OPTIMAL CROP SEQUENCES TO CONTROL CEPHALOSPORIUM STRIPE IN WINTER WHEAT

by

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APPROVAL

of a thesis submitted by

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ABSTRACT

Cephalosporium gramineum, a soil borne fungus, causes a stripe disease in winter wheat. The fungus restricts the flow of water and nutrients to the plant head resulting in significant yield losses. The disease is passed from winter wheat crop to winter wheat crop through Cephalosporium stripe infested straw. Rotating to non-host spring crops or fallow, allowing time for decomposition of infested residue, is the primary means of controlling Cephalosporium stripe.

The objective of this thesis was to determine economically optimal land use sequences to control Cephalosporium stripe in winter wheat. Control of the disease is a stochastic dynamic problem and as such was formulated within a stochastic dynamic programming framework. The economic criterion used was maximization of expected present value of returns over variable cost. The model was applied to a representative dryland grain farm in the Judith Basin of central Montana. The decision alternatives were winter wheat, barley, and fallow. The state variables included in the model were previous land use, years of control, level of Cephalosporium stripe infection in the last winter wheat crop, barley price, and winter wheat price. Transformation functions were derived for all of the state variables. Based on statistically estimated transformation functions, transition probability functions were developed for the stochastic state variables: past Cephalosporium stripe infection level, winter wheat price, and barley price. The relationship between Cephalosporium stripe infection level and winter wheat yield was also estimated.

The optimal policy is dominated by fallow and barley decisions when there are less than four years of control unless the past infection level is very low. Once three years of control has been exceeded, winter wheat decisions become optimal at higher levels of past infection and increase as winter wheat prices increase. Finally, it is evident that consideration of at least a three-year control sequence would increase annual returns significantly regardless of the past Cephalosporium stripe infection level.

CHAPTER 1

INTRODUCTION

Cephalosporium gramineum (Cephalosporium stripe) is a soil borne fungus causing a stripe disease in winter wheat. The disease was first described in 1934 by Nisikado et al. (1934) in Japan. It is now commonly observed in England, Scotland, and in the major winter wheat producing states of the United States.

The fungus poses two basic problems for the winter wheat producer: (1) yield losses due to clogging of the plant's vascular system resulting in smaller heads with shriveled and damaged kernels, and (2) the ability of the fungus to exist in wheat residue for a number of years, thereby threatening yields and therefore profits in future years as well as the current year (Mathre et al., 1977).

Research to develop a variety of winter wheat with improved resistance to Cephalosporium stripe and to develop chemical control methods is ongoing. The current solution to Cephalosporium stripe management is crop rotation and residue management. Infested areas are fallowed or seeded with a non-host spring crop to aid in the decay of the residue harboring the fungus. Other things equal, the longer the time between winter wheat crops, the smaller the expected infestation in a future crop. This study will focus on economically optimal strategies of crop rotation to control Cephalosporium stripe.

Statement of the Problem

Winter wheat producers seeking to maximize the present value of profits earned from producing winter wheat and other crops must take into account expected product and input prices and expected yields. Even in the absence of plant disease, crop rotation decisions, which affect yields, are made in the current season with an eye to the future. Fallowing will generally improve yields in a future year due to additional soil nutrients made available by the decomposition of plant materials and additional soil moisture, but generate no revenue in the current year. A spring crop is generally less profitable than winter wheat, but in contrast to fallowing, generates positive expected net revenues during the current year. However, spring crops deplete soil moisture and nutrients, lowering the expected yield (and hence profits) for a winter wheat crop in the following year.

The trade-offs described above are complicated by insect and plant disease. In addition to their effect on current yields, many pest and disease problems, such as the Cephalosporium stripe problem, are aggravated or lessened by cropping practices, to a degree that is not known with certainty.

The procedure for solving a problem of this nature must weigh these economic trade-offs simultaneously. Therefore, the question of how to optimally manage the level of Cephalosporium stripe infection in winter wheat will be addressed with stochastic dynamic programming. The decision alternatives that will be considered in the dynamic programming problem are summer fallow, barley, or winter wheat. In

addition to specifying the biological and cultural relationships already described, Markov processes for wheat and barley prices will be estimated in order to obtain a measure of expected current and future product prices to incorporate into the dynamic programming model.

Objectives

The specific objectives of this research project are:

1. To estimate the relationship between crop rotations and infection levels of Cephalosporium stripe in winter wheat.
2. To estimate the relationship between winter wheat yields and Cephalosporium stripe infection levels for winter wheat crops planted after a year of fallow and after a non-host spring crop.
3. To develop a dynamic programming model employing the relationships obtained from (1) and (2) above to analyze the economically optimal crop rotation strategies for controlling Cephalosporium stripe in winter wheat.

Organization of this thesis is as follows: the second chapter reviews the physiological research done on the Cephalosporium stripe fungus, develops the dynamics of Cephalosporium stripe, and specifies the relationship between winter wheat yields and infection levels. Chapter 3 presents the general decision model and the empirical model. The transformation functions, transition probabilities, and the dynamic programming recursive relationship are developed. The optimal policy is discussed in

Chapter 4, and Chapter 5 includes the summary and concluding remarks.

CHAPTER 2

THE CEPHALOSPORIUM STRIPE PROBLEM

Review of Literature

This chapter consists of two sections. The first summarizes past research by plant pathologists relating to the physiological aspects of the Cephalosporium stripe fungus and its effect on winter wheat yields. The second section develops the empirical models relating to Cephalosporium stripe infestations.

In the spring, during the early stages of plant development, winter wheat infected by Cephalosporium stripe may be recognized by a yellow stripe on lower leaves and sheaths. As plants mature, the infected plants are typically shorter in height than healthy plants, and also a much lighter color. The fungus clogs the vascular system of the plant causing early maturation with limited grain production and shriveled kernels. Mathre et al. (1977) estimated a 30 percent loss in yield for infected plants. In Kansas, from 1976 through 1982, it has been estimated that the average annual yield loss from Cephalosporium stripe infestation was approximately five million bushels (Brockus et al., 1983).

It is the unique growth process of winter wheat that makes it susceptible to Cephalosporium stripe infection. The fungus enters the plant through injured roots, or more often through roots that are

broken as the soil heaves during freeze-thaw cycles in the spring. According to Morton et al. (1980),

> Winter wheat is distinctive in its requirement for a vernalization period to initiate flowering. In comparing symptom development within wound-inoculated vernalized and nonvernalized winter wheat plants, Bruehl observed that the latter were resistant to stripe formation. He suggested that 'it is probable that the fungus is not particularly active until the host passes a certain stage of development.' In our studies, we found that stripe formation in nonvernalized winter wheat was evident only in the mature outer leaves.

Once the fungus has invaded a field it survives between winter wheat crops in infected straw and chaff. Once established, a variety of cultural and environmental factors appear to affect the longevity and severity of a Cephalosporium stripe infestation in and between winter wheat crops.

Pool and Sharp (1969) found that factors contributing to root growth in the fall increased the number of infected plants. The larger, deeper roots are more easily broken during freeze-thaw cycles in the spring, allowing the fungus to enter the plant. Their study indicates that large amounts of stubble, high soil temperature following planting, high soil moisture and fertilization of early plantings with $Ca_3(PO_4)_2$ create favorable conditions for the Cephalosporium stripe fungus. They also found that the fungus survived in naturally infected straws for as long as 45 months.

Recent studies indicate that reduced tillage practices will maintain high levels of Cephalosporium stripe infestations (Latin et al., 1982; Brockus et al., 1983; Mathre et al, 1977). No-till and minimum-till methods hold more residue on or near the soil surface, and getting rid of the host residue is instrumental in controlling

Cephalosporium stripe. Latin et al. (1982) compared conventional, reduced, and no-till methods on two- and three-year crop rotations. They found that given the rotation, conventional tillage practices produced the lowest levels of Cephalosporium stripe infestations, and as the amount of tillage went down (for a given rotation), the level of disease incidence increased. They also reported better control of Cephalosporium stripe with three-year rather than two-year rotations. Mathre et al. (1977) studied the effect of crop rotation on the incidence of Cephalosporium stripe at Moccasin, Montana. They also concluded that longer rotations give better control of Cephalosporium stripe, particularly when continuous cropping is practiced. Their recommendation is a minimum of three years between winter wheat crops if the disease has been observed.

Research indicates that factors such as seeding date, variety, and soil moisture also affect the severity and longevity of a Cephalosporium stripe infestation (Mathre et al., 1977; Pool and Sharp, 1969). At the present time, crop rotation appears to be the most reliable and generally accepted method of controlling Cephalosporium stripe.

The dynamics of Cephalosporium stripe (i.e., the relationship between the level of infection in the current crop and the level of infection in the next winter wheat crop) and its effect on winter wheat yields are an integral part of a decision model for Cephalosporium stripe management. Because of difficulties in obtaining data to estimate these relationships with statistical significance, the objectives of this section are to: (1) explain what data are necessary to develop the dynamics of Cephalosporium stripe infection, (2) explain

how data were generated and then used to estimate this relationship, and (3) specify the relationship between winter wheat yields and Cephalosporium stripe infection levels.

Cephalosporium Stripe Dynamics

Among the factors that contribute to the longevity and severity of the Cephalosporium stripe fungus, some, such as soil moisture and weather conditions, cannot be controlled by the producer. Seeding date, variety, and intervening years of fallow and/or spring crops are methods that the producer can employ to control the incidence and severity of the fungus.

This study examines the fallow/spring crop rotation method of control. Thus the decision model must consider the effect of the number of years of control on decomposition of Cephalosporium stripe infested straw. The general mathematical formulation of the Cephalosporium stripe infection model is:

$$I_{(t+1)+C} = f(I_t, C, \varepsilon_{(t+1)+C}) \qquad C = 1,2,3,\ldots N \qquad (2.01)$$

where

I_t = the percent of infected plants in a winter wheat field at time t

C = the number of years of control (years of fallow and/or non-host spring crops between winter wheat crops)

$I_{(t+1)+C}$ = the percent of infected plants in the same field the next time winter wheat is planted (i.e., one year after C years of control)

$\varepsilon_{(t+1)+C}$ = a random error term

Equation (2.01) simply states that the level of infection in a winter wheat crop depends on the level of infection in the last winter wheat crop, the number of years between the two crops, and a random error component. Conceptually, there is a different equation for each C considered.

Note that infection levels are not measured during years of control. The disease manifests itself in winter wheat and thus is only measurable when winter wheat is grown.

Data Requirements

To statistically estimate this relationship, observations must be taken on I_t and $I_{(t+1)+C}$ for given values of C. For example, to gather data on one year of control, a sequence of winter wheat, control, winter wheat, control, winter wheat, ... winter wheat would be repeated with measurements of infection taken during the winter wheat crops. Obviously, as the number of years between winter wheat crops increases, the length of the experiment also increases. A very long-term experiment would be necessary to generate the data to predict future levels of infection with a reasonable degree of confidence. Such research is further complicated by weather, pests, weeds, and other diseases that affect winter wheat yields and longevity of the Cephalosporium stripe fungus, making it difficult to establish cause and effect.

Available Data

The study by Mathre et al. (1977) on alternative crop rotations and their effect on Cephalosporium stripe longevity and yield loss at

the Moccasin experiment station provided some of the necessary data. The relationship between winter wheat yield and infection levels was estimated with this data. Unfortunately, severe cheat grass infestation forced abandonment of the plots in 1976. There was insufficient data to determine the effect of control on the decomposition of Cephalosporium stripe by regression analysis, except for the case of one year of control.

Based on the worst-case scenario of the Moccasin experiment, Johnston and Hehn (1984) compiled a computer program entitled CEPHLOSS. The program includes a set of equations that describe the relationship between I_t and $I_{(t+1)+C}$. The equations used in the program to predict future infection levels, given C years of control, are as follows:

$$I_{(t+1)+C} = \begin{cases} 2I_t & , \ C = 1 \\ I_t & , \ C = 2 \\ (1/3)^{(1/2)(C-1)} I_t & , \ C = 3,5,7,\ldots \\ (1/3)^{(1/2)(C-2)} (7/9) I_t & , \ C = 4,6,8,\ldots \end{cases} \tag{2.02}$$

A restriction was imposed on these relationships that I_t and $I_{(t+1)+C}$ could not exceed 90%.

These equations indicate that infection does not begin to decrease until there has been three years of control. After three years of control, a type of discontinuous geometric decline begins as years of control increase. Table 1 illustrates the predicted levels of infection ($I_{(t+1)+C}$) for 1 through 5 years of control, given 10 percent infected plants in the winter wheat crop at time t (I_t).

Table 1. Predicted infection for specified years of control, given initial infection equals 10%.

Years of Control (C)	Predicted Infection (Percent)
1	20.00
2	10.00
3	3.33
4	2.59
5	1.11

Data Generation

The equations of the CEPHLOSS program were used to generate data to estimate the dynamics of the Cephalosporium stripe fungus. Forty observations for $I_{(t+1)+C}$ were generated by substituting values of I_t from 10% through 90%, for $2 \leq C \leq 5$ in the equations listed above. At one year of control, the restriction that infection be less than or equal to 90% takes effect at I_t=45%. Thus only five observations are given for this case. (See Table 2 for all generated observations.) Note the equations do not include C=0 (continuous winter wheat).

Table 2. Effect of years of control on subsequent Cephalosporium stripe infections in winter wheat as predicted by CEPHLOSS.

	Years of Control				
I_t	1	2	3	4	5
10	20	10	3.33	2.59	1.11
20	40	20	6.67	5.19	2.23
30	60	30	10.00	7.75	3.33
40	80	40	13.33	10.38	4.44
45	90	45	15.00	11.67	5.00
50	--	50	16.67	12.94	5.56
60	--	60	20.00	15.56	6.67
70	--	70	23.33	18.15	7.75
80	--	80	26.67	20.74	8.09
90	--	90	30.00	23.31	10.00

Estimation of Cephalosporium Stripe Model

The next step was to formulate a single equation that closely duplicates the discontinuous relationship of the CEPHLOSS program, using the data from Table 2. An equation that exhibits a continuous geometric decline in infection with increasing years of control is assumed to be a reasonable approximation. Based on these considerations, the following equation was chosen for the Cephalosporium stripe model:

$$I_{(t+1)+C} = \text{Exp}(\alpha + \beta C + \epsilon_{(t+1)+C}) * I_t \qquad (2.03)$$

This equation is nonlinear in parameters, but the following double log transformation permits the use of ordinary least squares (OLS) regression to estimate the coefficients, α and β.

$$\log(I_{(t+1)+C}) = \alpha + \beta C + \log(I_t) + \varepsilon_{(t+1)+C} \quad (2.04)$$

In this form the coefficient on $\log(I_t)$ must be forced to equal 1 during estimation. However, this can be circumvented by subtracting $\log(I_t)$ from both sides of equation (2.04) and applying the following rule of logs:

$$\log(x) - \log(w) = \log(x/w).$$

Thus the final form of the equation to be estimated is:

$$\log\left(\frac{I_{(t+1)+C}}{I_t}\right) = \alpha + \beta C + \varepsilon_{(t+1)+C} \quad (2.05)$$

Equation (2.05) is linear in parameters, with one independent variable, C. Using the generated observations, application of OLS yielded the following coefficients (Equation 2.06). The unadjusted R squared was 0.9688, indicating that the curve fits the data.

$$\log\left(\frac{I_{(t+1)+C}}{I_t}\right) = 1.3210 - 0.76002 * C \quad (2.06)$$

Yield-Infection Relationship

A necessary component of the decision model is an estimate of the negative relationship between Cephalosporium stripe infestations and winter wheat yields. Winter wheat yields are assumed to depend on the previous land use (fallow or spring crop), and the level of Cephalosporium stripe infestation in the current winter wheat crop. Functionally, the general specification is

$$Y_t = f(L_{t-1}, I_t, \varepsilon_t) \quad (2.07)$$

where

Y_t = winter wheat yield in bushels per acre

L_{t-1} = the land use in year t-1

I_t = the proportion of infected plants per acre

ε_t = a random error term

Previous land use is included to reflect the higher yields, other things equal, associated with winter wheat crops planted on fallowed land versus crops planted on spring crop stubble. An additional assumption is that a given level of Cephalosporium stripe infestation will result in the same percentage reduction in yield irrespective of the previous land use (spring crop or fallow). Previous land use can be viewed as a parameter in the relationship, rather than a variable.

Equations (2.08) and (2.09) illustrate these hypothesized relationships.

$$Y_t^F = \gamma(1-bI_t) + \varepsilon_t \qquad (2.08)$$

$$Y_t^{SC} = \gamma'(1-bI_t) + \eta_t \qquad (2.09)$$

where

Y_t^F = winter wheat yield after fallow in growing season t (bushels/acre)

Y_t^{SC} = winter wheat yield after a spring crop in growing season t (bushels/acre)

γ = winter wheat yield in the absence of the Cephalosporium stripe fungus, given the previous land use is fallow (bushels/acre)

γ' = winter wheat yield in the absence of the Cephalosporium stripe fungus, given the previous land use is a spring crop (bushels/acre)

I_t = the proportion of Cephalosporium stripe infected plants per acre in growing season t

b = the percentage rate of yield loss due to higher infection levels

ε_t = a random error term

η_t = a random error term

Data Requirements and Availability

The Moccasin experiment provided 18 observations on levels of infection and winter wheat yields (Table 3). There are six observations from 1970 and 12 from 1972 with infection measured in number of infected plants per 20 linear feet. The previous land use for all observations is fallow, so that equation (2.08) can be estimated from the data, but not equation (2.09). Although b is assumed to be the same in these two equations, there are no observations available for the dependent variable, Y_t^{SC}; thus the parameter, γ', cannot be determined.

Two methods were considered to solve the problem of obtaining a value for γ': (1) Estimate γ and b from the Moccasin data and assume that γ' is some percentage (less than 100 percent) of γ, and (2) estimate b from the Moccasin data and find alternative winter wheat yield data representative of the Moccasin area to estimate γ and γ'. Because it was also necessary to acquire data on spring crop yields for the decision model, the second method was chosen so that all of the required yield figures in the model were estimated from the same data source. The Montana Crop and Livestock Reporting Service provided unpublished time series yield data from Judith Basin County for this purpose.

Table 3. Yield and Cephalosporium stripe infection data, Moccasin, Montana (1970, 1972).

Cephalosporium Incidence (No. of Infected Plants per 20 Linear Feet)	Winter Wheat Yield (Bushels per Acre)
<----------(1970)---------->	
59.67	22.5
37.67	26.3
38.67	25.6
19.33	24.1
26.67	24.9
26.67	23.9
<----------(1972)---------->	
59.00	36.9
36.00	31.2
21.50	46.3
10.50	48.2
78.00	32.2
73.00	27.9
13.50	45.9
20.50	46.5
63.50	37.2
106.00	33.6
11.50	47.1
18.00	46.4

Estimation of the Yield-Infection Relationship

The first step in estimating b from equations (2.08) and (2.09) was to use ordinary least squares to obtain a simple linear relationship between yield and infection from the Moccasin data. A binary variable was included for year effects. In mathematical notation this relationship is stated below:

$$Yld_t^F = \alpha - \beta N_t - \phi D_t + \varepsilon_t \qquad (2.10)$$

where

Yld_t^F = yield after fallow (bushels/acre)

α = intercept parameter

N_t = number of infected plants per 20 linear feet

β = the slope associated with the explanatory variable (N_t)

D_t = the binary variable for year effects (D_t=1 for t=1970, D_t=0 for t=1972)

ϕ = parameter for the binary variable

ε_t = the random error term

The results of this regression are as follows:

$$Yld_t^F = \underset{(25.507)}{47.620} - \underset{(-5.143)}{0.18013N_t} - \underset{(-8.555)}{16.806D_t} \qquad (2.11)$$

The numbers in parentheses are the t-ratios for the estimated coefficients. The R squared was 0.8559 (adjusted R squared was 0.8367).

In equation (2.11), infection (N_t) is measured as the number of infected plants per 20 linear feet. Equations (2.08) and (2.09) require infection (I_t) to be measured as the proportion of infected plants per acre. Thus I_t equals N_t divided by the number of plants per 20 linear feet. There are assumed to be 160 plants per 20 linear feet. With this information and D_t set equal to zero, the general form of equations (2.08) and (2.09) can be derived in the following manner:

$$\begin{aligned} Y_t^F &= \alpha - \beta N_t \qquad (2.12)\\ &= \alpha - (160*\beta)(N_t/160)\\ &= \alpha - (160*\beta) I_t\\ &= \alpha[1 - (160*\beta/\alpha) I_t]\\ &= \alpha(1 - bI_t) \end{aligned}$$

where

$b = 160*\beta/\alpha$

Substitution of the estimated values for α and β results in a value of 0.605 for b.

The binary variable has been omitted from this derivation for two reasons. First, the inclusion of D_t in equation (2.11) affects the intercept of the equation, not the slope. Thus the derivation of the slope term in equations (2.08) and (2.09) from β will be unaffected. Secondly, the intercept, α, which is affected by D_t, will be replaced by appropriate estimations of γ and γ', as described below.

Estimation of Intercept Parameters (γ and γ')

The data from Judith Basin County were used to estimate trend lines for winter wheat yields after fallow and continuously cropped. There were 40 observations for winter wheat yield after fallow and 36 observations for continuously cropped winter wheat yields. Both data sets begin with 1945 and run through 1984. (There were four years where there were no observations on continuously cropped winter wheat.)

The mathematical specification of the trend lines is:

$$Yld^F = \lambda + \delta T + \epsilon \qquad (2.13)$$

$$Yld^C = \lambda' + \delta' T + \eta \qquad (2.14)$$

where

Yld^F = winter wheat yield after fallow (bushels/acre)

Yld^C = winter wheat yield on stubble (bushels/acre)

λ = winter wheat yield after fallow when T=0

λ' = winter wheat yield on stubble when T=0

δ = average annual rate of yield increase (after fallow)

δ' = average annual rate of yield increase (on stubble)

T = the independent variable, time (T=1,2,...40, T=1 => 1945, T=40 => 1984)

ϵ = a random error term

η = a random error term

Results of the estimation are given below:

$$Yld^F = \underset{(13.748)}{16.729} + \underset{(8.4352)}{.43628}(T) \qquad (2.15)$$

$$Yld^C = \underset{(7.8453)}{10.410} + \underset{(6.7770)}{.37476}(T) \qquad (2.16)$$

Long-run trended yield figures can be calculated for a given year by substitution of an appropriate value for T into these equations. The year 1984 is used in this thesis, thus T=40, giving:

$$Yld^F = 34.18 \qquad (2.17)$$

and

$$Yld^C = 25.40 \qquad (2.18)$$

It must be assumed that these data include the effects of Cephalosporium stripe infection over these years, so the equations will underestimate γ and γ' (i.e., these figures are for yield in the absence of infection). Since there are no data available to ascertain the average level of infection over this time period quantitatively, Don Mathre (Professor of Plant Pathology, Montana State University) provided an estimate of five percent. This implies that when infection is five percent, yield after fallow is 34.18 and yield on stubble is 25.40 bushels per acre. Solving for γ and γ' in equations (2.08) and (2.09) gives

$$\gamma = \frac{34.18}{(1-(.605225)(.05))} = 35.25 \tag{2.19}$$

and

$$\gamma' = \frac{25.4}{(1-(.605225)(.05))} = 26.19 \tag{2.20}$$

which results in the final equations:

$$Y_t^F = 35.25\ (1-(.605)(I_t)) \tag{2.21}$$

$$Y_t^{SC} = 26.19\ (1-(.605)(I_t)) \tag{2.22}$$

CHAPTER 3

FORMULATION AND IMPLEMENTATION OF EMPIRICAL MODEL

The General Decision Model

Plant disease is an ongoing threat to small grain production. If left unchecked, yields and therefore net revenues are generally decreased. Many diseases can be controlled through chemical, biological, or cultural practices, but these control methods also have an effect on net revenues. Control of Cephalosporium stripe can be accomplished through cultural practices. Of the three practices mentioned above, cultural practices will generally have the smallest impact on costs for the producer, but may also be slower in achieving control of the disease. Thus yields may be affected for longer periods of time.

The objective is to minimize the effects of Cephalosporium stripe on net returns throughout the grower's planning horizon. The fundamental question is whether control of Cephalosporium stripe is warranted, given the expected physical and economic conditions. In addition to Cephalosporium stripe infestations, other factors that affect revenues and costs must be evaluated in the decision making process.

Considerations on the cost side include the variable costs of fallow, winter wheat, and spring crops. The variable cost of a crop

will be higher if the land has been cropped in the previous period rather than fallowed. Continuously cropped land generally requires more fertilizer and chemical control of weeds. Thus previous land use affects the variable cost in a particular growing season (Appendix D).

Total revenue is governed by product price and yield. Yields will generally be higher on land that was previously fallowed. In the case of winter wheat, Cephalosporium stripe infection levels have a negative impact on yields. Obviously, product prices must be incorporated into the decision making process as well.

Crop rotation and Cephalosporium stripe infestations are both dynamic processes. As such, current decisions have impacts on future conditions. For example, if the current decision is fallow, the immediate returns will be negative (the variable cost of fallow); but if a crop is planted in the next growing season, yields are generally improved. In addition, fallow adds to the years between winter wheat crops, so future Cephalosporium stripe infection levels will also be affected. The decision to plant a non-host spring crop will usually yield positive immediate returns, but if a crop is planted in the succeeding year, yields will generally be lower than if fallow had been chosen. Spring crops also add a year to the control process so that future winter wheat yields will be affected through future Cephalosporium stripe infection levels. A winter wheat decision has higher expected immediate returns, but has future repercussions on Cephalosporium stripe infestations by returning the system to zero years of control. The system is also put in a continuous-crop versus a fallow-crop situation if the next decision is a spring crop.

The interaction of these variables and decisions may indicate that sacrificing a little in the current time period may permit greater returns thereafter; or they may suggest that it is optimal to take advantage of a currently high winter wheat price, in spite of probable increases in infection. In determining the optimal strategy for control of Cephalosporium stripe infestations in winter wheat, all trade-offs must be evaluated.

An additional complicating factor is the stochastic nature of product prices and Cephalosporium stripe infection levels. At the time of decision making, the magnitude of these variables is not known with certainty. Therefore revenues will not be known with certainty. Accordingly, the problem must be viewed as stochastic, and returns should be viewed in an expected value framework.

In summary, the optimal strategy for control of Cephalosporium stripe infestations in winter wheat involves determination of the sequence of decisions regarding cropping or fallowing the land, such that the expected present value of net returns is maximized. A decision specifies one of the possible alternatives, given expected economic and physical conditions at a particular point in time. A stochastic dynamic problem such as this is efficiently handled by dynamic programming.

Dynamic Programming

Dynamic programming is a mathematical optimization technique useful in solving multistage decision processes. The basic principles of dynamic programming, including the term itself, are credited to

Bellman (1957). Howard (1960), White (1969), and Dreyfus and Law (1977) are widely recognized for providing additional mathematical procedures and intuitive insights to the general theory of dynamic programming. Dynamic programming problems must meet certain computational criteria, but the equations used to describe the system must be tailored to fit the particular situation. No standardized algorithm exists to solve all dynamic programming problems.

Description of Dynamic Programming Problems

Dynamic programming problems entail making a sequence of interrelated decisions in order to optimize an appropriately defined objective function. The problem is divided into stages, with a decision required at each stage. A stage is a time interval dependent upon the process under study. For the Cephalosporium stripe problem, the decision alternatives to crop or to fallow are made on an annual basis. Thus the appropriate length of a stage is one year. The total number of stages to be considered, referred to as the planning horizon, is also dependent on the particular problem.

Each stage has a number of states associated with it. A state describes the condition of the process at a given stage, and is defined by the magnitude of the state variables. The state variables in the Cephalosporium stripe problem must describe both the economic and physical (yield potential) conditions that will be encountered in a given stage. Winter wheat price and the spring crop price are obvious choices to describe the economic conditions. In addition, winter wheat yields will be affected by previous land use, years of control, and the

level of Cephalosporium stripe infection in the last winter wheat crop, all of which are dependent upon past decisions. Spring crops are not subject to Cephalosporium stripe infestations, so that yield will depend on the previous land use only.

The effect of a decision at each stage is to transform the current state into a state associated with the next stage. These state transitions may occur with certainty or be governed by a probability distribution. With the Cephalosporium stripe problem, product prices and infection levels are stochastic variables, while previous land use and years of control are deterministic.

Dynamic programming requires that the optimal decision, given the state of the process at a particular stage, be independent of the previous stages. This is the Markov property of dynamic programming. Fulfilling the Markov requirement is contingent on an accurate description of the system by the state variables. Given that the Markov requirement is met for the decision process model, the principle of optimality is the logical basis for the dynamic programming objective function. From Bellman (1961):

> An optimal policy has the property that whatever the initial state and initial decision are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decision (p. 57).

A policy defines the decision to be made for a given state at each stage, for all possible combinations of states and stages. For example, an optimal policy would indicate fallow, winter wheat, or spring crop at each time period in the planning horizon, for all possible combinations of product price, previous land use, years of

control, and past levels of Cephalosporium stripe infection, such that the expected present value of net returns earned from producing winter wheat and spring crops are maximized.

The principal of optimality allows a multistage problem to be separated into a series of one-stage problems and solved through a recursive equation. The solution procedure begins by finding the optimal policy for the last year of a T year planning horizon. Thus the relationship between chronological time and stages is backwards. Figure 1 illustrates this relationship.

Time	1	2		T-1	T	T+1
Stage	N	N-1		2	1	0

Figure 1. Relationship between chronological time and stages.

Accordingly, the nth stage refers to the point in time when there are n stages (years) remaining in the planning horizon.

Once the solution for stage one is found, the procedure moves backward stage by stage -- each time finding the optimal policy -- until the optimal policy for the first year of the planning horizon is determined.

A recursive relationship identifies the optimal policy for each state at stage n, given the optimal policy at stage n-1 is available. The recursive equation is maximized (or minimized) and consists of two components: expected immediate returns and the optimal expected returns associated with the previous stage. The general form of the dynamic programming recursive equation, or objective function, is:

$$V_n(i) = \underset{k}{\text{Max}}\left[q_i^k + \beta \sum_{j=1}^{M} p_{ij}^k \, V_{n-1}(j)\right] \qquad \begin{matrix} i = 1,2,\ldots M \\ j = 1,2,\ldots M \end{matrix} \tag{3.01}$$

where

n = number of stages remaining in planning horizon

i = the ith state; a specific set of values of the state variables

$V_n(i)$ = discounted expected returns of an n stage process, given the ith state and an optimal policy

Max = the maximum operator

k = the decision variable

q_i^k = the expected immediate returns associated with the kth decision and ith state

β = the discount factor

j = the jth state; a specific set of values of the state variables

p_{ij}^k = the conditional probability of being in the jth state in stage n-1 given the ith state and kth decision in stage n

$V_{n-1}(j)$ = discounted expected returns associated with an optimal policy in stage n-1 given the jth state

M = number of states

Evaluation of this equation begins with n=1 and continues until n is equal to the number of years in the planning horizon. Conceptually there is no limit to the number of stages that could be considered. When the returns (q_i^k) and transition probabilities (p_{ij}^k) are independent of the stage, i.e., not dependent on n, the optimal policy converges to a function of the state only as $n \to \infty$. A positive test for convergence is available through Howard's (1960) "policy iterative" method. Before the specific recursive equation for the Cephalosporium

stripe model can be evaluated, all components discussed in general in the preceding section must be specified.

The Empirical Model

The data used in the formulation of the Cephalosporium stripe empirical model are representative of Judith Basin County in central Montana. Cephalosporium stripe infections vary across fields; thus the analysis takes place on a field-specific basis rather than a whole farm basis.

Stages

A 25-year planning horizon is assumed, with a decision concerning land use required annually at winter wheat seeding time in the fall. Accordingly, there are 25 stages, each one year in length.

Barley seeding time in the spring is another potential decision point. It is not included in this model. A decision to fallow in the fall negates the consideration of planting barley in the spring.

State Variables

The state variables, identified in the general decision model, are designated in the following manner:

L = previous land use

C = years of control

I = Cephalosporium stripe infection level in the last winter wheat crop (percent infected plants)

P^B = price of barley (dollars/bushel)

P^W = price of winter wheat (dollars/bushel)

Decision Alternatives

Two methods of cultural control are available: (1) fallow and (2) growing a non-host spring crop. Clearly there are several possibilities included in (2) above, and the choices will be region-specific. In order to keep the problem manageable, barley is the only spring crop considered in the model. It is a viable alternative for winter wheat producers in central Montana. Consequently, there are three alternatives in the decision set: fallow, winter wheat, and barley.

Some restrictions were placed on the decision variable. Two cropping sequences, fallow-fallow and winter wheat-winter wheat, were excluded *a priori* from the model. The soils at the experimental site on which this study is based are unusually shallow -- about 20 inches of soil above a gravel substrata. Therefore there is seldom any advantage to a second year of fallow (for soil moisture management) because the soil profile is nearly always at field capacity after one season of summer fallow (Burt and Stauber, 1977). The exclusion of two consecutive years of winter wheat is more difficult to defend. However, the Moccasin study does not include data on this rotation and the Cephalosporium stripe infection relationship derived earlier is based on a worst case scenario which probably would preclude two years of winter wheat.

A third constraint forces a winter wheat decision after six years of control. It is felt that this constraint would not bias the final results and was necessary to limit the number of states associated with Cephalosporium stripe infection levels and years of control.

Given these constraints, the decision alternatives are summarized in Table 4.

Table 4. Decision alternatives of the empirical model, given previous land use and years of control.

Previous Land Use	Years of Control	Decision Alternative, k_n
Fallow	1-5	Winter Wheat (1) Barley (2)
	6	Winter Wheat (1)
Winter wheat	0	Fallow (0) Barley (2)
Barley	1-5	Fallow (0) Winter Wheat (1) Barley (2)
	6	Winter Wheat (1)

Transformation Functions

Previous land use. Previous land use is a deterministic state variable, assuming a value of 0, 1 or 2, indicating fallow, winter wheat or barley, respectively. Its transition from stage to stage is dependent upon the decision in the previous stage, as shown below.

$$L_{n-1} = k_n, \quad k_n = 0,1,2 \tag{3.02}$$

where

k_n = fallow, winter wheat, barley for 0,1,2 respectively

Years of control. Years of control is a deterministic state variable that denotes the number of years between winter wheat crops. Barley and fallow add a year to control. Winter wheat returns years of control to zero. The transformation function is specified as follows:

$$C_{n-1} = \begin{cases} C_n + 1, \text{ if } k_n = 0, 2 \text{ and } C_n \leq 5 \\ 0 \quad , \text{ if } k_n = 1 \end{cases} \tag{3.03}$$

Infection level in last winter wheat crop. In defining the transformation function for the infection level variable, it is important to note that I_n, by itself, does not define the expected level of infection in the current time period. It is the level of infection in the last winter wheat crop, a stochastic variable that changes in value from stage n to stage n-1, only if the current decision is winter wheat. Given a winter wheat decision in stage n, the transformation function, shown below in general notation, contains a random element.

$$I_{n-1} = f(I_n, C_n, \epsilon), \; k_n=1 \tag{3.04}$$

The random relationship between infection levels, given years of control, is specified in equation (2.06). Converting this equation to n stage notation gives the transformation function for the infection variable as follows:

$$\ln(I_{n-1}) = 1.3210 - 0.76002 * C_n + \ln(I_n), \; k_n=1 \tag{3.05}$$

If the decision in stage n is not winter wheat, a year is added to control, but the level of infection in the last winter wheat crop does not change and is simply carried along to the next stage. Thus the transformation function, as shown below, is not stochastic when the decision in stage n is barley or fallow.

$$I_{n-1} = I_n, \quad k_n = 0,2 \tag{3.06}$$

Winter wheat and barley prices. The transformation functions for the two price state variables formulate the relationship between price

in year t (stage n) and year t+1 (stage n-1). The two equations were estimated using 33 years (1951-1983) of Montana wheat and barley prices expressed in 1984 dollars. Because time series data tend to have positive correlation in the successive error terms, both equations were modeled with autoregressive error structures. A zero-one variable was included in the equations to account for the high prices observed in 1973. Many models with various orders on the autoregressive error term and with own and cross price right-hand side variables were estimated as both stochastic and nonstochastic difference equations. Selection of the final equation for barley and winter wheat was based on t ratios, adjusted R squared, and standard errors of the estimate.

The winter wheat equation is a second order autoregressive model. Prices are expressed in natural logs. Equation (3.07) gives the estimated coefficients with t-values in parentheses.

$$\ln(P^{W}_{t+1}) = \underset{(17.3540)}{1.5462} + \underset{(3.0287)}{0.2892}D_t + \mu_{t+1} \qquad (3.07)$$

$$\mu_{t+1} = \underset{(7.2055)}{1.1509}\mu_t - \underset{(2.8630)}{0.4573}\mu_{t-1} + \varepsilon_{t+1}$$

where

$\ln(P^{W}_{t+1})$ = winter wheat price in year t+1 in natural logs

D_t = the binary variable; $D_t = \begin{cases} 1, \text{ for 1973} \\ 0, \text{ elsewhere} \end{cases}$

μ_{t+1} = the second order autoregressive error

The adjusted R squared was 0.7075 and the standard error is 0.1519 in natural logs.

Adjustment of the equation for the autoregressive error structure and setting D_t=0 (for 1984) gives equation (3.08).

$$\ln(P^W_{t+1}) = 0.4737 + 1.1509\ \ln(P^W_T) - 0.4573\ \ln(P^W_{t-1}) \qquad (3.08)$$

This equation has two lagged values of the dependent variable, indicating the need for two winter wheat price state variables to describe the decision process from stage n to stage n-1. To eliminate the need for the additional state variable, the method of reducing the order of a Markov process described by Taylor and Burt (1984) was applied to equation (3.08). While some information is lost and the conditional variance of P^W_{t+1} given P^W_t is increased by this modification, these drawbacks are felt to be preferable to increasing the dimension of the problem. The reduction of the lag gives equation (3.09),

$$\ln(P^W_{t+1}) = 0.3251 + 0.7897\ \ln(P^W_t) \qquad (3.09)$$

with variance = 0.0292 and standard deviation = 0.171. Note that this standard deviation is not all that much larger than that for equation (3.07), i.e., 0.152.

The barley price equation is a first order nonstochastic difference equation with a first order autoregressive error structure. Prices are expressed in natural logs. Equation (3.10) gives the estimation results.

$$\underset{}{\ln(P^B_{t+1})} = \underset{(2.0146)}{0.20057} + \underset{(4.7735)}{0.56492}D_t + \underset{(7.8858)}{0.77578}\ E(\ln(P^B_t)) + \mu^b_{t+1} \qquad (3.10)$$

$$\mu^b_{t+1} = \underset{(2.3904)}{0.38924}\mu_t + \varepsilon_{t+1}$$

where

$\ln(P^B_{t+1})$ = barley price in year t+1 in natural logs

D_t = the binary variable; D_t = 1, for 1973; 0, elsewhere

$E(\ln(P_t^B))$ = the nonstochastic difference equation term

μ_{t+1}^b = the first order autoregressive error

The adjusted R squared is 0.6721 and the standard error in natural logs is 0.1250. The model in equation (3.10) is a discrete intervention type with the once and for all shock of 1973 being dissipated according to geometric decay over the period after 1973, i.e., a geometric distributed lag effect on the 1973 dummy variable.

Equation (3.10) is adjusted for the nonstochastic difference equation term and autoregressive error term along with setting D_t=0 for 1984 resulting in equation (3.11).

$$\ln(P_{t+1}^B) = 0.54634 + 0.38924 \ln(P_t^B) \qquad (3.11)$$

Transition Probabilities

Years of control and previous land use are deterministic state variables that make the transition from a given state in stage n to a new state in stage n-1, as defined by their transformation functions, with a probability of one.

The remaining state variables, Cephalosporium stripe infection level, winter wheat price, and barley price, are continuous random variables for which transition probabilities must be calculated. To facilitate computations, these continuous random variables are made discrete by specifying an arbitrary number of discrete intervals, with midpoint values assigned to represent the associated state intervals. The transition probabilities are calculated by finding the probability of being within the upper and lower bound of an interval (state)

identified by its associated midpoint. The remainder of this section details the computations necessary to derive the transition probabilities for these random variables.

Given a winter wheat decision in stage n, the desired transition probability for past Cephalosporium stripe infection is:

$$p^{k}_{(h^*)ij} = PR(I_{n-1} = j \mid I_n = i^*, C_n = h^*), k_n = 1 \qquad (3.12)$$

where

$p^{k}_{(h^*)ij}$ = the probability of going to the jth infection state in stage n-1, given the ith infection state, h* years of control, and a winter wheat decision in stage n

i = the ith infection state

j = the jth infection state

PR = the probability operator

i* = the midpoint of the ith infection interval

h* = the number of years of control

Note that states i and j are identically defined, but intuitively the i^{th} state is an experienced infection level and j is an infection level to be realized when the winter wheat crop is grown during stage n. Also the probability is associated with a discrete interval on the continuous variable I.

Equation (3.05) was used along with the following standardized normal variate to calculate the transition probabilities:

$$z = \frac{\ln(I_{n-1}) - \bar{x}^*}{s^*} \qquad (3.13)$$

where

z = the standard normal variate

$\bar{x}^*$ = the estimated mean = $1.3210 - 0.76002 * C_n + \ln(I_n)$

s^* = the standard deviation = 1.679 in natural logs

Under normal circumstances, s^* would be equal to the standard error of the regression equation associated with $\bar{x}^*$. Since equation (2.06) was not estimated using the actual observations on infection from the Moccasin experiment, the following calculation of s^* was done to improve the approximation of the estimate of the standard error:

$$s^* = \sqrt{\sum_{i=1}^{n} \frac{(I_i^a - I_i^p)^2}{n-2}} = 1.679 \qquad (3.14)$$

where

I^a = observed infection levels (percents in natural logs), after 1 year of control (Appendix A)

I^p = predicted infection levels (from equation 2.06) after 1 year of control ($I^p \leq 90\%$) (Appendix B)

n = total number of observations

In choosing interval lengths, two seemingly conflicting objectives were considered: (1) keeping the number of states (intervals) associated with infection levels at a manageable size, and (2) keeping the intervals small enough so that the midpoints are representative of the interval. In order to achieve these goals, the range of infection levels (0-90 percent) was first divided into one-unit intervals with probabilities calculated for each interval. These micro-intervals were then partitioned into 10 larger intervals. The conditional probabilities associated with the new intervals were determined by taking

the simple average of the micro-interval probabilities within each of the larger intervals. The boundaries of the intervals are 0, 5, 15, 25, ... 75, 85, 90 with midpoints calculated as the simple average of the upper and lower boundaries of a given interval. Note that the first and last intervals are only one-half as wide as the others. Table 5 gives the infection level transition probabilities for one year of control. The transition probabilities for two through six years of control are presented in Appendix C.

Table 5. Transition probabilities for Cephalosporium stripe infection level, given one year of control.

I_n	I_{n-1}									
	2.5	10	20	30	40	50	60	70	80	87.5
2.5	.5819	.3664	.0494	.0024	.0001	.0000	.0000	.0000	.0000	.0000
10	.0205	.3872	.2917	.1543	.0835	.0395	.0157	.0054	.0017	.0007
20	.0000	.0433	.2310	.2011	.1478	.1200	.0936	.0664	.0428	.0540
30	.0000	.0011	.0612	.1654	.1536	.1170	.0968	.0862	.0770	.2417
40	.0000	.0000	.0075	.0681	.1279	.1241	.1000	.0821	.0721	.4182
50	.0000	.0000	.0009	.0216	.0789	.1121	.1049	.0866	.0720	.5229
60	.0000	.0000	.0007	.0188	.0739	.1098	.1050	.0872	.0723	.5324
70	.0000	.0000	.0007	.0188	.0739	.1098	.1050	.0872	.0723	.5324
80	.0000	.0000	.0007	.0188	.0739	.1098	.1050	.0872	.0723	.5324
87.5	.0000	.0000	.0007	.0188	.0739	.1098	.1050	.0872	.0723	.5324

The required conditional probabilities for barley and winter wheat prices respectively are specified below:

$$\tilde{p}_{ij} = PR(\ln(P^B_{n-1}) = j \mid \ln(P^B_n) = \tilde{i}) \qquad (3.15)$$

where

$\tilde{p}_{ij}$ = the probability of going to the jth barley price state in stage n-1, given the ith barley price state in stage n

i = the ith barley price state

j = the jth barley price state

PR = the probability operator

$\tilde{I}$ = the midpoint of the ith barley price interval (state)

and

$$\bar{p}_{ij} = PR(\ln(P^{W}_{n-1}) = j \mid \ln(P^{W}_{n}) = \bar{I}) \tag{3.16}$$

where

$\bar{p}_{ij}$ = the probability of going to the jth winter wheat price state in stage n-1, given the ith winter wheat price state in stage n

i = the ith winter wheat price state

j = the jth winter wheat price state

PR = the probability operator

$\bar{I}$ = the midpoint of the ith winter wheat interval (state)

Note that these transition probabilities are not dependent upon the decision variable.

The range of barley and winter wheat prices is centered at the long run equilibrium of the respective equations, \$2.45 for barley and \$4.69 for winter wheat, with endpoints approximately three standard deviations from the long run mean. Figures 2 and 3 show the midpoints and intervals used in the model for winter wheat and barley, respectively, in natural units.

The interval represented by the highest and lowest price levels is open-ended. That is, the probability associated with these midpoints

represents the probability that price is less than or equal to the lowest interval boundary and greater than or equal to the highest interval boundary, respectively.

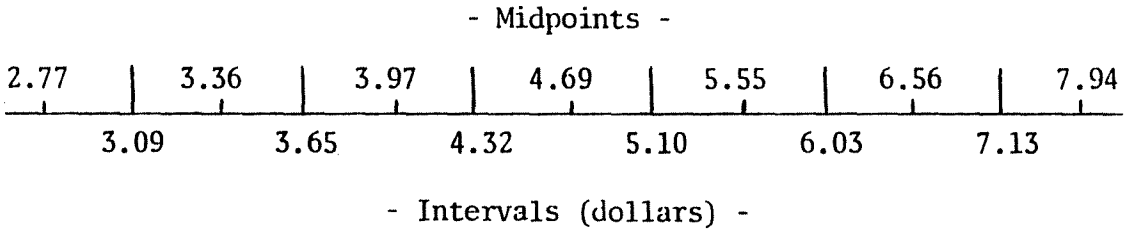


Figure 2. Winter wheat price intervals and midpoints.

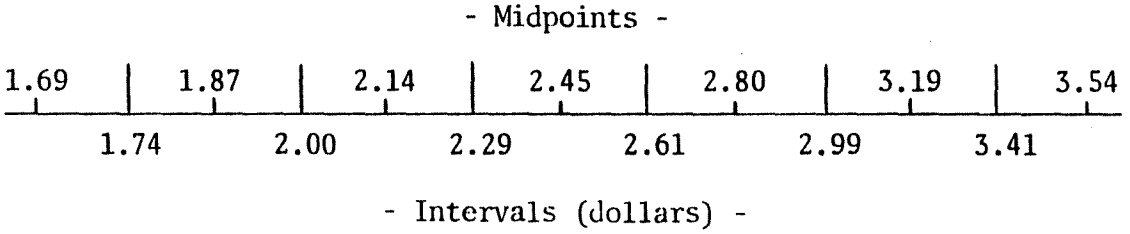


Figure 3. Barley price intervals and midpoints.

The barley price transition probabilities are computed using equation (3.11) and the standardized normal variate below. The interval boundaries and midpoints were expressed in natural logs.

$$Z = \frac{\ln(P^{B}_{n-1}) - \bar{x}'}{s'} \qquad (3.17)$$

where

Z = the standardized normal variate

$\bar{x}'$ = the estimated mean in natural logs = $0.5463 + 0.3892 \ln(P^{B}_{n})$

s' = the estimated standard deviation in natural logs = 0.1250

The probabilities associated with each interval in Figure 3 were calculated by first partitioning the range into 60 small intervals and calculating the transition probabilities as previously described. With these probabilities the long-run equilibrium probability matrix was calculated. A property of Markov chains is convergence of the probability of being in a certain state j, to a constant after a large number of transitions provided the transition probability matrix is regular. This steady state probability (π_j) is independent of the initial state of the system. Accordingly, each of the rows of the matrix has identical probabilities. Since the price transitions do not depend upon the decision variable, these long-run probabilities can be derived without knowing the optimal policy. For details on calculating long-run probabilities, see Howard (1960).

The $\tilde{p}_{ij}$ associated with Figure 3 were then calculated as illustrated below.

$$\tilde{p}_{ij} = \sum_{g_i=1}^{N} \left(\frac{\sum_{h_j=1}^{N} M_{g_i h_j} \pi_{g_i}}{\delta_i} \right) \tag{3.18}$$

where

$\tilde{p}_{ij}$ = the probability of moving to the jth state in stage n-1, given the ith state in stage n

N = the number of micro-intervals in an interval defined by Figure 3

g_i = the gth micro-interval within the ith large interval

h_j = the hth micro-interval within the jth large interval

$M_{g_i h_j}$ = the probability of moving to the hth state in stage n-1, given the gth state in stage n

π_{g_i} = the steady state probability of the gth micro-interval of state i

$\delta_i = \sum_{g_i=1}^{N} \pi_{g_i}$; the steady state probability associated with the ith large interval

Summing the inner term of equation (3.18) gives the probability of going to any micro-interval in state j, given a micro-interval in state i. The outer summation adds across all of the micro-intervals of state i. The numerator is the joint probability of going from state i to state j. The denominator is the marginal probability of being in the i^{th} state in the long run. Thus the division gives the desired conditional probabilities.

The winter wheat price transition probabilities were calculated in the same manner, using equation (3.09) in the z statistic. Tables 6 and 7 give the price transition probabilities.

Table 6. Transition probabilities for the barley price state variable.

p^B_n \ p^B_{n-1}	1.69	1.87	2.14	2.45	2.80	3.19	3.54
1.69	.0680	.2659	.4023	.2187	.0422	.0029	.0001
1.87	.0296	.1749	.3884	.3097	.0882	.0089	.0003
2.14	.0116	.1017	.3275	.3780	.1568	.0231	.0012
2.45	.0040	.0519	.2423	.4036	.2423	.0519	.0040
2.80	.0012	.0231	.1568	.3780	.3276	.1017	.0116
3.19	.0003	.0089	.0882	.3097	.3884	.1749	.0296
3.54	.0001	.0029	.0422	.2186	.4023	.2660	.0680

Table 7. Transition probabilities for the winter wheat price state variable.

P^W_n \ P^W_{n-1}	2.77	3.36	3.97	4.69	5.55	6.56	7.94
2.77	.4989	.3199	.1482	.0303	.0027	.0001	.0000
3.36	.1775	.3353	.3261	.1355	.0238	.0018	.0000
3.97	.0486	.1929	.3591	.2867	.0977	.0141	.0009
4.69	.0084	.0672	.2407	.3675	.2407	.0672	.0084
5.55	.0009	.0141	.0977	.2867	.3591	.1929	.0486
6.56	.0000	.0018	.0238	.1355	.3261	.3353	.1775
7.94	.0000	.0001	.0027	.0303	.1482	.3199	.4989

Expected Immediate Returns

The expected immediate returns (q_i^k in equation 3.01) are defined in general as expected total revenue (product price times yield) minus variable cost on a per-acre basis. Variable cost data (Appendix D) were obtained from the 1982 Enterprise Costs for Judith Basin County. Since prices and infection levels are statistically independent, their expectations can be calculated and then the product of the expectations is used to get the expected gross revenue.

A conditional expectation of product price is used in determining the expected immediate returns because there is approximately a one year lag between the decision point (winter wheat seeding time) and the receipt of any revenue from the crop. The state variables, P^W_n and P^B_n, give the current winter wheat and barley price, respectively. With

this information, expectations of winter wheat and barley prices at marketing are formed. These expectations, though formed and implemented in stage n, are actually the conditional expectations of P^W_{n-1} and P^B_{n-1}, as shown below.

$$\bar{P}^W_{n-1} = E(P^W_{n-1} \mid P^W_n = \bar{i}) \tag{3.19}$$

$$\bar{P}^B_{n-1} = E(P^B_{n-1} \mid P^B_n = \tilde{i}) \tag{3.20}$$

where

$\bar{P}^W_{n-1}$ = the expected winter wheat price at marketing, given the ith winter wheat price state in stage n

$\bar{i}$ = the midpoint of the ith winter wheat price state

E = the expectation operator

$\bar{P}^B_{n-1}$ = the expected barley price at marketing, given the ith barley price state in stage n

$\tilde{i}$ = the midpoint of the ith barley price state

Computationally the conditional expectations for winter wheat and barley price respectively are:

$$\bar{P}^W_{n-1}(i) = \sum_{\bar{j}=j=1}^{7} \bar{p}_{ij}\, \bar{j} \qquad , i = 1,7 \tag{3.21}$$

and

$$\bar{P}^B_{n-1}(i) = \sum_{\tilde{j}=j=1}^{7} \tilde{p}_{ij}\, \tilde{j} \qquad , i = 1,7 \tag{3.22}$$

where

$\bar{j}$ = the midpoint of the jth winter wheat price state

$\tilde{j}$ = the midpoint of the jth barley price state

If the decision in stage n is winter wheat, an additional source of uncertainty, expected infection level, enters the expected immediate returns function. This expectation is conditional on the years of control and the level of Cephalosporium stripe in the last winter wheat crop. The expectation of the infection level in a winter wheat crop in stage n is the conditional expectation of I_{n-1}. That is, in stage n-1, the level of infection in the last winter wheat crop (I_{n-1}) would be equal to the level of infection in the winter wheat crop at stage n.

$$\bar{I}_{n-1} = E(I_{n-1} \mid I_n=i^* \text{ and } C_n=h^*),\ k_n=1 \qquad (3.23)$$

where

$\bar{I}_{n-1}$ = the expected current Cephalosporium stripe infection, given the ith infection level, h* years of control, and a winter wheat decision in stage n

E = the expectation operator

i* = the midpoint of the ith infection interval

h* = the number of years of control

The conditional expected value of the current infection level is calculated as follows:

$$\bar{I}_{n-1}(h^*,i) = \sum_{j^*=j=1}^{10} p^*(h^*)ij\ j^* \quad ,\ i = 1,10;\ \ h^* = 1,6 \qquad (3.24)$$

All variables except j*, the midpoint of the j^{th} infection level, have been defined previously. In the winter wheat yield equations (2.21) and (2.22), $\bar{I}_{n-1}$ is substituted for I_t, and used in the determination of expected immediate returns for winter wheat.

Trend lines from the Judith Basin data were estimated to obtain yield figures for barley on fallow and continuously cropped. The data

include years 1956 through 1984. For barley on fallow the trend line is:

$$BY^F = \underset{(9.9331)}{26.92} + \underset{(2.9927)}{.4723(T)} \tag{3.25}$$

For continuously cropped barley, the trend line is:

$$BY^C = \underset{(9.0331)}{18.06} + \underset{(5.5805)}{.6495(T)} \tag{3.26}$$

Substituting T=29 gives the yields of 40.62 and 36.90 bushels per acre respectively for barley on fallow and continuously cropped barley.

Integrating the information on variable cost, expected prices and yields, equation (3.27) gives the expected immediate returns function associated with each of the decision alternatives. The -$17.83 for a fallow decision is the negative of the variable cost of fallow.

$$q_i^k = \begin{cases} -17.83, & k_n=0 \\ \bar{P}^W_{n-1} * (35.25\ (1-.605 * \bar{I}_{n-1})) - 59.39, & k_n=1,\ L_n=0 \\ \bar{P}^W_{n-1} * (26.19\ (1-.605 * \bar{I}_{n-1})) - 72.17, & k=1,\ L=2 \\ \bar{P}^B_{n-1} * (40.62) - 53.90, & k=2,\ L_n=0 \\ \bar{P}^B_{n-1} * (36.90) - 78.64, & k=2,\ L_n=1,2 \end{cases} \tag{3.27}$$

The Discount Rate

The discount rate (β), used to find the present value of $V_{n-1}(i)$ at each iteration, is $1/(1+r)$, where r is the real interest rate (4½%).

The Recursive Equation

Expression of the dynamic programming recursive relationship for the Cephalosporium stripe decision model requires a broader definition

of state and state transition probabilities. Up to this point, i and j have been used to designate states for a single stochastic variable. This model contains five state variables; therefore, i and j now refer to a vector of five values. For example, the i^{th} state is designated,

$$i = (L_n^*, C_n^*, I_n^*, P_n^{B*}, P_n^{W*})$$

where the superscript denotes a specific value of the state variables.

To implement the model, a joint transition probability function is needed. Calculation of the joint transition probability function is determined by the relationship between the stochastic state variables. If these variables are mutually independent, the joint transition probability function can be derived by multiplication of the three individual transition probability functions.

It is easy to argue that the transition probability function for past Cephalosporium stripe infection levels is independent of the price variables. But the same cannot be said for the independence of winter wheat and barley prices. To test for independence of these variables, the winter wheat residuals from equation (3.07) were regressed on the barley residuals from equation (3.10). The estimated coefficient on the independent variable (barley residuals) was 0.32320, with a t-value of 1.4554, indicating the price series were, at most, weakly correlated. In other words, although the prices themselves were highly correlated, the contemporaneous correlation of the regression residuals was not significant.

Noting that the past infection level variable is only stochastic when the decision is winter wheat, and given the mutual independence of

the stochastic state variables, the joint transition probability function is given by equation (3.28).

$$p_{ij} = \begin{cases} p^{*k}_{(h^*)ij} \cdot \tilde{p}_{ij} \cdot \bar{p}_{ij} & , k_n = 1 \\ \tilde{p}_{ij} \cdot \bar{p}_{ij} & , k_n = 0,2 \end{cases} \tag{3.28}$$

where

p_{ij} = the probability of moving from the ith vector of state variables in stage n to the jth vector of state variables in stage n-1

and $p^{*}_{(h^*)ij}$, $\tilde{p}_{ij}$, and $\bar{p}_{ij}$ are as defined in equations (3.12), (3.15), and (3.16), respectively.

With the above modification, the recursive relationship can be expressed as:

$$V_n(L_n, C_n, I_n, P^B_n, P^W_n) = \max_{k_n} (q(L_n, C_n, \bar{I}_{n-1}, \bar{P}^B_{n-1}, \bar{P}^W_{n-1}) + \beta (\sum_{j=1}^{M} p^k_{ij} V_{n-1}(L_{n-1}, C_{n-1}, I_{n-1}, P^B_{n-1}, P^W_{n-1}))) \tag{3.29}$$

$$n = 1,2,\ldots,25$$
$$i = 1,2,\ldots,m$$
$$j = 1,2,\ldots,m$$

Terminal Value

The solution procedure, which begins by solving for $V_1(i)$, requires a value for $V_0(j)$. It is assumed here that the state variables will not affect the value of the firm's assets at liquidation of the firm, thus $V_0(j)$ equals zero. It can be shown that the level of $V_0(j)$ is unimportant; only the differences across j are relevant in affecting the optimization (Howard, 1960).

CHAPTER 4

RESULTS

Solution of the recursive equation yields the optimal policy and expected present value of net returns for all combinations of states and stages. The optimal policy appeared to be invariant to stages with 20 years left in the planning horizon (n=20). There are 6,370 states in each stage of the Cephalosporium stripe decision model. Sections of the optimal policy which illustrate the trade-offs involved in the decision making process are highlighted in this chapter.

In Tables 8, 9, 10 and 11, the previous land use is fallow. Thus there are only two decision alternatives: winter wheat (W) and barley (B). Examined separately, each table illustrates a control/no control frontier. For given winter wheat and barley prices, this frontier depends on the years of control and the past stripe infection level. These factors determine the expected level of infection in the current crop, thus affecting winter wheat yields. As expected, the concentration of winter wheat decisions lies in the lower left corner of each table where years of control are highest and past infection levels are lowest.

Comparison of rows in Tables 8 and 9 demonstrates the effect of a higher winter wheat price, other things equal. A higher winter wheat price makes winter wheat the more profitable decision at higher levels of past infection. For example, in row three of Table 8 (three years of

Table 8. Optimal policy under a 25-year planning horizon for varying years of control and infections in last winter wheat crop, given a previous land use of fallow, a barley price of $1.87 and a winter wheat price of $3.36.

Years of Control	Infection in Last Winter Wheat Crop (%)									
	2.5	10	20	30	40	50	60	70	80	87.5
1	W	B	B	B	B	B	B	B	B	B
2	W	B	B	B	B	B	B	B	B	B
3	W	W	B	B	B	B	B	B	B	B
4	W	W	W	B	B	B	B	B	B	B
5	W	W	W	W	W	W	W	W	W	W

Table 9. Optimal policy under a 25-year planning horizon for varying years of control and infections in last winter wheat crop, given a previous land use of fallow, a barley price of $1.87 and a winter wheat price of $4.69.

Years of Control	Infection in Last Winter Wheat Crop (%)									
	2.5	10	20	30	40	50	60	70	80	87.5
1	W	B	B	B	B	B	B	B	B	B
2	W	W	B	B	B	B	B	B	B	B
3	W	W	W	W	B	B	B	B	B	B
4	W	W	W	W	W	W	W	W	B	B
5	W	W	W	W	W	W	W	W	W	W

Table 10. Optimal policy under a 25-year planning horizon for varying years of control and infections in last winter wheat crop, given a previous land use of fallow, a barley price of $2.45 and a winter wheat price of $3.36.

Years of Control	Infection in Last Winter Wheat Crop (%)									
	2.5	10	20	30	40	50	60	70	80	87.5
1	B	B	B	B	B	B	B	B	B	B
2	W	B	B	B	B	B	B	B	B	B
3	W	B	B	B	B	B	B	B	B	B
4	W	W	B	B	B	B	B	B	B	B
5	W	W	W	W	B	B	B	B	B	B

Table 11. Optimal policy under a 25-year planning horizon for varying years of control and infections in last winter wheat crop, given a previous land use of fallow, a barley price of $1.69 and a winter wheat price of $2.77.

Years of Control	Infection in Last Winter Wheat Crop (%)									
	2.5	10	20	30	40	50	60	70	80	87.5
1	B	B	B	B	B	B	B	B	B	B
2	W	B	B	B	B	B	B	B	B	B
3	W	W	B	B	B	B	B	B	B	B
4	W	W	W	B	B	B	B	B	B	B
5	W	W	W	W	W	W	W	W	W	W

control), there are winter wheat decisions at the two lowest infection levels, while in the same row of Table 9 there are four winter wheat decisions. This relationship holds, in general, throughout the optimal policy.

Tables 8 and 10 demonstrate the trade-offs that occur when barley price increases, *ceteris paribus*. Again, it is not surprising to find more barley decisions at higher barley prices when the other variables are held constant.

In Table 11, both grain prices are at their lowest levels. The barley decision in the uppermost left-hand corner is unique in the policy. A pattern of no barley decisions at relatively low barley prices and low past infection levels extends throughout the policy. The three other state variables are primarily responsible for the decision between fallow or winter wheat in these cases.

Tables 12 and 13 illustrate portions of the optimal policy for a previous land use of winter wheat and, accordingly, zero years of control. The decision alternatives are limited to fallow (F) and barley (B) under these circumstances.

Low barley prices coupled with a previous land use of winter wheat partially explain the fallow-barley frontier. Barley does not become optimal until its price reaches $2.80. But since the expected immediate returns of continuously cropped barley are positive at even the lowest barley price and the immediate returns to fallow are negative, the role of the other variables, in a longer run framework, must be evaluated.

Table 12. Optimal policy under a 25-year planning horizon for varying barley prices and infections in last winter wheat crop, given a previous land use of winter wheat, zero years of control and a winter wheat price of $3.36.

Barley Price	Infection in Last Winter Wheat Crop (%)									
	2.5	10	20	30	40	50	60	70	80	87.5
$1.69	F	F	F	F	F	F	F	F	F	F
$1.87	F	F	F	F	F	F	F	F	F	F
$2.14	F	F	F	F	F	F	F	F	F	F
$2.45	F	F	F	F	F	F	F	F	F	F
$2.80	B	B	B	B	B	B	B	B	B	B
$3.19	B	B	B	B	B	B	B	B	B	B
$3.54	B	B	B	B	B	B	B	B	B	B

Table 13. Optimal policy under a 25-year planning horizon for varying barley prices and infections in last winter wheat crop, given a previous land use of winter wheat, zero years of control and a winter wheat price of $4.69.

Barley Price	Infection in Last Winter Wheat Crop (%)									
	2.5	10	20	30	40	50	60	70	80	87.5
$1.69	F	F	F	F	F	F	F	F	F	F
$1.87	F	F	F	F	F	F	F	F	F	F
$2.14	F	F	F	F	F	F	F	F	F	F
$2.45	F	F	F	F	F	F	F	F	F	F
$2.80	F	B	B	B	B	B	B	B	B	B
$3.19	F	B	B	B	B	B	B	B	B	B
$3.54	B	B	B	B	B	B	B	B	B	B

In the optimal policy, most of the winter wheat decisions occur at the two lowest infection levels when the years of control are one, two, or three, unless the winter wheat price is in the upper range. Thus, many of the fallow decisions in these tables, where the given winter wheat price is low to medium, are probably the first of a three-year control sequence (for example, F-B-F). This sequence allows both a barley and a wheat crop to be planted on fallow. Once the barley price becomes high enough, a different type of control sequence (such as B-B-F) may be optimal for a given winter wheat price.

Not all of the fallow decisions in these tables should be interpreted as the beginning of a longer sequence of control. Fallow associated with the two lowest infection levels is most likely indicative of the end of a control sequence. In Table 13, which has a higher winter wheat price than Table 12, two of the barley decisions in the first column (rows 5 and 6) have been replaced by fallow decisions. The expectation of a higher winter wheat price in the next time period, together with the low past infection level, prompts the change in order to exploit the increase in yield associated with a fallow-wheat rather than barley-wheat sequence. In the optimal policy, all of the barley decisions at the lowest past infection level are eventually replaced by fallow decisions, as the winter wheat price continues to rise. Some of the barley decisions in the 5 to 10 percent past infection level range also change to fallow under these circumstances.

Tables 14, 15, and 16 illustrate the optimal policy, given a previous land use of barley, for given winter wheat and barley prices, with varying years of control and past infection levels.

Table 14. Optimal policy under a 25-year planning horizon for varying years of control and infections in last winter wheat crop, given a previous land use of barley, a barley price of $3.19 and a winter wheat price of $4.69.

Years of Control	Infection in Last Winter Wheat Crop (%)									
	2.5	10	20	30	40	50	60	70	80	87.5
1	F	F	F	F	F	F	F	F	F	F
2	F	F	B	B	B	B	B	B	B	B
3	W	F	B	B	B	B	B	B	B	B
4	W	F	F	F	B	B	B	B	B	B
5	W	W	F	F	F	F	F	F	F	F

Table 15. Optimal policy under a 25-year planning horizon for varying years of control and infections in last winter wheat crop, given a previous land use of barley, a barley price of $2.45 and a winter wheat price of $4.69.

Years of Control	Infection in Last Winter Wheat Crop (%)									
	2.5	10	20	30	40	50	60	70	80	87.5
1	F	F	F	F	F	F	F	F	F	F
2	F	F	F	B	F	F	F	F	B	B
3	F	F	F	F	F	F	F	F	F	F
4	W	F	F	F	F	F	F	F	B	B
5	W	W	F	F	F	F	F	F	F	F

Table 16. Optimal policy under a 25-year planning horizon for varying years of control and infections in last winter wheat crop, given a previous land use of barley, a barley price of $2.45 and a winter wheat price of $5.55.

Years of Control	Infection in Last Winter Wheat Crop (%)									
	2.5	10	20	30	40	50	60	70	80	87.5
1	F	F	F	F	F	F	F	F	F	F
2	F	F	F	F	F	F	F	B	B	B
3	W	F	F	F	F	F	F	F	F	F
4	W	W	F	F	F	F	F	F	F	F
5	W	W	W	F	F	F	F	F	F	F

As with the first tables, the control/no control frontier is delineated, with wheat decisions increasing in each table as years of control increase, other variables constant. Tables 15 and 16 show the effect of a higher winter wheat price on the frontier. Again, wheat decisions are observed at higher infection levels and with fewer years of control when the price increases. Recalling the infection relationship, it is not surprising that wheat decisions begin at three or more years of control. The fallow decisions that appear when years of control are greater than or equal to three probably imply a winter wheat decision in the next time period.

The trade-offs between methods of control can be seen by comparing Tables 14 and 15. Table 14, with the greater concentration of barley decisions, has a higher barley price. The odd pattern of barley decisions in Table 15 most likely indicates a very fine line between

fallow and barley decisions. If similar tables were constructed for a wider range of barley prices, the gradual filling in the block observed in Table 14 could be seen. For example, when barley price is $2.14, there are no barley decisions at two years of control.

The importance of previous land use is shown in Table 17. There are more winter wheat decisions, other things equal, when the previous land use is fallow. If the previous land use is barley and there is a high probability of winter wheat in the next period, the current decision is fallow.

Table 17. Optimal policy under a 25-year planning horizon for varying infection levels and previous land use, given four years of control, a winter wheat price of $4.69 and a barley price of $2.45.

Previous Land Use	Infection in Last Winter Wheat Crop (%)									
	2.5	10	20	30	40	50	60	70	80	87.5
Fallow	W	W	W	W	W	B	B	B	B	B
Barley	F	F	F	F	F	F	F	F	B	B

It should be noted that in row 1 of Table 17, fallow is not one of the decision alternatives. However, assuming the returns (further yield increases) to a second year of fallow are in fact marginal, the decisions should not be biased.

Some very broad statements can be made about the optimal policy. If the years of control are less than three and the infection level in the last winter wheat crop is greater than 25 percent, the decision is usually to control. When there are less than three years of control

and past infection levels are in approximately the 0 to 25 percent range, winter wheat decisions become more prevalent, especially when the winter wheat price is in its upper range. Once three years of control has been exceeded, winter wheat decisions become optimal at higher levels of past infection and increase as winter wheat prices increase. Conversely, it takes a lower winter wheat price to bring about a winter wheat decision, given the past infection level, as years of control increase. This is consistent with the infection relationship, which does not predict declines in current infection until there have been three years of control.

The results presented so far were derived with the condition that the decision maker would consider a maximum of six years of control. To compare the effect of maximum years of control on monetary returns in a given situation, additional results were obtained in which the maximum years of control were reduced to one, two, three, and four years, respectively. Each of the different maximum control specifications yields a set of net present values for each state at each stage of the 25-year planning horizon. Given a vector of the state variables, the discounted expected returns associated with each of the specified values for maximum years of control can be compared. The results are an indicator of the economic value of considering the specified values for maximum years of control. Note these are not the infinite expected returns associated with optimal policies.

The significance of the difference in monetary returns due to the length of the years of control maximums are more meaningful when presented on an annual basis rather than a discounted net present value

for the planning horizon. Therefore, the net present values were amortized to derive the comparable annual return figures in dollars per acre. The annual return information, given a vector of state variable values under a 25-year planning horizon, is presented in Table 18.

Table 18. Amortized returns from optimal crop sequences in relation to maximum years of control and past Cephalosporium stripe infection levels under a 25-year planning horizon, given a previous land use of fallow, one year of control, a barley price of $2.45 and a winter wheat price of $4.69.

Maximum Years of Control	Infection in Last Winter Wheat Crop (%)									
	2.5	10	20	30	40	50	60	70	80	87.5
1	28.47	20.32	15.96	13.91	12.85	12.33	12.29	12.29	12.29	12.29
2	40.17	35.53	32.19	29.40	27.10	25.33	23.98	22.96	22.16	21.68
3	42.30	39.56	37.92	36.76	35.91	35.08	34.27	33.50	32.80	32.32
4	42.48	39.72	38.30	37.44	36.72	36.12	35.67	35.50	34.95	34.68
6	42.59	39.83	38.53	37.76	37.22	36.80	36.44	36.12	35.84	35.66

Looking down each of the columns of Table 18, the cost of limiting the number of years between winter wheat crops to one, two, or three throughout the planning horizon is clearly illustrated. For example, if the Cephalosporium stripe infection level in the last winter wheat crop was in the zero to five percent interval (column one), the amortized returns for a maximum one-, two-, and three-year control sequence are $28.47, $40.17, and $42.30 per acre, respectively.

Looking at the same column but comparing the amortized returns to maximum three, four, and six years of control shows gains associated

with allowing six-year control sequences. The gains are small when past infection levels are in the lower range, but in the upper range of past infection levels the returns to a maximum six years of control, rather than three or four, are more significant.

A general recommendation from these results would be to follow a three-year control sequence when past Cephalosporium stripe infections are low to medium, but to consider longer control sequences when past infection levels are more severe. These findings are consistent with the recommendations of the Montana Small Grain Guide (1985) which suggests a minimum of three years without winter wheat when Cephalosporium stripe has been observed.

CHAPTER 5

SUMMARY

Cephalosporium stripe is a fungal vascular disease of winter wheat caused by the soil borne pathogen Cephalosporium gramineum. Infested winter wheat plants produce fewer and smaller kernels than healthy plants, resulting in significant yield losses. Once an area is infested, control of the disease is important because the fungus survives for long periods of time in winter wheat residues, enabling it to affect subsequent winter wheat crops.

Rotating to non-host spring crops or fallow is the primary method of controlling the disease. This allows time for residue decomposition before winter wheat is seeded again. The number of years of fallow and spring crops between winter wheat crops, together with the Cephalosporium stripe infection level in the last winter wheat crop, determine the level of infection in the current winter wheat crop. For a given past infection level, the expected current infection level will decline as the years of control increase.

The producer seeking to minimize the effects of Cephalosporium stripe infestations on profits over his/her planning horizon must make a sequence of interrelated decisions concerning land use. Of the land use alternatives, winter wheat has on average the highest immediate returns, but neither Cephalosporium stripe infection levels nor winter wheat prices are known with certainty when the decision about land use

is made. In addition, future returns will be affected by planting winter wheat in the current season because the control sequence is ended. Fallowing the land results in negative immediate returns, but enhances the level of soil nutrients and soil moisture available for subsequent crops, thereby increasing future crop yields and net returns. Fallow and spring crops are both non-host land uses with respect to Cephalosporium stripe that, other things equal, increase the yield and net returns from subsequent winter wheat crops by lowering the expected Cephalosporium stripe infection level. Barley also generates positive immediate returns, but again the market price is not known with certainty at seeding time.

It is clear that the control of Cephalosporium stripe through cropping sequences is a stochastic, dynamic problem. It is dynamic because current land use decisions affect future yields, and stochastic because product prices and Cephalosporium stripe infection levels can only be predicted in a probabilistic sense.

The objective of this thesis was to determine economically optimal land use sequences to control Cephalosporium stripe for a representative farm. A stochastic dynamic programming model was developed to identify the optimal policy concerning land use sequences over the firm's planning horizon. The decision maker's objective was maximization of expected present value of returns over variable cost. Expected returns are determined by expected crop yields and expected product prices.

The setting for the economic model was a representative dryland grain farm in the Judith Basin of Central Montana. The farm's land use

alternatives were winter wheat, barley, and fallow. Barley was selected over other spring crops after examination of historical cropping patterns in the area.

The following state variables were included in the optimization model to describe the economic and physical condition of the system: previous land use, years of control (the number of years of non-host land use between winter wheat crops), the level of Cephalosporium stripe in the last winter wheat crop, winter wheat price, and barley price. Previous land use and years of control are deterministic state variables, while winter wheat and barley prices are stochastic. The level of Cephalosporium stripe infection in the last winter wheat crop is either deterministic or stochastic, depending on the current decision. The decision alternatives are winter wheat, barley, and fallow. If the decision is winter wheat, the past infection level variable is stochastic. If the decision is not winter wheat, the level of Cephalosporium stripe infection in the last winter wheat crop does not change and, accordingly, the variable is then deterministic.

Implementation of the empirical decision model required the statistical estimation of several functional relationships. First, a relationship depicting the dynamics of Cephalosporium stripe as a function of years of control was determined using output from a simulation model developed by plant pathologists from Montana State University (CEPHLOSS). The relationship between Cephalosporium stripe infection level and winter wheat yield was estimated from data collected at the Moccasin experiment station in the Judith Basin of Montana. The differentials in yields for winter wheat and barley

produced on stubble and fallow were estimated from unpublished data obtained from the Montana Crop Reporting Service. Equations describing the relationships between winter wheat and barley prices in year t and year t+1 were statistically estimated using Montana data. Finally, costs of crop production and fallow for a representative Judith Basin dryland grain farm were obtained from Montana State University Cooperative Extension Service costs and returns publications.

Transformation functions for the state variables are derived and presented. The transition probability distributions for the stochastic state variables were also developed and presented. This information is incorporated into the dynamic programming model through a joint transition probability function and net returns function.

The model was solved for all positive integer valued planning horizons of 25 years or less. For a given planning horizon there are 6,370 possible combinations of the state variables. Optimization of the model yields a land use decision and a discounted net present value of returns for each of these possible states.

Winter wheat decisions occurred most often with one, or a combination, of the following circumstances: high winter wheat prices, years of control greater than or equal to three, and lower past infection levels. At the beginning of a control sequence defined by low barley prices, and at the end of a control sequence when conditions were favorable for winter wheat in the next decision period, the predominant decision was fallow. Barley was the optimal method of control when there was a good possibility that one or more additional years of

control would be required after the current decision. Given these conditions, barley decisions increase as barley prices increase.

Amortized net present values for alternative maximum years of control in a specified state under a 25-year planning horizon were examined. The results indicated that long sequences of control increased annual returns significantly if past Cephalosporium stripe infection levels were severe. However, control sequences no longer than three years capture most of the economic value of control if past infection levels were low to moderate. Unwillingness to consider control sequences of greater than two years in length resulted in significant reductions in annual returns regardless of the past infection level.

The results of this study indicate that the Cephalosporium stripe problem is not trivial in terms of returns to the winter wheat producer. However, the quality of the results are data dependent. The most obvious inadequacy in the model is the lack of experimental data to statistically estimate the infection relationship. Experimentation designed to provide such data would improve the reliability of the results.

The results are also region specific, especially with regard to the method of control. The choice of the spring crop is separable from the control/no control decision. The effect of fallow on crop yields is largely determined by soil composition and depth. Two years of fallow may be optimal in some areas. In others, one year may not have the impact on yield shown in this study, thus reducing the number of fallow decisions.

The model could be extended to allow for decisions regarding land use to be made in the spring as well as the fall. In a semi-annual model, the inclusion of a state variable measuring soil moisture would provide valuable information. It is clear that there is a threshold value for soil moisture for profitable crop production. That is, even if all other conditions indicated a crop should be planted, the level of soil moisture could indicate that the outcome would be uneconomical.

The present annual model would be improved by fall soil moisture measurements when winter wheat was being considered following a summer in barley. However, given the unusually shallow soils at the experimental site, soil moisture in the fall is not informative when the land was in summer fallow. Thus the present model is essentially complete.

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APPENDICES

APPENDIX A

OBSERVED INFECTION FROM MOCCASIN EXPERIMENT FOR YEARS 1972 AND 1974

The following table gives observed levels of Cephalosporium stripe infection, after one year of control, at Moccasin, Montana. The data have been converted to percentages (based on 160 plants per 20 linear feet), and then to natural logs.

Table 19. Observed Cephalosporium stripe infection at Moccasin, Montana for years 1972 and 1974.

Year	Observed Infection (I^a)
1972	3.608
	3.114
	3.887
	3.820
	3.681
	4.193
1974	2.687
	1.928
	1.799
	2.108
	2.457
	1.375
	1.173
	1.203
	0.733

APPENDIX B

PREDICTED INFECTION, GIVEN PAST INFECTION LEVELS FROM THE MOCCASIN EXPERIMENT, FOR THE YEARS 1972 AND 1974

The following table gives predicted infection levels for years 1972 and 1974 from equation (2.06). There is one year of control and past infection levels are from the Moccasin experiment (years 1970 and 1972--Table 3). The infection levels from Table 3 were converted to percent infected plants for use in equation (2.06). Predicted infection is constrained to be less than or equal to 90 percent (4.5000 in natural logs).

Table 20. Predicted Cephalosporium stripe infection, given past infection levels from the Moccasin experiment, for years 1972 and 1974.

Year	Predicted Infection (I^p)
1972	4.234
	3.774
	3.800
	3.106
	3.428
	4.428
1974	4.222
	3.728
	4.500
	4.296
	4.500
	3.213
	2.496
	2.747
	3.035

APPENDIX C

TRANSITION PROBABILITIES FOR CEPHALOSPORIUM STRIPE INFECTION LEVEL FOR TWO THROUGH SIX YEARS OF CONTROL

Table 21. Transition probabilities for Cephalosporium stripe infection level, given two years of control.

	I_{n-1}									
I_n	2.5	10	20	30	40	50	60	70	80	87.5
2.5	.8450	.1546	.0004	.0000	.0000	.0000	.0000	.0000	.0000	.0000
10	.1996	.5938	.1700	.0328	.0035	.0003	.0000	.0000	.0000	.0000
20	.0032	.3885	.3023	.1851	.0841	.0275	.0072	.0016	.0003	.0001
30	.0000	.1470	.3038	.1964	.1532	.1040	.0559	.0249	.0097	.0052
40	.0000	.0338	.2426	.2013	.1456	.1235	.0995	.0694	.0419	.0424
50	.0000	.0054	.1366	.2041	.1471	.1158	.1022	.0888	.0709	.1291
60	.0000	.0007	.0593	.1722	.1553	.1158	.0961	.0868	.0784	.2354
70	.0000	.0001	.0216	.1189	.1524	.1219	.0956	.0822	.0753	.3321
80	.0000	.0000	.0070	.0698	.1323	.1255	.0995	.0815	.0718	.4125
87.5	.0000	.0000	.0027	.0427	.1098	.1233	.1030	.0831	.0709	.4645

Table 22. Transition probabilities for Cephalosporium stripe infection level, given three years of control.

	I_{n-1}									
I_n	2.5	10	20	30	40	50	60	70	80	87.5
2.5	.9871	.0129	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000
10	.5892	.3992	.0115	.0001	.0000	.0000	.0000	.0000	.0000	.0000
20	.1635	.6439	.1754	.0164	.0008	.0000	.0000	.0000	.0000	.0000
30	.0212	.5421	.3023	.1119	.0199	.0024	.0002	.0000	.0000	.0000
40	.0015	.3940	.3001	.1954	.0822	.0216	.0043	.0008	.0001	.0000
50	.0001	.2581	.3026	.2048	.1391	.0650	.0221	.0062	.0015	.0005
60	.0000	.1484	.3080	.1953	.1560	.1055	.0538	.0219	.0077	.0035
70	.0000	.0747	.2912	.1942	.1516	.1235	.0837	.0459	.0213	.0139
80	.0000	.0336	.2497	.2007	.1452	.1246	.1004	.0688	.0401	.0370
87.5	.0000	.0170	.2095	.2060	.1433	.1212	.1048	.0810	.0541	.0631

Table 23. Transition probabilities for Cephalosporium stripe infection level, given four years of control.

I_n	I_{n-1}									
	2.5	10	20	30	40	50	60	70	80	87.5
2.5	.9998	.0002	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000
10	.9105	.0895	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000
20	.5740	.4224	.0036	.0000	.0000	.0000	.0000	.0000	.0000	.0000
30	.3301	.6148	.0543	.0007	.0000	.0000	.0000	.0000	.0000	.0000
40	.1588	.6563	.1740	.0107	.0003	.0000	.0000	.0000	.0000	.0000
50	.0604	.6169	.2714	.0477	.0034	.0002	.0000	.0000	.0000	.0000
60	.0191	.5486	.3065	.1082	.0160	.0015	.0001	.0000	.0000	.0000
70	.0053	.4742	.3062	.1640	.0426	.0067	.0008	.0001	.0000	.0000
80	.0014	.4010	.2996	.1967	.0787	.0187	.0033	.0005	.0001	.0000
87.5	.0004	.3480	.2976	.2069	.1057	.0325	.0072	.0013	.0002	.0000

Table 24. Transition probabilities for Cephalosporium stripe infection level, given five years of control.

I_n	I_{n-1}									
	2.5	10	20	30	40	50	60	70	80	87.5
2.5	.9998	.0002	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000
10	.9988	.0012	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000
20	.9373	.0627	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000
30	.7493	.2506	.0001	.0000	.0000	.0000	.0000	.0000	.0000	.0000
40	.5748	.4234	.0018	.0000	.0000	.0000	.0000	.0000	.0000	.0000
50	.4448	.5418	.0133	.0000	.0000	.0000	.0000	.0000	.0000	.0000
60	.3360	.6166	.0470	.0004	.0000	.0000	.0000	.0000	.0000	.0000
70	.2412	.6530	.1034	.0024	.0000	.0000	.0000	.0000	.0000	.0000
80	.1629	.6597	.1686	.0085	.0002	.0000	.0000	.0000	.0000	.0000
87.5	.1160	.6519	.2143	.0173	.0006	.0000	.0000	.0000	.0000	.0000

Table 25. Transition probabilities for Cephalosporium stripe infection level, given six years of control.

I_n	I_{n-1}									
	2.5	10	20	30	40	50	60	70	80	87.5
2.5	.9998	.0002	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000
10	1.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000
20	.9998	.0002	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000
30	.9921	.0079	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000
40	.9483	.0517	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000
50	.8595	.1405	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000
60	.7556	.2444	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000
70	.6608	.3390	.0002	.0000	.0000	.0000	.0000	.0000	.0000	.0000
80	.5807	.4181	.0012	.0000	.0000	.0000	.0000	.0000	.0000	.0000
87.5	.5283	.4686	.0031	.0000	.0000	.0000	.0000	.0000	.0000	.0000

APPENDIX D

VARIABLE COSTS OF SPECIFIED LAND USES IN JUDITH BASIN COUNTY

Table 26. Variable costs of specified land uses in Judith Basin County.

Land Use	Variable Cost[a] (Dollars/Acre)
Fallow	$17.83
Barley on stubble	78.64
Barley on fallow	53.90
Winter wheat on stubble	72.17
Winter wheat on fallow	59.39

[a]Source: Fogle, 1982.