	0.06471955	1.47	0.1402
YR	2	0.23195279	31.53	0.0001

Test 1.
TEST OF HYPOTHESIS USING THE TYPE I MS FOR CRW(BL*TIL) AS ERROR TERM

SOURCE	DF	TYPE I SS	F VALUE	PR > F
TIL(BL)	6	0.05363543	1.66	0.2147

Test 2.
TEST OF HYPOTHESIS USING THE TYPE I MS FOR TIL(BL) AS ERROR TERM

SOURCE	DF	TYPE I SS	F VALUE	PR > F
BL	3	0.02402959	0.90	0.4957

From the mean square error of the model we obtain $\hat{\sigma}^2_{error}$ = 0.00367880, and from the ANOVA table σ^2_{BL}, σ^2_{WP} and σ^2_{SP} can be estimated. Before these variance components are used for transforming the yield equation and estimating the GLS parameters, tests are carried out to see if they are significantly different from zero. The F-value of 1.47 gives the test statistic for the null hypothesis of $\sigma^2_{SP} = 0$, indicating that σ^2_{SP} is not significantly different from zero. Similarly, test 1 and test 2 indicate that the null hypotheses $\sigma^2_{WP} = 0$ and $\sigma^2_{BL} = 0$ are not rejected at the 5% level. Hence, as all the variance components are not significantly different from zero, OLS is used to estimate the yield equation.

A2.2.2 Yield Component Equations

1. DEPENDENT VARIABLE: LSTDA
   NUMBER OF OBSERVATIONS IN DATA SET = 216

GENERAL LINEAR MODELS PROCEDURE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE
MODEL	28	1.71742952	0.06133677
ERROR	187	0.04493420	0.00024029
CORRECTED TOTAL	215	1.76236372	
MODEL F =	255.26		PR > F = 0.0
R-SQUARE	C.V.	ROOT MSE	LSTDA MEAN
0.974503	0.1513	0.01550128	10.24261296

SOURCE	DF	TYPE I SS	F VALUE	PR > F
LEMERA	1	1.69155969	7039.66	0.0
CRATE	1	0.00957738	39.86	0.0001
LTUN	1	0.00004221	0.18	0.6756
BL	3	0.00143693	1.99	0.1165
TIL	2	0.00000057	0.00	0.9988
TIL(BL)	6	0.00345342	2.40	0.0297
CRW(BL*TIL)	12	0.00607770	2.11	0.0182
YR	2	0.00528163	10.99	0.0001

Test 1.
TESTS OF HYPOTHESES USING THE TYPE I MS FOR CRW(BL*TIL) AS ERROR TERM

SOURCE	DF	TYPE I SS	F VALUE	PR > F
TIL(BL)	6	0.00345342	1.14	0.3987

Test 2.
TESTS OF HYPOTHESES USING THE TYPE I MS FOR TIL(BL) AS ERROR TERM

SOURCE	DF	TYPE I SS	F VALUE	PR > F
BL	3	0.00143693	0.83	0.5231

Test 1 and test 2 indicate that the null hypotheses $\sigma^2_{WP}=0$ and $\sigma^2_{BL}=0$ can be accepted. However, with a F-value of 2.11, the null hypothesis of $\sigma^2_{SP} = 0$ is rejected at the 5% significance level. Hence, the sub-plot variance component must be considered in the estimation of the standard error of this yield component.

Since tillage, block and whole-plot variance components are not significantly different from zero, these variables are removed and the equation re-estimated to obtain $\hat{\sigma}^2_{SP}$. The new output is given below.

DEPENDENT VARIABLE: LSTDA

NUMBER OF OBSERVATIONS IN DATA SET = 216
GENERAL LINEAR MODELS PROCEDURE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE
MODEL	28	1.71742952	0.06133677
ERROR	187	0.04493420	0.00024029
CORRECTED TOTAL	215	1.76236372	
MODEL F =	255.26		PR > F = 0.0

R-SQUARE	C.V.	ROOT MSE	LSTDA MEAN
0.974503	0.1513	0.01550128	10.24261296

SOURCE	DF	TYPE I SS	F VALUE	PR > F
LEMERA	1	1.69155969	7039.66	0.0
CRATE	1	0.00957738	39.86	0.0001
LTUN	1	0.00004221	0.18	0.6756
CRW(BL*TIL)	23	0.01096861	1.98	0.0068
YR	2	0.00528163	10.99	0.0001

The null hypothesis of $\sigma^2_{SP} = 0$ is rejected at the 1% significance level. Therefore, the procedure outlined by Fuller and Battese (1973) is used to estimate the standard errors of the coefficients. If two of the three variance components in equations (iv) and (v) are zero, the transformation reduces to the following.

$$\alpha_{2i} = \alpha_{1i} = 1 - \left[\sigma^2_{\varepsilon} / (\sigma^2_{\varepsilon} + K_i\, \sigma^2_s)\right]^{1/2}$$

where,

σ^2_s is the non zero variance component.

Since all the variance components, σ^2_{BL} and σ^2_{WP}, except σ^2_{SP} are zero the following transformation is used.

$$Y_{ij} - \alpha\, \bar{Y}_i = \sum_{k=1}^{p} \left(X_{ijk} - \alpha\, \bar{X}_{ik} \right) \beta_k + U_{ij} \qquad \text{...(ix)}$$

where,

$$\alpha = 1 - \left(\frac{\hat{\sigma}^2_{mse}}{\hat{\sigma}^2_{mse} + \hat{\sigma}^2_{SP}}\right)^{1/2} \qquad \ldots (x)$$

$\bar{Y}_i$ = mean of the dependent variable for sub-plot i $\quad i=1,\ldots,n$

$\bar{X}_{ik}$ = mean of independent variable k for sub-plot i $\quad i=1,\ldots,n$; $k=1,\ldots,p$

$\hat{\sigma}^2_{mse}$ = estimated mean square error (MSE) of the equation

$\hat{\sigma}^2_{SP}$ = estimated variance component due to sub-plots.

2. DEPENDENT VARIABLE: LEARPS

NUMBER OF OBSERVATIONS IN DATA SET = 216
GENERAL LINEAR MODELS PROCEDURE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE
MODEL	26	0.20831917	0.00801228
ERROR	189	0.46192005	0.00244402
CORRECTED TOTAL	215	0.67023923	
MODEL F =	3.28		PR > F = 0.0001

R-SQUARE	C.V.	ROOT MSE	LEARPS MEAN
0.310813	239.1633	0.04943705	-0.02067083

SOURCE	DF	TYPE I SS	F VALUE	PR > F
LTUN	1	0.00737485	3.02	0.0840
BL	3	0.01002001	1.37	0.2544
TIL	2	0.00251731	0.51	0.5983
TIL(BL)	6	0.01194127	0.81	0.5600
CRW(BL*TIL)	12	0.02303231	0.79	0.6652
YR	2	0.15343342	31.39	0.0001

Test 1.
TESTS OF HYPOTHESES USING THE TYPE I MS FOR CRW(BL*TIL) AS ERROR TERM

SOURCE	DF	TYPE I SS	F VALUE	PR > F
TIL(BL)	6	0.01194127	1.04	0.4484

Test 2.
TESTS OF HYPOTHESES USING THE TYPE I MS FOR TIL(BL) AS ERROR TERM

SOURCE	DF	TYPE I SS	F VALUE	PR > F
BL	3	0.01002001	1.68	0.2696

The F-value of 0.79 gives the test statistic for the null hypothesis of $\sigma^2_{SP} = 0$, indicating that σ^2_{SP} is not significantly different from zero. Similarly, test 1 and test 2 indicate that the null hypotheses $\sigma^2_{WP} = 0$ and $\sigma^2_{BL} = 0$ can be accepted. Hence, as all the variance components are not significantly different from zero, OLS can be used to estimate this yield component equation.

3. DEPENDENT VARIABLE: LHT

NUMBER OF OBSERVATIONS IN DATA SET = 216

GENERAL LINEAR MODELS PROCEDURE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE
MODEL	27	2.18194608	0.08081282	42.14
ERROR	188	0.36049070	0.00191750	PR > F
CORRECTED TOTAL	215	2.54243678		0.0001

R-SQUARE	C.V.	ROOT MSE	LHT MEAN
0.858211	0.8481	0.04378931	5.16336296

SOURCE	DF	TYPE I SS	F VALUE	PR > F
LHTI	1	0.28635187	149.34	0.0001
CRATE	1	0.73996734	385.90	0.0001
BL	3	0.01463105	2.54	0.0576
TIL	2	0.17672798	46.08	0.0001
TIL(BL)	6	0.12931754	11.24	0.0001
CRW(BL*TIL)	12	0.11903141	5.17	0.0001
YR	2	0.71591889	186.68	0.0001

Test 1.
TEST OF HYPOTHESIS USING THE TYPE I MS FOR CRW(BL*TIL) AS ERROR TERM

SOURCE	DF	TYPE I SS	F VALUE	PR > F
TIL(BL)	6	0.12931754	2.17	0.1190

Test 2.
TEST OF HYPOTHESIS USING THE TYPE I MS FOR TIL(BL) AS ERROR TERM

SOURCE	DF	TYPE I SS	F VALUE	PR > F
BL	3	0.01463105	0.23	0.8749

Test 1 and test 2 indicate that the null hypotheses $\sigma^2_{WP}=0$ and $\sigma^2_{BL}=0$ can be accepted. However, with a F-value of 5.17, the null hypothesis of $\sigma^2_{SP} = 0$ is rejected at the 5% significance level. Hence, the sub-plot variance component must be considered in the estimation of the standard errors of the coefficients.

Since block and whole-plot variance components are not significantly different from zero, these variables are removed and the equation re-estimated to obtain $\hat{\sigma}^2_{SP}$. The new output is given below.

DEPENDENT VARIABLE: LHT

NUMBER OF OBSERVATIONS IN DATA SET = 216
GENERAL LINEAR MODELS PROCEDURE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE
MODEL	27	2.18194608	0.08081282	42.14
ERROR	188	0.36049070	0.00191750	PR > F
CORRECTED TOTAL	215	2.54243678		0.0001

R-SQUARE	C.V.	ROOT MSE	LHT MEAN
0.858211	0.8481	0.04378931	5.16336296

SOURCE	DF	TYPE I SS	F VALUE	PR > F
LHTI	1	0.28635187	149.34	0.0001
CRATE	1	0.73996734	385.90	0.0001
TIL	2	0.17553864	45.77	0.0001
CRW(BL*TIL)	21	0.26416934	6.56	0.0001
YR	2	0.71591889	186.68	0.0001

The F-value of 6.56 indicates that the null hypothesis of σ^2_{SP} is rejected. Therefore, the transformation approach has to be adopted in estimating this equation. As in the case of the equation estimating number of plants per acre, σ^2_{SP} is the only nonzero variance component. Hence, transformation given by equations (ix) and (x) is used in estimating plant height.

A2.2.3 CRW Damage Equations

1. DEPENDENT VARIABLE: CRATE
   NUMBER OF OBSERVATIONS IN DATA SET = 216

GENERAL LINEAR MODELS PROCEDURE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE
MODEL	27	64.96451375	2.40609310	8.64
ERROR	188	52.35819690	0.27850105	PR > F
CORRECTED TOTAL	215	117.32271065		0.0001

R-SQUARE	C.V.	ROOT MSE	CRATE MEAN
0.553725	18.9740	0.52773198	2.78134259

SOURCE	DF	TYPE I SS	F VALUE	PR > F
EGG	1	3.79945489	13.64	0.0003
TMTEG	1	10.31449093	37.04	0.0001
BL	3	0.58256674	0.70	0.5548
TIL	2	0.61599251	1.11	0.3331
TIL(BL)	6	1.69612730	1.02	0.4168
CRW(BL*TIL)	12	5.88141203	1.76	0.0576
YR	2	42.07446934	75.54	0.0001

Test 1.
TEST OF HYPOTHESIS USING THE TYPE I MS FOR CRW(BL*TIL) AS ERROR TERM

SOURCE	DF	TYPE I SS	F VALUE	PR > F
TIL(BL)	6	1.69612730	0.58	0.7423

Test 2.
TEST OF HYPOTHESIS USING THE TYPE I MS FOR TIL(BL) AS ERROR TERM

SOURCE	DF	TYPE I SS	F VALUE	PR > F
BL	3	0.58256674	0.69	0.5921

Test 1 and test 2 indicate that the null hypotheses $\sigma^2_{WP}=0$ and $\sigma^2_{BL}=0$ can be accepted. However, with a F-value of 1.76, the null hypothesis of $\sigma^2_{SP} = 0$ is accepted at the 5% level but is rejected at the 6% significance level. Hence, the sub-plot variance component is considered in the estimation of the standard errors of the coefficients of this CRW damage equation.

Since tillage, block and whole-plot variance components are not significantly different from zero, these variables are removed and the equation re-estimated to obtain $\hat{\sigma}^2_{SP}$. The new output is given below.

DEPENDENT VARIABLE: CRATE
NUMBER OF OBSERVATIONS IN DATA SET = 216

GENERAL LINEAR MODELS PROCEDURE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE
MODEL	27	64.96451375	2.40609310
ERROR	188	52.35819690	0.27850105
CORRECTED TOTAL	215	117.32271065	
MODEL F =	8.64		PR > F = 0.0001

R-SQUARE	C.V.	ROOT MSE	CRATE MEAN
0.553725	18.9740	0.52773198	2.78134259

SOURCE	DF	TYPE I SS	F VALUE	PR > F
EGG	1	3.79945489	13.64	0.0003
TMTEG	1	10.31449093	37.04	0.0001
CRW(BL*TIL)	23	8.77609859	1.37	0.1298
YR	2	42.07446934	75.54	0.0001

As indicated by the F-value of 1.37 the null hypothesis of $\sigma^2_{SP}=0$ is accepted. Therefore, OLS is used in estimating this equation.

2. DEPENDENT VARIABLE: CRATE
   NUMBER OF OBSERVATIONS IN DATA SET = 144

GENERAL LINEAR MODELS PROCEDURE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE
MODEL	28	66.80083663	2.38574417
ERROR	115	36.14275712	0.31428484
CORRECTED TOTAL	143	102.94359375	
MODEL F =	7.59		PR > F = 0.0001

R-SQUARE	C.V.	ROOT MSE	CRATE MEAN
0.648907	19.0374	0.56061113	2.94479167

SOURCE	DF	TYPE I SS	F VALUE	PR > F
ADLT	1	23.25491738	73.99	0.0001
EGG	1	4.24450257	13.51	0.0004
TMTEG	1	12.94094344	41.18	0.0001
TMTADLT	1	3.98912497	12.69	0.0005
BL	3	1.66292641	1.76	0.1580
TIL	2	0.76988779	1.22	0.2976
TIL(BL)	6	1.79898095	0.95	0.4597
CRW(BL*TIL)	12	10.45117007	2.77	0.0024
YR	1	7.68838306	24.46	0.0001

Test 1.
TESTS OF HYPOTHESES USING THE TYPE I MS FOR CRW(BL*TIL) AS ERROR TERM

SOURCE	DF	TYPE I SS	F VALUE	PR > F
TIL(BL)	6	1.79898095	0.34	0.9000

Test 2.
TESTS OF HYPOTHESES USING THE TYPE I MS FOR TIL(BL) AS ERROR TERM

SOURCE	DF	TYPE I SS	F VALUE	PR > F
BL	3	1.66292641	1.85	0.2390

Test 1 and test 2 indicate that the null hypotheses $\sigma^2_{WP} = 0$ and $\sigma^2_{BL} = 0$ can be accepted. However, with a F-value of 2.77, the null hypothesis of $\sigma^2_{SP} = 0$ is rejected at the 5% significance level. Hence, the sub-plot variance component must be considered in the estimation of this CRW damage equation.

Since tillage, block and whole-plot variance components are not significantly different from zero, these variables are removed and the equation re-estimated to obtain $\hat{\sigma}^2_{SP}$. The new output is given below.

DEPENDENT VARIABLE: CRATE
NUMBER OF OBSERVATIONS IN DATA SET = 144

GENERAL LINEAR MODELS PROCEDURE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE
MODEL	28	66.80083663	2.38574417
ERROR	115	36.14275712	0.31428484
CORRECTED TOTAL	143	102.94359375	
MODEL F =	7.59		PR > F = 0.0001

R-SQUARE	C.V.	ROOT MSE	CRATE MEAN
0.648907	19.0374	0.56061113	2.94479167

SOURCE	DF	TYPE I SS	F VALUE	PR > F
ADLT	1	23.25491738	73.99	0.0001
EGG	1	4.24450257	13.51	0.0004
TMTEG	1	12.94094344	41.18	0.0001
TMTADLT	1	3.98912497	12.69	0.0005
CRW(BL*TIL)	23	14.68296521	2.03	0.0077
YR	1	7.68838306	24.46	0.0001

The null hypothesis of $\sigma^2_{SP}=0$ is rejected at the 1% level. Therefore, the transformation approach is used in estimating the standard errors of the coefficients of this equation. As in the case of the equation estimating number of plants per acre, σ^2_{SP} is the only nonzero variance component. Hence, transformation given by equations (ix) and (x) is used.

3. DEPENDENT VARIABLE: CRATE
NUMBER OF OBSERVATIONS IN DATA SET = 144

GENERAL LINEAR MODELS PROCEDURE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE
MODEL	26	62.79672127	2.41525851
ERROR	117	40.14687248	0.34313566
CORRECTED TOTAL	143	102.94359375	
MODEL F =	7.04		PR > F = 0.0001

R-SQUARE	C.V.	ROOT MSE	CRATE MEAN
0.610011	19.8920	0.58577783	2.94479167

SOURCE	DF	TYPE I SS	F VALUE	PR > F
ADLT	1	23.25491738	67.77	0.0001
TMTADLT	1	16.18274894	47.16	0.0001
BL	3	2.20614665	2.14	0.0985
TIL	2	0.32127316	0.47	0.6273
TIL(BL)	6	2.20614323	1.07	0.3836
CRW(BL*TIL)	12	6.80444042	1.65	0.0865
YR	1	11.82105151	34.45	0.0001

Test 1.
TESTS OF HYPOTHESES USING THE TYPE I MS FOR CRW(BL*TIL) AS ERROR TERM

SOURCE	DF	TYPE I SS	F VALUE	PR > F
TIL(BL)	6	2.20614323	0.65	0.6914

Test 2.
TESTS OF HYPOTHESES USING THE TYPE I MS FOR TIL(BL) AS ERROR TERM

SOURCE	DF	TYPE I SS	F VALUE	PR > F
BL	3	2.20614665	2.00	0.2156

The F-value of 1.65 gives the test statistic for the null hypothesis of $\sigma^2_{SP} = 0$, indicating that σ^2_{SP} is not significantly different from zero at the 5% significance level. Similarly, test 1 and test 2 indicate that the null hypotheses $\sigma^2_{WP} = 0$ and $\sigma^2_{BL} = 0$ can be accepted. Hence, as all the variance components are not significantly different from zero at the five percent level, OLS can be used to estimate this CRW damage equation.

A2.2.4 ECB Damage Equations

1. DEPENDENT VARIABLE: TUN
   NUMBER OF OBSERVATIONS IN DATA SET = 216

GENERAL LINEAR MODELS PROCEDURE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE
MODEL	28	10636.03737848	379.85847780
ERROR	187	4791.83093885	25.62476438
CORRECTED TOTAL	215	15427.86831733	
MODEL F =	14.82		PR > F = 0.0001

R-SQUARE	C.V.	ROOT MSE	TUN MEAN
0.689404	35.2806	5.06209091	14.34807861

SOURCE	DF	TYPE I SS	F VALUE	PR > F
SHOT	1	898.91688225	35.08	0.0001
HTI	1	5329.26400583	207.97	0.0001
TMTSHOT	1	13.17700404	0.51	0.4742
BL	3	173.05747607	2.25	0.0839
TIL	2	1202.35862433	23.46	0.0001
TIL(BL)	6	65.63733068	0.43	0.8604
CRW(BL*TIL)	12	381.72830383	1.24	0.2576
YR	2	2571.89775145	50.18	0.0001

Test 1.
TESTS OF HYPOTHESES USING THE TYPE I MS FOR CRW(BL*TIL) AS ERROR TERM

SOURCE	DF	TYPE I SS	F VALUE	PR > F
TIL(BL)	6	65.63733068	0.34	0.9002

Test 2.
TESTS OF HYPOTHESES USING THE TYPE I MS FOR TIL(BL) AS ERROR TERM

SOURCE	DF	TYPE I SS	F VALUE	PR > F
BL	3	173.05747607	5.27	0.0405

Test 1 and the ANOVA table indicate that the null hypotheses $\sigma^2_{WP} = 0$ and $\sigma^2_{SP} = 0$ can be accepted. However, as indicated by test 2 the null hypothesis of $\sigma^2_{BL} = 0$ is rejected at the 5% significance level. Hence, the block variance component must be considered in the estimation of the standard errors of the coefficients of this ECB damage equation.

Since whole-plot and sub-plot variance components are not significantly different from zero, these variables are removed and the equation re-estimated to obtain $\hat{\sigma}^2_{BL}$. The new output is given below.

DEPENDENT VARIABLE: TUN

NUMBER OF OBSERVATIONS IN DATA SET = 216

GENERAL LINEAR MODELS PROCEDURE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE
MODEL	10	10373.94184469	1037.39418447
ERROR	205	5053.92647264	24.65329987
CORRECTED TOTAL	215	15427.86831733	
MODEL F =	42.08		PR > F = 0.0001

R-SQUARE	C.V.	ROOT MSE	TUN MEAN
0.672416	34.6054	4.96520894	14.34807861

SOURCE	DF	TYPE I SS	F VALUE	PR > F
SHOT	1	898.91688225	36.46	0.0001
HTI	1	5329.26400583	216.17	0.0001
TMTSHOT	1	13.17700404	0.53	0.4656
BL	3	173.05747607	2.34	0.0745
TIL	2	1202.35862433	24.39	0.0001
YR	2	2757.16785217	55.92	0.0001

As indicated by the F-value of 2.34, the null hypothesis of $\sigma^2_{BL}=0$ is accepted at the 5% significance level and OLS is used to estimate this equation.

2. DEPENDENT VARIABLE: TUN
NUMBER OF OBSERVATIONS IN DATA SET = 144

GENERAL LINEAR MODELS PROCEDURE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE
MODEL	27	5346.60567102	198.02243226
ERROR	116	3093.19553712	26.66547877
CORRECTED TOTAL	143	8439.80120814	
MODEL F =	7.43		PR > F = 0.0001
R-SQUARE	C.V.	ROOT MSE	TUN MEAN
0.633499	28.5358	5.16386278	18.09607458

SOURCE	DF	TYPE I SS	F VALUE	PR > F
LGLAR2	1	2934.53888703	110.05	0.0001
HTI	1	17.40868960	0.65	0.4207
TMTLGLR2	1	837.33835195	31.40	0.0001
BL	3	154.09548434	1.93	0.1292
TIL	2	31.82755563	0.60	0.5523
TIL(BL)	6	66.45298651	0.42	0.8676
CRW(BL*TIL)	12	263.55147367	0.82	0.6259
YR	1	1041.39224229	39.05	0.0001

Test 1.
TESTS OF HYPOTHESES USING THE TYPE I MS FOR CRW(BL*TIL) AS ERROR TERM

SOURCE	DF	TYPE I SS	F VALUE	PR > F
TIL(BL)	6	66.45298651	0.50	0.7939

Test 2.
TESTS OF HYPOTHESES USING THE TYPE I MS FOR TIL(BL) AS ERROR TERM

SOURCE	DF	TYPE I SS	F VALUE	PR > F
BL	3	154.09548434	4.64	0.0526

Test 1 and the ANOVA table indicate that the null hypotheses $\sigma^2_{WP}=0$ and $\sigma^2_{SP} = 0$ can be accepted. However, as indicated by test 2 the null hypothesis of $\sigma^2_{BL} = 0$ is accepted at the 5% level but is rejected at the 6% significance level. Hence, the block variance component is considered in the estimation of this ECB damage equation.

Since whole-plot and sub-plot variance components are not significantly different from zero, these variables are removed and the equation re-estimated to obtain $\hat{\sigma}^2_{BL}$. The new output is given below.

DEPENDENT VARIABLE: TUN
NUMBER OF OBSERVATIONS IN DATA SET = 144

GENERAL LINEAR MODELS PROCEDURE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE
MODEL	9	4952.04794580	550.22754953
ERROR	134	3487.75326234	26.02800942
CORRECTED TOTAL	143	8439.80120814	
MODEL F =	21.14		PR > F = 0.0001
R-SQUARE	C.V.	ROOT MSE	TUN MEAN
0.586749	28.1927	5.10176532	18.09607458

SOURCE	DF	TYPE I SS	F VALUE	PR > F
LGLAR2	1	2934.53888703	112.75	0.0001
HTI	1	17.40868960	0.67	0.4149
TMTLGLR2	1	837.33835195	32.17	0.0001
BL	3	154.09548434	1.97	0.1210
TIL	2	31.82755563	0.61	0.5441
YR	1	976.83897725	37.53	0.0001

As indicated by the F-value of 1.97, the null hypothesis of $\sigma^2_{BL}=0$ is accepted and OLS is used in estimating this equation.

3. DEPENDENT VARIABLE: TUN
   NUMBER OF OBSERVATIONS IN DATA SET = 144

GENERAL LINEAR MODELS PROCEDURE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE
MODEL	29	5477.92250098	188.89387934
ERROR	114	2961.87870716	25.98139217
CORRECTED TOTAL	143	8439.80120814	
MODEL F =	7.27		PR > F = 0.0001

R-SQUARE	C.V.	ROOT MSE	TUN MEAN
0.649058	28.1674	5.09719454	18.09607458

SOURCE	DF	TYPE I SS	F VALUE	PR > F
LGLAR2	1	2934.53888703	112.95	0.0001
SHOT	1	1222.91829294	47.07	0.0001
HTI	1	11.17237205	0.43	0.5133
TMTLGLR2	1	296.58783830	11.42	0.0010
TMTSHOT	1	12.98057219	0.50	0.4811
BL	3	145.61165474	1.87	0.1389
TIL	2	59.04941456	1.14	0.3246
TIL(BL)	6	90.62779128	0.58	0.7445
CRW(BL*TIL)	12	201.76821134	0.65	0.7977
YR	1	502.66746656	19.35	0.0001

Test 1.
TESTS OF HYPOTHESES USING THE TYPE I MS FOR CRW(BL*TIL) AS ERROR TERM

SOURCE	DF	TYPE I SS	F VALUE	PR > F
TIL(BL)	6	90.62779128	0.90	0.5266

Test 2.
TESTS OF HYPOTHESES USING THE TYPE I MS FOR TIL(BL) AS ERROR TERM

SOURCE	DF	TYPE I SS	F VALUE	PR > F
BL	3	145.61165474	3.21	0.1041

The F-value of 0.65 gives the test statistic for the null hypothesis of $\sigma^2_{SP} = 0$, indicating that σ^2_{SP} is not significantly different from zero at the 5% significance level. Similarly, test 1 and test 2 indicate that the null hypotheses $\sigma^2_{WP} = 0$ and $\sigma^2_{BL} = 0$ can be accepted. Hence, as all the variance components are not significantly different from zero, OLS can be used to estimate this ECB damage equation.

APPENDIX 3

SIMULATION COMPUTER PROGRAM

```
program BugSim1;
uses CRT,PRINTER,UtilMod;
const
  maxsn = 500;
type
  costrec  = record
               cprice   : real;                  {corn price}
               tillcost : array[1..3] of real; {tillage costs}
               ccost    : real;                  {crw control cost}
               ecost    : real;                  {ecb control cost}
             end;
  earray   = array[1..12] of real;
  ematrix  = array[1..50] of earray;
  parrec   = record
               a  : array[1..7] of real;       {h2}
               b  : array[1..6] of real;       {ear}
               c  : array[1..6] of real;       {stand}
               d  : array[1..8] of real;       {yield}
               ab : array[1..6] of real;       {ecb, full info}
               bb : array[1..4] of real;       {ecb,larvae only}
               cb : array[1..8] of real;       {ecb, shothole only}
               aw : array[1..6] of real;       {crw, full info}
               bw : array[1..4] of real;       {crw, adult only}
               cw : array[1..5] of real;       {crw, egg only}
             end;
```

1This program was written by Robert P. King.

```
vparrec  = record
             sd1  : array[1..5] of real;     {ecb, full info}
             sd2  : array[1..5] of real;     {ecb, larvae only}
             sd3  : array[1..6] of real;     {ecb, shothole only}
             sd4  : array[1..3] of real;     {crw, full info}
             sd5  : array[1..3] of real;     {crw, adult only}
             sd6  : array[1..4] of real;     {crw, egg only}
             sd7  : array[1..5] of real;     {h2}
             sd8  : array[1..5] of real;     {ear}
             sd9  : array[1..3] of real;     {stand}
             sd10 : array[1..5] of real;     {yield}
           end;
sarray   = array[1..4] of real;
smatrix  = array[1..10] of sarray;
revrec   = record
             rev : array[1..maxsn] of real;
           end;
var
  resfname  : string[12];
  errfname  : string[12];
  infile    : text;
  i,j,k     : integer;
  ns        : integer;
  ei,wi     : integer;
  cflag     : char;
  nstate    : integer;
  mp        : parrec;        {model parameters}
  vp        : vparrec;       {variance parameters}
  costr     : costrec;       {cost and price info}
  e         : ematrix;       {matrix of random errors}
  till      : integer;       {tillage indicator}
  strat     : sarray;        {array of strategy parameters}
  icond     : smatrix;       {array of initial conditions}
```

```
  srev       : revrec;        {record of net revenue levels}
  scrw       : integer;       {strategy type indicator for CRW}
  secb       : integer;       {strategy type indicator for ECB}
  h1         : real;          {early height}
  s1         : real;          {early stand}
  avgshot    : real;          {average shotholes}
  netrev     : revrec;        {net revenue}
  crwcontrol : integer;
  ecbcontrol : integer;
  avgnr      : real;
  avgcrw     : real;
  avgecb     : real;
  stdnr      : real;
  stdcrw     : real;
  stdecb     : real;
  eu,ra      : sarray;
{*******************************************************************
*                          PROCEDURE GETMP                          *
*  This procedure reads a text file that contains model parameters. *
*******************************************************************}
procedure GetMp(var mp  : parrec);
var
  fname   :  string[12];
  mpfile  :  text;
  i       :  integer;
begin {procedure GetMP}
  write('Enter the model parameter file name:     ');
  readln(fname);
  writeln(lst,'Model parameter file name:        ',fname);
  Assign(mpfile,fname);
  Reset(mpfile);
  with mp do
    begin
      for i:=1 to 6 do
```

```
        read(mpfile,a[i]);
      readln(mpfile,a[7]);
      for i:=1 to 5 do
        read(mpfile,b[i]);
      readln(mpfile,b[6]);
      for i:=1 to 5 do
        read(mpfile,c[i]);
      readln(mpfile,c[6]);
      for i:=1 to 7 do
        read(mpfile,d[i]);
      readln(mpfile,d[8]);
      for i:=1 to 5 do
        read(mpfile,ab[i]);
      readln(mpfile,ab[6]);
      for i:=1 to 3 do
        read(mpfile,bb[i]);
      readln(mpfile,bb[4]);
      for i:=1 to 7 do
        read(mpfile,cb[i]);
      readln(mpfile,cb[8]);
      for i:=1 to 5 do
        read(mpfile,aw[i]);
      readln(mpfile,aw[6]);
      for i:=1 to 3 do
        read(mpfile,bw[i]);
      readln(mpfile,bw[4]);
      for i:=1 to 4 do
        read(mpfile,cw[i]);
      readln(mpfile,cw[5]);
    end;
  close(mpfile);
end; {procedure GetMP}
```

```
{*********************************************************************
*                          PROCEDURE GETVP                           *
* This procedure reads a text file that contains variance parameters.*
*********************************************************************}

procedure GetVp(var vp  : vparrec);

var
  fname   :  string[12];
  vpfile  :  text;
  i       :  integer;

begin {procedure GetVP}
  write('Enter the variance parameter file name:  ');
  readln(fname);
  writeln(lst,'Variance parameter file name:      ',fname);
  Assign(vpfile,fname);
  Reset(vpfile);
  with vp do
    begin
      for i:=1 to 4 do
        read(vpfile,sd1[i]);
      readln(vpfile,sd1[5]);
      for i:=1 to 4 do
        read(vpfile,sd2[i]);
      readln(vpfile,sd2[5]);
      for i:=1 to 5 do
        read(vpfile,sd3[i]);
      readln(vpfile,sd3[6]);
      for i:=1 to 2 do
        read(vpfile,sd4[i]);
      readln(vpfile,sd4[3]);
      for i:=1 to 2 do
        read(vpfile,sd5[i]);
      readln(vpfile,sd5[3]);
      for i:=1 to 3 do
        read(vpfile,sd6[i]);
```

```
      readln(vpfile,sd6[4]);
      for i:=1 to 4 do
        read(vpfile,sd7[i]);
      readln(vpfile,sd7[5]);
      for i:=1 to 4 do
        read(vpfile,sd8[i]);
      readln(vpfile,sd8[5]);
      for i:=1 to 2 do
        read(vpfile,sd9[i]);
      readln(vpfile,sd9[3]);
      for i:=1 to 4 do
        read(vpfile,sd10[i]);
      readln(vpfile,sd10[5]);
    end;
  close(vpfile);
end; {procedure GetVP}

{*****************************************************************
*                     PROCEDURE GETCOSTR                         *
*****************************************************************}
procedure GetCostR(var costr  : costrec;
                   var ra     : sarray);
var
  fname   :  string[12];
  crfile  :  text;
  i       :  integer;
begin {procedure GetCostR}
  writeln;
  writeln;
  write('Enter the cost and price file name:      ');
  readln(fname);
  writeln(lst,'Cost and price file name:         ',fname);
  Assign(crfile,fname);
  Reset(crfile);
```

```
  with costr do
    begin
      readln(crfile,cprice);
      for i:=1 to 2 do
        read(crfile,tillcost[i]);
      readln(crfile,tillcost[3]);
      readln(crfile,ccost);
      readln(crfile,ecost);
    end;
    readln(crfile,ra[1],ra[2],ra[3],ra[4]);
  close(crfile);
end; {procedure GetCostR}


{*******************************************************************
*                        PROCEDURE GETICOND                        *
*******************************************************************}
procedure GetICond(var icond   : smatrix;
                   var s1,h1   : real;
                   var avgshot : real);
var
  fname   :  string[12];
  icfile  :  text;
  i,j     :  integer;
begin {procedure GetICond}
  writeln;
  writeln;
  write('Enter the initial condition file name:     ');
  readln(fname);
  writeln(lst,'Initial condition file name:      ',fname);
  Assign(icfile,fname);
  Reset(icfile);
  for j:=1 to 10 do
    begin
```

```
      for i:=1 to 3 do
        read(icfile,icond[j,i]);
      readln(icfile,icond[j,4]);
    end;
  readln(icfile,s1);
  readln(icfile,h1);
  readln(icfile,avgshot);
  close(icfile);
{  writeln(lst);
  writeln(lst,'Egg count:   ',icond[1]:7:2,'     Adult count: ',
                              icond[2]:7:2);
  writeln(lst,'Shot holes: ',icond[3]:7:2,'     Larvae:       ',
                              icond[4]:7:2);}
end; {procedure GetICond}

{**********************************************************************
*                      PROCEDURE GETSTRATINFO                         *
**********************************************************************}
procedure GetStratInfo(var till    : integer;
                       var strat   : sarray);
begin {procedure GetStratInfo}
  ClrScr;
  write('Enter the tillage indicator:    ');
  readln(till);
  writeln;
  write('Enter the CRW B-C ratio:        ');
  readln(strat[1]);
  writeln;
  write('Enter the ECB B-C ratio:        ');
  readln(strat[2]);
  writeln(lst);
  writeln(lst,'Strategy Information');
  write(lst,'    Tillage:       ');
  if (till = 0)
```

```
    then writeln(lst,'Chisel');
  if (till = 1)
    then writeln(lst,'Ridge');
  if (till = 2)
    then writeln(lst,'No Till');
  writeln(lst,'     CRW B-C Ratio: ',strat[1]:5:2);
  writeln(lst,'     ECB B-C Ratio: ',strat[2]:5:2);
end; {procedure GetStratInfo}

{*********************************************************************
*                      PROCEDURE SETCRWCONTROL                       *
*********************************************************************}

procedure SetCRWControl(mp          : parrec;
                        vp          : vparrec;
                        cr          : costrec;
                        strat       : sarray;
                        icond       : sarray;
                        h1,s1       : real;
                        avgshot     : real;
                        till        : integer;
                        scrw        : integer;
                        secb        : integer;
                        var crwcon  : integer);
var
  ecbcontrol  : integer;
  crwcontrol  : integer;
  bestcost    : array[1..2] of real;
  bestrev     : array[1..2] of real;
  netrev      : array[1..2] of real;
  i,j         : integer;
  crw,ecb     : real;
  lh2         : real;
  lear        : real;
  lstand      : real;
```

```
  lyield       : real;
  yield        : real;
  sy           : real;

begin {procedure SetCRWControl}
  for crwcontrol:=0 to 1 do
    begin
      for ecbcontrol:=0 to 1 do
        begin
          with mp do
            begin
              if (secb = 1)
                then
                  ecb:=rmax(1.0,(ab[1]+ab[2]*avgshot+ab[3]*icond[4]+
                            ab[4]*(avgshot*ecbcontrol)
                            +ab[5]*(icond[4]*ecbcontrol)+ab[6]*0.5));
              if (secb = 2)
                then
                  begin
                    ecb:=cb[1]+cb[2]*h1+cb[3]*avgshot+
                           cb[4]*avgshot*ecbcontrol
                                   +cb[5]*0.33+cb[6]*0.33;
                    if (till = 1)     {ridge till}
                      then ecb:=rmax(1.0,(ecb+cb[7]));
                    if (till = 2)     {min till}
                      then ecb:=rmax(1.0,(ecb+cb[8]));
                  end;
              if (secb = 3)
                then
                  ecb:=rmax(1.0,(bb[1]+bb[2]*icond[4]+bb[3]*icond[4]
                                   *ecbcontrol+bb[4]*0.5));
              if (scrw = 1)
                then
```

```
    crw:=aw[1]+aw[2]*icond[2]+aw[3]*icond[1]+
             aw[4]*(icond[2]*crwcontrol)
             +aw[5]*(icond[1]*crwcontrol)+aw[6]*0.5;
if (scrw = 2)
  then
    crw:=bw[1]+bw[2]*icond[2]+bw[3]*icond[2]*crwcontrol+
              bw[4]*0.5;
if (scrw = 3)
  then
    crw:=cw[1]+cw[2]*icond[1]+cw[3]*icond[1]*crwcontrol+
              cw[4]*0.33+cw[5]*0.33;

lh2:=a[1]+a[2]*ln(h1)+a[3]*crw+a[4]*0.33+a[5]*0.33;
if (till = 1)           {ridge till}
  then lh2:=lh2+a[6];
if (till = 2)           {min till}
  then lh2:=lh2+a[7];
lear:=b[1]+b[2]*ln(ecb)+b[3]*0.33+b[4]*0.33;
if (till = 1)           {ridge till}
  then lear:=lear+b[5];
if (till = 2)           {min till}
  then lear:=lear+b[6];

lstand:=c[1]+c[2]*ln(s1)+c[3]*crw+c[4]*ln(ecb)+c[5]*0.33
            +c[6]*0.33;

lyield:=d[1]+d[2]*lstand+d[3]*lear+d[4]*lh2+d[5]*0.33
           +d[6]*0.33;
if (till = 1)           {ridge till}
  then lyield:=lyield+d[7];
if (till = 2)           {min till}
  then lyield:=lyield+d[8];
sy:=vp.sd10[1]+vp.sd10[2]*0.33+vp.sd10[3]*0.33;
```

```
            if (till = 1)
              then sy:=sy+vp.sd10[4];
            if (till = 2)
              then sy:=sy+vp.sd10[5];
            sy:=sqr(sy);
            yield:=exp(lyield+(sy/2));
          end;

        with cr do
          begin
            netrev[ecbcontrol+1]:=yield*cprice;
          end;
      end;

    if (((netrev[2]-netrev[1])/cr.ecost) < strat[2])
      then
        begin
          bestrev[crwcontrol+1]:=netrev[1];
          bestcost[crwcontrol+1]:=cr.ccost*crwcontrol;
        end
      else
        begin
          bestrev[crwcontrol+1]:=netrev[2];
          bestcost[crwcontrol+1]:=cr.ccost*crwcontrol+cr.ecost;
        end;

  end;
 if (((bestrev[2]-bestrev[1])/(bestcost[2]-bestcost[1])) > strat[1])
   then
     crwcon:=1
   else
     crwcon:=0;
{WRITE(LST,'CRW B-C Ratio:   ');
```

```
WRITELN(LST,((BESTREV[2]-BESTREV[1])/(BESTCOST[2]-BESTCOST[1])):
                                                          10:5);}
end; {procedure SetCRWControl}



{*********************************************************************
*                        PROCEDURE SIMYEAR                           *
*  This procedure simulates a strategy for one crop year.  It is     *
*  repeatedly as part of the Monte Carlo simulations.  It returns a  *
*  net revenue level.                                                *
*********************************************************************}

procedure SimYear(mp          : parrec;
                  vp          : vparrec;
                  cr          : costrec;
                  e           : earray;
                  strat       : sarray;
                  icond       : sarray;
                  h1,s1       : real;
                  avgshot     : real;
                  till        : integer;
                  scrw        : integer;
                  secb        : integer;
                  crwcontrol  : integer;
                  var ecbcon  : integer;
                  var r       : real);
var
  ecbcontrol  : integer;
  netrev      : array[1..2] of real;
  crw,ecb     : real;
  lh2         : real;
  lear        : real;
  lstand      : real;
  lyield      : real;
  yield       : real;
```

```
  sy          : real;
  s           : array[1..10] of real;

begin {procedure SimYear}
  for ecbcontrol:=0 to 1 do
    begin
      with mp do
        begin
          if (secb = 1)
            then
              ecb:=rmax(1.0,(ab[1]+ab[2]*icond[3]+ab[3]*icond[4]+
                            ab[4]*(icond[3]*ecbcontrol)
                            +ab[5]*(icond[4]*ecbcontrol)+ab[6]*0.5));
          if (secb = 2)
            then
              begin
                ecb:=rmax(1.0,(cb[1]+cb[2]*h1+cb[3]*icond[3]+
                              cb[4]*icond[3]*ecbcontrol
                              +cb[5]*0.33+cb[6]*0.33));
                if (till = 1)     {ridge till}
                  then ecb:=rmax(1.0,(ecb+cb[7]));
                if (till = 2)     {min till}
                  then ecb:=rmax(1.0,(ecb+cb[8]));
              end;
          if (secb = 3)
            then
              ecb:=rmax(1.0,(bb[1]+bb[2]*icond[4]+bb[3]*icond[4]
                            *ecbcontrol+bb[4]*0.5));

          if (scrw = 1)
            then
              crw:=aw[1]+aw[2]*icond[2]+aw[3]*icond[1]+
                     aw[4]*(icond[2]*crwcontrol)
```

```
            +aw[5]*(icond[1]*crwcontrol)+aw[6]*0.5;
if (scrw = 2)
  then
    crw:=bw[1]+bw[2]*icond[2]+bw[3]*icond[2]*crwcontrol+
              bw[4]*0.5;
if (scrw = 3)
  then
    crw:=cw[1]+cw[2]*icond[1]+cw[3]*icond[1]*crwcontrol+
              cw[4]*0.33+cw[5]*0.33;

lh2:=a[1]+a[2]*ln(h1)+a[3]*crw+a[4]*0.33+a[5]*0.33;
if (till = 1)           {ridge till}
  then lh2:=lh2+a[6];
if (till = 2)           {min till}
  then lh2:=lh2+a[7];

lear:=b[1]+b[2]*ln(ecb)+b[3]*0.33+b[4]*0.33;
if (till = 1)           {ridge till}
  then lear:=lear+b[5];
if (till = 2)           {min till}
  then lear:=lear+b[6];

lstand:=c[1]+c[2]*ln(s1)+c[3]*crw+c[4]*ln(ecb)+c[5]*0.33
            +c[6]*0.33;

lyield:=d[1]+d[2]*lstand+d[3]*lear+d[4]*lh2+d[5]*0.33
              +d[6]*0.33;
if (till = 1)           {ridge till}
  then lyield:=lyield+d[7];
if (till = 2)           {min till}
  then lyield:=lyield+d[8];
sy:=vp.sd10[1]+vp.sd10[2]*0.33+vp.sd10[3]*0.33;
if (till = 1)
```

```
            then sy:=sy+vp.sd10[4];
          if (till = 2)
            then sy:=sy+vp.sd10[5];
          sy:=sqr(sy);
          yield:=exp(lyield+(sy/2));
        end;
      with cr do
        begin
          netrev[ecbcontrol+1]:=yield*cprice;
        end;
    end;
  if (((netrev[2]-netrev[1])/cr.ecost) > strat[2])
    then
      ecbcontrol:=1
    else
      ecbcontrol:=0;

{WRITE(LST,'ECB B-C Ratio:   ');
WRITELN(LST,((NETREV[2]-NETREV[1])/(cr.eCOST)):10:5);}
  with mp do
    begin
      s[1]:=vp.sd1[1]+vp.sd1[2]*ecbcontrol+vp.sd1[3]*e[12];
      if (till = 1)
        then s[1]:=s[1]+vp.sd1[4];
      if (till = 2)
        then s[1]:=s[1]+vp.sd1[5];
      s[1]:=s[1]*e[1];
      ecb:=rmax(1.0,(ab[1]+ab[2]*icond[3]+ab[3]*icond[4]+ab[4]
               *(icond[3]*ecbcontrol+ab[5]*(icond[4]*ecbcontrol)
               +ab[6]*e[12]+s[1]));

      s[4]:=(vp.sd4[1]+vp.sd4[2]*crwcontrol+vp.sd4[3]*e[12])*e[4];
      crw:=aw[1]+aw[2]*icond[2]+aw[3]*icond[1]+aw[4]*(icond[2]*
```

```
    crwcontrol)+aw[5]*(icond[1]*crwcontrol)+aw[6]*e[12]+s[4];

s[7]:=vp.sd7[1]+vp.sd7[2]*e[11]+vp.sd7[3]*e[12];
if (till = 1)
  then s[7]:=s[7]+vp.sd7[4];
if (till = 2)
  then s[7]:=s[7]+vp.sd7[5];
s[7]:=s[7]*e[7];
lh2:=a[1]+a[2]*ln(h1)+a[3]*crw+a[4]*e[11]+a[5]*e[12]+s[7];
if (till = 1)           {ridge till}
  then lh2:=lh2+a[6];
if (till = 2)           {min till}
  then lh2:=lh2+a[7];

s[8]:=vp.sd8[1]+vp.sd8[2]*e[11]+vp.sd8[3]*e[12];
if (till = 1)
  then s[8]:=s[8]+vp.sd8[4];
if (till = 2)
  then s[8]:=s[8]+vp.sd8[5];
s[8]:=s[8]*e[8];
lear:=b[1]+b[2]*ln(ecb)+b[3]*e[11]+b[4]*e[12]+s[8];
if (till = 1)           {ridge till}
  then lear:=lear+b[5];
if (till = 2)           {min till}
  then lear:=lear+b[6];

s[9]:=(vp.sd9[1]+vp.sd9[2]*e[11]+vp.sd9[3]*e[12])*e[9];
lstand:=c[1]+c[2]*ln(s1)+c[3]*crw+c[4]*ln(ecb)+c[5]*e[11]
              +c[6]*e[12]+s[9];

s[10]:=vp.sd10[1]+vp.sd10[2]*e[11]+vp.sd10[3]*e[12];
if (till = 1)
  then s[10]:=s[10]+vp.sd10[4];
```

```
      if (till = 2)
        then s[10]:=s[10]+vp.sd10[5];
      s[10]:=s[10]*e[10];
      lyield:=d[1]+d[2]*lstand+d[3]*lear+d[4]*lh2+d[5]*e[11]
                    +d[6]*e[12]+s[10];
      if (till = 1)           {ridge till}
        then lyield:=lyield+d[7];
      if (till = 2)           {min till}
        then lyield:=lyield+d[8];
      yield:=exp(lyield);
    end;

  with cr do
    begin
   r:=yield*cprice-tillcost[till+1]-ccost*crwcontrol-ecost*ecbcontrol;
    end;

  ecbcon:=ecbcontrol;

{WRITELN(LST,'Yield: ',YIELD:8:2,'     ECB: ',ECB:8:2,'     CRW: ',
          CRW:8:2,     '     Height: ',exp(lh2):8:2);}
end; {procedure SimYear}

{*********************************************************************
*                      PROCEDURE PRINTHEADER                         *
*********************************************************************}
procedure PrintHeader;
begin {procedure Printheader}
  writeln(lst);
  writeln(lst);
  writeln(lst,' Information State                              Control'
  writeln(lst,'   CRW      ECB         Net Return        CRW
end; {procedure PrintHeader}
```

```
{*********************************************************************
*                    PROCEDURE PRINTRESULT                           *
*********************************************************************}
procedure PrintResult(wi,ei          : integer;
                      avgnr,stdnr    : real;
                      avgcrw,stdcrw  : real;
                      avgecb,stdecb  : real;
                      eu             : sarray);
begin {procedure PrintResult}
  writeln(lst);
  writeln(lst,'     ',wi:1,'          ',ei:1,'           ',avgnr:10:2,
          '           ',avgcrw:3:1,'           ',avgecb:3:1);
  writeln(lst,'                                  (',stdnr:10:2,
          ')        (',stdcrw:3:1,')        (',stdecb:3:1,')');
  writeln(lst,'       ',eu[1]:10:2,eu[2]:10:2,eu[3]:10:2,eu[4]:10:2);
end; {procedure PrintResult}

{*********************************************************************
*                      PROCEDURE LOOPMENU                            *
*********************************************************************}
procedure Loopmenu(var rflag : char);
begin {procedure Loopmenu}
  clrscr;
  gotoxy(23,23);
  writeln('Do you want to try a new strategy?');
  writeln(' ');
  write('                              Enter Y or N:    ');
  repeat
    rflag:=upcase(ReadKey);
  until ((rflag = 'Y') or (rflag = 'N'));
end; {procedure LoopMenu}

begin {program BugSim}
  ClrScr;
```

```
write('Enter the number of states of nature:     ');
readln(nstate);
writeln;
writeln;
GetMP(mp);                          {Read model parameter file}
GetVP(vp);                          {Read variance parameter file}
GetCostr(costr,ra);                 {Read Cost file}
GetICond(icond,s1,h1,avgshot);      {Read initial condition file}
writeln(lst);
write('Enter the error file name:                ');
readln(errfname);
writeln(lst,'Error file name:                 ',errfname);
Assign(infile,errfname);
Reset(infile);
for i:=1 to nstate do
  begin
    for j:=1 to 11 do
      begin
        read(infile,e[i,j]);
      end;
    readln(infile,e[i,12]);
  end;
close(infile);
writeln(lst);
write('Enter the results file name:            ');
readln(resfname);
writeln(lst,'Results file name:               ',resfname);
writeln(lst,'Number of states of nature:      ',nstate:5);
cflag:='Y';
while (cflag = 'Y') do
  begin
    GetStratInfo(till,strat);       {Enter strategy information}
    FillChar(netrev,SizeOf(netrev),0);
```

```
PrintHeader;
for wi:=1 to 3 do
  begin
    for ei:=1 to 3 do
      begin
        ns:=0;
        avgnr:=0.0;
        avgcrw:=0.0;
        avgecb:=0.0;
        stdnr:=0.0;
        stdcrw:=0.0;
        stdecb:=0.0;
        for k:=1 to 4 do
          eu[k]:=0.0;
        for j:=1 to 10 do
          begin
            SetCRWControl(mp,vp,costr,strat,icond[j],h1,s1,
                          avgshot,till,wi,ei,crwcontrol);

            for i:=1 to nstate do
              begin
                ns:=ns+1;
                SimYear(mp,vp,costr,e[i],strat,icond[j],h1,
                        s1,avgshot,till,wi,ei,crwcontrol,
                        ecbcontrol,netrev.rev[ns]);
                avgnr:=avgnr+netrev.rev[ns];
                stdnr:=stdnr+sqr(netrev.rev[ns]);
                avgcrw:=avgcrw+crwcontrol;
                stdcrw:=stdcrw+sqr(crwcontrol);
                avgecb:=avgecb+ecbcontrol;
                stdecb:=stdecb+sqr(ecbcontrol);
                for k:=1 to 4 do
                  begin
```

```
                    if (ra[k] > 0.0)
                   then eu[k]:=eu[k]-exp(-ra[k]*netrev.rev[ns]);
                    if (ra[k] < 0.0)
                   then eu[k]:=eu[k]+exp(-ra[k]*netrev.rev[ns]);
                  end;
              end;
          end;
        avgnr:=avgnr/(nstate*10);
        stdnr:=sqrt((stdnr/(nstate*10))-sqr(avgnr));
        avgcrw:=avgcrw/(nstate*10);
        stdcrw:=sqrt((stdcrw/(nstate*10))-sqr(avgcrw));
        avgecb:=avgecb/(nstate*10);
        stdecb:=sqrt((stdecb/(nstate*10))-sqr(avgecb));
        for k:=1 to 4 do
          begin
            eu[k]:=eu[k]/(nstate*10);
            if (ra[k] > 0.0)
              then eu[k]:=-ln(-eu[k])/ra[k];
            if (ra[k] < 0.0)
              then eu[k]:=-ln(eu[k])/ra[k];
          end;
      PrintResult(wi,ei,avgnr,stdnr,avgcrw,stdcrw,avgecb,stdecb,eu);
{save results}
            end;
        end;
      LoopMenu(cflag);
    end;
  ClrScr;
end. {program BugSim}
```

APPENDIX 4

SCOUTING COST SURVEY QUESTIONNAIRE AND RESULTS

A4.1 Scouting Cost Survey Questionnaire

1. What are the services offered by your consultancy to a farmer?

2. What are the consultancy fees typically charged?

3. Are your services offered only as a 'package deal' or do you also offer scouting services for individual pests?

If you do, what are the services and what is the fee charged?

4. What is the hourly wage paid to the scouts employed?

5. What is the size of a typical corn field that you scout?

6. For this typical field, how many locations do you normally sample?

   1. Corn rootworm adults ____________________
   2. ECB shotholing ($1^{st.}$ gen) ____________________
   3. ECB larvae sampling ____________________
   4. ECB 2^{nd} gen egg sampling ____________________

7. How many plants do you normally sample at each location in a field?

1. Corn rootworm adults ______________________
2. ECB shotholing ($1^{st.}$ gen) ______________________
3. ECB larvae sampling ______________________
4. ECB 2^{nd} gen egg sampling ______________________

8. What is the total number of hours normally required to sample this typical field for

1. Corn rootworm adults ______________________
2. ECB shotholing ($1^{st.}$ gen) ______________________
3. ECB larvae sampling ______________________
4. ECB 2^{nd} gen egg sampling ______________________

9. If you require any special equipment for scouting, please mention it along with its purchase cost.

	Equipment	Cost
1. Corn rootworm adults	____________	________
2. ECB shotholing ($1^{st.}$ gen)	____________	________
3. ECB larvae sampling	____________	________
4. ECB 2^{nd} gen egg sampling	____________	________

10. For this typical field, how many individuals are normally actively engaged in scouting (yourself and/or hired scouts)?

1. Corn rootworm adults ______________________
2. ECB shotholing ($1^{st.}$ gen) ______________________
3. ECB larvae sampling ______________________
4. ECB 2^{nd} gen egg sampling ______________________

If your answers do not fit in the spaces provided, please feel free to attach additional papers.

Due Date: July 31, 1989.

Please return in enclosed envelope. Thank you.

A4.2 Survey Results

Firm No.	Services Offered	Consult. fees	Services offered as
1.	-Crop scouting -Soil testing	$1.50-6.00 .75-6.00	Package Package
2.	-Key time scout. -Soil sampling & mapping -Spec. insect scouting -Newsletter -weed scout & herbi advice -Manure mgmt. -Residual nitrogen	$150 base plus $3.50/A CRW $.75/A	Package & individual
3.	-Fertility mgmt. -Full Crop pest mgmt.	$2.00/A $4.00-7.00/A $1.00/trip(indiv)	Both
4.	-hybrid selection -herbi & pesti mgmt -field scouting -tillage recommend -fertility " -soil sampling -manure analysis -nitrate testing	$4/A	Package
5.	-High intensity soil test -Nitrate test -crop planning -Field scouting -trouble shooting -seminars	$.60/scouting trip $50/hour for others	Package for scouting
6.	-Crop planning -Soil samples -pest monitoring -Aerial IR photo -Newsletter -Weigh wagon -fert, chem, variety tillage recomm. -crop budgeting	$3.40/A	Package

Survey Results (continued)

Firm No.	Services Offered	Consult. fees	Services offered as
7.	-Crop scouting -Fertility mgmt	$3.50-4.50/A	Package
8.	-soil fertility -crop planning -field monitoring, weed insect disease -prod records	$ 3.50/A	Package
9.	-Soil testing -Scouting -Infrared photo Fert/herb recommen	$3-4/A	Package Indiv. pes
10.	-Soil testing -Crop scouting weed insect disease	$3 for each or $5 for both	Package

Survey Results (continued)

Firm No.	Wage of scouts	Size of typical corn field
1.	$5-8	40-300 A
2.	$5	80A
3.	not applicable	35A
4.	$6.25	60A
5.	$4.50/A	80A
6.	$250 plus $400/week	80A
7.	not applicable	65A
8.	$900-$1400 per month	80A
9.	$5/hr $50/A/visit	80-160
10.	$5.50/hr	60A

Survey Results (continued)

Firm No.	locations sampled	plants/ location	hours reqd	special equip & cost
CRW adults				
1.	-	-	-	
2.	10-50 plants		80 acres/hr (other things monitored too)	
3. (larva)	5 5 silk clippings	5-10	30-45 mins	
4.	8	16	30 min	
5.	-	-	-	
6.	1	10-50	1 hr	
7.	20	1	30 min	
8.	3-5	10	35 min	
9.	5	20	2-3 hrs	
10.	2-5	10	15 min	
ECB1 shotholes				
1.	-	-	-	
2.	10	20	as CRW	air filter helmets $300.00
3.	10	10	30 or <	
4.	15	50	45 min (variable)	
5.	6-8	20	1 hr	
6.	1	100	30 min	
7.	5	20	30 min	
8.	3-5	10	35 min	
9.	5	20	2-3hrs	
10.	5	10	20 min	

REFERENCES

Anderson, J.R., "Simulation: Methodology and Application in Agricultural Economics", *Review of Marketing and Agricultural Economics*, 42(1974):3-36.

Anderson, J.R., J.L. Dillon and J.B. Hardaker, *Agricultural Decision Analysis*, The Iowa State University Press, Ames, Iowa 50010, 1977.

Andow, D. A. and K. Kiritani, "The Economic Injury Level and the Control Threshold", *Japanese Pesticide Information* 43(1983):3-8.

Andow, D. A. and K. R. Ostlie, "First Generation European Corn Borer Response to Three Conservation Tillage Systems in Minnesota", Unpublished, 1989.

Arrow, K.J. "Liquidity Preferences", Lecture VI in *Lecture Notes for Economics 285, The Economics of Uncertainty*, Stanford University, (undated):33-53.

Bosch, D. J. "The Value of Soil Water and Weather Information in Increasing Irrigation Efficiency", Ph.D. dissertation, University of Minnesota, 1984.

Bosch, D. J. and V. R. Eidman, "Valuing Information when Risk Preferences are Nonneutral: An Application to Irrigation Scheduling," *American Journal of Agricultural Economics*, 69(1987):658-68.

Briggs, D.W., "The Optimal Control of Northern Corn Rootworm in Minnesota in the Presence of Dynamic Externalities", Ph.D. dissertation, University of Minnesota, 1989.

Brindley T.A., A.N. Sparks, W.B. Showers and W.D. Guthrie, "Recent Research Advances on the European Corn Borer in North America", Paper # J-7841, Iowa Agriculture and Home Economics Experiment

Station, Ames, Iowa, Proj. 1923, March 1974.

Byerlee, D. and J.R. Anderson, "Risk, Utility and the Value of Information in Farmer Decision Making", *Review of Marketing and Agricultural Economics*, 50(1982):231-46.

Carlson, G.A., "A Decision Theoretic Approach to Crop Disease Prediction and Control", *American Journal of Agricultural Economics* 52(1970):216-26.

Chavas, Jean-Paul and R.D. Pope, "Information: Its Measurement and Valuation", *American Journal of Agricultural Economics*, 66(1984): 705-10.

Chiang, H.C., "Bioeconomics of the Northern and Western Corn Rootworms," *Annual Review of Entomology*, 18(1973):47-72.

Chiang, H.C. and A.C. Hodson, "Population Fluctuations of the European Corn Borer, Pyrausta Nubilalis , at Waseca, Minnesota, 1948 to 1957", *Annals of the Entomological Society of America*, 52(1959): 710-24.

Clawson, M., "Methods of Measuring the Demand for and Value of Outdoor Recreation", Washington D.C.: Resources for the future, 1959.

Cochran, Mark and Lindon J. Robison, "Redefining the Economic Threshold", Paper submitted to Western Agricultural Economics Association's annual meeting, Lincoln, Nebraska, July 1981.

Cousens, R., C.J. Doyle, B.J. Wilson and G.W. Cussans, "Modelling the Economics of Controlling *Avena fatua* in Winter Wheat", *Pesticide Science*, 17(1986):1-12.

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

Feder, G. and U. Regev, "Biological Interactions and Environmental Effects in the Economics of Pest Control", *Journal of Environmental Economics and Management*, 2(1975):75-91.

Foster, R.E., J.J. Tollefson and K.L. Steffey, "Sequential Sampling for Adult Corn Rootworms (Coleoptera: Chrysomelidae), *Journal of Economic Entomology*, 11(1982):287-91.

Foster, R.E., J.J. Tollefson, J.P. Nyrop, and G.L. Hein, "Value of Adult Corn Rootworm (Coleoptera: Chrysomelidae) Population Estimates in Pest Management Decision Making", *Journal of Economic Entomology*, 79(1986):303-10.

Fuller, W.A. and G.E. Battese, "Transformations for Estimation of Linear Models with Nested-Error Structure", *Journal of the American Statistical Association*, 68(1973):626-32.

Fuller, E.I. and C. Dornbush, "Minnesota Farm Machinery Economic Cost Estimates for 1987", AG-FO-2308, MN Ext. Service, University of Minnesota, 1987.

Keeney, R.L. and H Raiffa, *Decisions with Multiple Objectives: Preferences and Value Tradeoffs*, John Wiley and Sons, New York, 1976.

Grube, A.H., "Economic Analysis of Field Scouting and Insecticide Use in Cotton Production" Ph.D. Dissertation, North Carolina State University, Raleigh, North Carolina, 1979.

Hall, D.C., and R.B. Norgaard, "On the timing and Application of Pesticides", *American Journal of Agricultural Economics*, May 1973, 198-201.

Hayami, Y. and W. Peterson, "Social Returns to Public Information Services: Statistical Reporting of U.S. Farm Commodities", *American Economic Review*, 62(1972):119-30.

Headley, J.C. "Defining the Economic Threshold", *Pest Control Strategies for the Future*, National Academy of Science-National Resource Council, Washington D.C., 1972:100-108.

Johnston, J, *Econometric Methods*, Third Edition, McGraw-Hill Inc., 1984.

Joshi, J.R., J.F. Moncrief, D.A. Andow, J.B. Swan and G.L. Malzer, "Effect of Tillage and Swine Manure on N Uptake and Corn Yield", *A Report on Field Research in Soils*, Soil Series 128, Miscellaneous Publications 2, MN Ag Ext Station, Univ. of Minnesota, 1989: 271-82.

Just, R.E., D.L. Hueth and A. Schmitz, *Applied Welfare Economics and the Public Policy*, Prentice Hall Inc. N.J. 07632, 1982.

King, R.P., "Operational techniques for applied decision analysis under uncertainty", Ph.D. dissertation, Michigan State University, 1979.

King, R. P., D. W. Lybecker, E. E. Schweizer and R. L. Zimdahl, "Bioeconomic Modeling to Simulate Weed Control for Continuous Corn", *Weed Science*, 34(1986):972-79.

Knowles, G.J. "Estimating Utility of Gain Functions for Southwest Minnesota Farmers", Ph.D. dissertation, University of Minnesota, 1980.

Krysan, J. L. and T. F. Branson, "Biology, Ecology and Distribution of Diabrotica", USDA ARS, Northern Grain Insects Research Laboratory, Rural Route # 3.

Law, A.M. and W.D. Kelton, *Simulation Modeling and Analysis*, McGraw-Hill Book Co., New York, 1982.

Lazarus, W. F. and B. L. Dixon, "Agricultural Pests as Common Property: Control of Corn Rootworm", *American Journal of Agricultural Economics*, 66(1984):456-65.

Lazarus, W. F., and E. R. Swanson, "Insecticide Use and Crop Rotation under Risk: Rootworm Control in Corn", *American Journal of Agricultural Economics*, 65(1983):738-47.

Moffitt, L.J., "Incorporating Environmental Considerations in Pest Control Advice for Farmers", *American Journal of Agricultural Economics*, 70(1988):628-34.

Moffitt, L.J. and R.L. Farnsworth, "Thresholds for Chemical Control of Agricultural Pests in a Dynamic Ecosystem", *Canadian Journal of Agricultural Economics*, 35(1987):627-37.

Montgomery, D.C. *Design and Analysis of Experiments*, Second edition, John Wiley & Sons, Inc., 1984.

Murrell, L., "Selling Field Scouting", *Solutions*, May/June 1986:30-33.

Musser, W. N., B. V. Tew and J. E. Epperson, "An Economic Examination of an Integreted Pest Management Production System with a Contrast between E-V and Stochastic Dominance Analysis", *Southern Journal of Agricultural Economics*, July 1981:119-24.

Naylor, T.H., J.L. Balintty, D.S. Burdick, K. Chu, *Computer Simulation Techniques*, John Wiley and Sons Inc, New York, 1966.

North Central Regional Publication, No. 98 "Corn Pest Management for the Midwest: A Guide for Pest and Problem Diagnosis."

Nyrop, J.P., R.E. Foster and D.W. Onstad, "Value of Sample Information in Pest Control Decision Making", *Journal of Economic Entomology*, 79(1986):1421-29.

Osteen, C.D., A.W. Johnson and C.C. Dowler. "Applying the Economic Threshold Concept to Control Lesion Nematode on Corn", USDA ERS Tech. Bul. 1670, 1982.

Ostlie, K., D. Noetzel and D. Sreenivasam in "Estimated Annual Losses due to Insects in Minnesota 1981-1983", AG-BU-2541, University of Minnesota, Ag. Ext. Service, 1985:23.

Ostlie, K and D. Noetzel, "Managing Corn Rootworms", AG-FO-3281, Minnesota Extension Service, University of Minnesota, 1987.

Pedigo, L.P., S.H. Hutchins and L.G. Higley, "Economic Injury Levels in Theory and Practice", *Annual Review of Entomology*, 31(1986): 341-68.

Minnesota Department of Health and Minnesota Department of Agriculture, "Pesticides and Groundwater: Surveys of Selected

Minnesota Wells", Agricultural Impacts on Groundwater Conference, National Water Wells Association, Moines, Iowa, March 22, 1988.

Pindyck, R.S. and D.L. Rubinfeld, *Econometric Models and Economic Forecasting*, McGraw-Hill Book Co., New York, 1976:308-416.

Pingali, P.L. and G.A. Carlson, "Human Capital, Adjustment in Subjective Probabilities and the Demand for Pest Control", *American Journal of Agricultural Economics*, 67(1985)853-61.

Pratt, J.W. "Risk Aversion in the Small and in the Large", Econometrica, 32(1964):122-36.

Randall, A., B.C. Ives and E. Eastman, "Bidding Games for Valuation of Aesthetic Environment Improvements", *Journal of Environ. Econ. and Manage.* 1(1974):132-49.

Raskin, R and M.J. Cochran, "Interpretations and Transformations of Scale for the Pratt-Arrow Absolute Risk Aversion Coefficient: Implications for Generalized Stochastic Dominance", *Western Journal of Agricultural Economics,* 11(1986):204-10.

Regev, U., A.P. Gutierrez and G. Feder, "Pests as a Common Property Resource: A Case Study of Alfalfa Weevil Control", *American Journal of Agricultural Economics*, 58(1976):186-97.

Regev, U., H. Shalit and A.P. Gutierrez, "On the Optimal Allocation of Pesticides with Increasing Resistance: The Case of Alfalfa Weevil", Journal of Environmental Economics and Management", 10(1983):86-100.

Robison, L.J. and P.J. Barry *The Competitive Firm's Response to Risk*, Macmillan Publishing Company, N.Y. 10022, 1987.

Shannon, C.E. and W. Weaver, "The Mathematical Theory of Communication", 4th. edition, University of Illinois press, Urbana, Illinois, 1969.

Smith, R. F., "History and Complexity of Integreted Pest Management", *Pest Control Strategies*, ed. E. H. Smith and D. Pimental, New York: Academic Press, 1978.

"Shatzow outlines latest EPA Pesticide Program Priorities", *Farm Chemicals*, Feb. 1985:16.

Steffey, K.L. and J.J. Tollefson, "Spatial Disperson of Northern and Western Corn Rootworm Adults in Iowa Cornfields", *Environmental Entomology*, 11(1982):283-86.

Steffey K.L., J.J. Tollefson and P.N. Hinz, "Sampling Plan for Population Estimation of Northern and Western Corn Rootworm Adults in Iowa Cornfields", *Environmental Entomology*, 11(1982):287-91.

Stern, V.M., R. van den Bosch and K.S. Hagen, "The Integration of Chemical and Biological Control of the Spotted Alfalfa Aphid, part 1: The Integreted Control Concept", *Hilgardia*, 29(1959):81-101.

Swanson, J.A. and D.C. Dahl, "The U.S. Pesticide Industry: Usage Trends and Market Development", Staff Paper Series P89-5, Department of Agricultural and Applied Economics, University of Minnesota, St. Paul MN 55108, January 1989.

Taylor C.R. and D.R. Burt. "Near Optimal management strategies for controlling wild oats in spring wheat", *American Journal of Agricultural Economics*, 66(1984):50-60.

Theil, H. "Economics and Information Theory", North-Holland Publishing Company, Amsterdam, 1967.

Vandermeer, J, and D.A. Andow, "Prophylactic and Responsive Components of an Integrated Pest Management Program", *Journal of Economic Entomology*, 79(1986):299-302.

Wilson, P.N. and V.R. Eidman, "An Empirical Test of the Interval Approach for Estimating Risk Preferences", *Western Journal of Agricultural Economics*, 8(1983):170-82.

Zacharias, Thomas P., and Arthur H. Grube, "Integreted Pest Management Strategies for Approximately Optimal Control of Corn Rootworm and Soybean Cyst Nematode", *American Journal of Agricultural Economics*, 68(1986):704-15.