AN ABSTRACT OF THE DISSERTATION OF

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The impact of recent severe droughts throughout the United States, the potential for climate change to intensify the frequency and severity of drought, and discussion about the future of government assistance in agriculture highlight the need for a transition from drought as ‘disaster’ to drought as ‘managed risk’. However, guidance for agricultural producers about optimal drought preparedness and response is insufficient. It is particularly unclear what optimal drought preparedness and response should look like, in practice, for farm systems with uncertain water supplies and intra- and inter-year dynamics.

A mathematical programming model that captures the stochastic and dynamic aspects of an irrigated row crop farm is developed and used to explore the nature of optimal drought preparedness and response. Results indicate several important characteristics. First, drought has the potential to generate heterogeneous impacts, even across a set of homogeneous farms. Second, a farm system with inter-year dynamics can continue to experience the effects of drought after the drought itself subsides; additionally, the effects of drought in one year can intensify the impact of drought in subsequent years. Third, in the presence of discount and interest rates, crop diversification does not maximize expected profit, even though it is often considered a drought management tool. Fourth, the primary

effect of water supply uncertainty is the abandonment of more fall-prepared fields. Hence, the multi-peril crop insurance program's prevented planting provision is identified as an optimal drought preparedness tool, even if unsubsidized. Finally, the predicted effects of climate change for snowmelt-dependent farm systems require distinctly different forms of adaptation, and cause profit losses of different magnitudes.

Because the model captures both intra- and inter-year dynamics, it provides 1) a more thorough understanding of the complex tradeoffs that producers face when preparing for and responding to drought, 2) a more complete picture of the dynamic impacts of drought, and 3) important insights about the administration of drought assistance programs. Lastly, it elucidates the meaning of optimal drought preparedness; a notion that has received increased attention in the policy arena, but whose practical form has been only vaguely alluded to.

Economics of Drought Preparedness and Response in Irrigated Agriculture

by
Dannele E. Peck

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I understand that my dissertation will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my dissertation to any reader upon request.

Dannele E. Peck, Author

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Economics of Drought Preparedness and Response in Irrigated Agriculture

1 Introduction

Climate variability is a major source of uncertainty for agriculture in the United States, generating an expected annual loss of $80-95 billion (Easterling and Mendelsohn 2000). Drought is one manifestation of climate variability that continues to challenge agriculture, particularly in the semi-arid regions of the western United States, where the frequency of drought is high (Wilhite and Rhodes 1993). Tannehill (1947, p. 15) wrote of the unique nature of drought, particularly the challenge of recognizing it in advance:

> We have no good definition of drought. We may say truthfully that we scarcely know a drought when we see one. We welcome the first clear day after a rainy spell. Rainless days continue for a time and we are pleased to have a long spell of such fine weather. It keeps on and we are a little worried. A few days more and we are really in trouble. The first rainless day in a spell of fine weather contributes as much to a drought as the last, but no one knows how serious it will be until the last dry day is gone and the rains have come again. We are not sure about it until the crops have withered and died.

Agricultural producers throughout much of the United States have recently experienced the creeping nature of drought to which Tannehill eluded over 50 years ago. The 1999-2006 drought is one of the most severe in the last 100 years (Heim and Lawrimore 2006). At the peak of the drought, in 2004, two-thirds of the western United States was affected (Heim and Lawrimore 2006). Indices such as the Standardized Precipitation Index (SPI), Palmer Drought Severity Index (PDSI), Surface Water Supply Index (SWSI), and Crop Moisture Index (CMI) have sharpened the definition and detection of agricultural drought, but the science of drought prediction is still in its infancy (Dole 2000). Agricultural producers, as a result, rely largely on past experience and providence to account for the risk of drought in their farm management plans (i.e. to prepare for drought), and to adjust farm plans in the event of drought (i.e. to respond to drought).

Research suggests that global climate change, particularly increased evaporation rates, and a larger proportion of precipitation in the form of rain versus snow, will enhance the frequency and intensity of drought in many areas of the western United States (Gleick 2000; Intergovernmental Panel on Climate Change 2001a; Intergovernmental Panel on Climate Change 1998). It will become increasingly important, in the event of such climate changes, to understand the characteristics of drought preparedness and response in farm management plans. Drought preparedness and response has concomitantly appeared in the policy arena, as policymakers discuss the future of government assistance in agriculture, including, for example, subsidized crop insurance (a drought preparedness tool) and disaster assistance programs (a drought response tool) (Knutson 2001; Western Drought Coordination Council 1999). Australia set an extreme example for U.S. policymakers in the late 1980s by removing drought from the list of recognized natural disasters. Agricultural producers in Australia continue to struggle with the policy-transition from drought as a 'disaster' to which they simply respond, to drought as a 'managed risk' for which they prepare (Stehlik 2005). Although drought preparedness has garnered increased attention in the U.S., guidance for producers about how to incorporate drought preparedness into the farm's broader management plan remains insufficient.

Economic studies have increased the understanding of drought preparedness and response. However, simplifying assumptions about farm systems' uncertainty and dynamics, which are commonly used to improve model tractability, result in an incomplete understanding of the many tradeoffs producers face. Four alternative sets of assumptions are common: 1) certainty with no dynamics (Adams and Cho 1998; Bernardo et al. 1987; Jaeger 2004; Michelsen and Young 1993), 2) certainty with *intra*- or *inter*-year dynamics (Garrido and Gomez-Ramos 2000; Haouari and Azaiez 2001; Iglesias, Garrido, and Gomez-

Ramos 2003; Thompson and Powell 1998), 3) uncertainty with *intra*-year dynamics (Adams et al. 1995; Keplinger et al. 1998; Mejias, Varela-Ortega, and Flichman 2004; Taylor and Young 1995; Turner and Perry 1997), and 4) uncertainty with *inter*-year dynamics (and in some cases *intra*-year dynamics as well) (Toft and O'Hanlon 1979; Weisensel, Van Kooten, and Schoney 1991). The fourth set of assumptions most thoroughly captures the decision-making environment of a producer who faces uncertainty and a dynamic farm system. Few studies use this set of assumptions, however, to address optimal drought preparedness and response (where "optimal" refers throughout this dissertation to the solution that maximizes a mathematical programming model's farm-level objective function; nowhere in this dissertation is "optimal" used to indicate Pareto optimality or social efficiency). No studies have used this set of assumptions in the context of an irrigated crop farm.

Uncertainty and dynamics make it challenging for a producer to identify optimal drought preparedness and response plans. Because of uncertainty, producers typically do not know, prior to decision making, whether drought will occur in the near future, when or how frequently it will occur in the more distant future, how severe drought will be, or for how long any one drought will persist. Because of intra- and inter-year dynamics, producers also have to consider how current decisions will affect opportunities and outcomes in future periods. Producers whose farm systems involve both uncertainty and dynamics have to keep two things in mind when making drought preparedness and response plans: 1) the cost of drought preparedness includes foregone opportunities if drought does not materialize, and 2) the dynamic effect of their plan on future decisions is state-dependent. The challenge, in summary, is to determine "whether the long-run rewards will be greater if one hedges against drought in their year-to-year operations, or plunges ahead boldly, facing up to drought only when it actually hits" (Clawson et al. 1980, p. 45). Given the considerable complexity of such a decision environment, it is difficult to derive an optimal drought preparedness and response plan based on intuition alone.

This dissertation helps to develop the intuition of optimal drought preparedness and response by creating and solving a multi-year dynamic and stochastic farm decision model to obtain an optimal plan and examining the tradeoffs and parameters that shape that plan. The model is parameterized for a hypothetical irrigated row-crop farm in the Vale Oregon Irrigation District (VOID) of eastern Oregon. A row-crop system was chosen because it involves both intra- and inter-year dynamics. The primary intra-year dynamic is that fall field-preparation and planting decisions affect spring planting decisions. The primary inter-year dynamic is that the crop choice for a particular field in year *t* limits crop choices for that field in future years, via agronomic constraints. VOID was chosen as the study area for the following reasons: 1) water supplies for the upcoming growing season are uncertain at the time fall decisions are made; 2) VOID producers experience drought frequently (most recently a three-year drought that ended in 2004), and have consequently adopted several preparedness and response tools, and 3) producers have indicated a desire to enhance their ability to prepare for and respond to drought.

The farm decision model can be modified in numerous ways to address a suite of research questions. This dissertation focuses on research questions that relate to three bodies of literature: farm-level drought preparedness and response; drought-related farm policy, and mathematical modeling of stochastic and dynamics farm systems. Gaps in these bodies of literature are identified in the literature review. Research objectives include the following: 1) to understand the tradeoffs that drive the optimal form and degree of drought preparedness and response identified by the model, and generalize them for potential application in other farm systems, 2) to determine the role of inter-year dynamics in the management and impact of drought, 3) to explore the usefulness of the multi-peril crop insurance program's prevented planting provision, at the farm-level, as a drought preparedness tool, and 4) to highlight the advantages and disadvantages of using integer stochastic programming to model a stochastic and dynamic farm system. An overview of research findings is provided next.

The optimal (i.e. expected profit-maximizing) form and degree of drought preparedness and response is considered first. Drought preparedness is defined in this dissertation as the means by which an agricultural producer plans for drought before they know specifically when it will occur. This is in contrast to drought response, which is defined here as an action taken once a producer knows that a drought will occur. Drought response tools are shown to be part of the optimal farm plan, but drought preparedness tools are also prevalent. The magnitude of profit loss attributable to drought under optimal preparedness and response is difficult to generalize because it exhibits large variation depending on the crops planted at the time the drought occurs. Economic parameters, such as the interest and discount rates, play an important role in the solution's characteristics. The effects of uncertainty are then examined to determine how the impacts of drought differ when anticipated versus not. The primary effect of drought under water supply uncertainty, in contrast to certainty, is identified, and shown to have implications for the multi-peril crop insurance program's prevented planting provisions.

Inter-year dynamics is an important characteristic of many farm systems. Yet the role of inter-year dynamics in drought preparedness and response, or its implications for profit impacts of drought, is not well-understood. Producers indicate that inter-year dynamics sometimes result in the persistence of drought's effects well after the drought subsides. The model's solution is examined for evidence of such persistence. Drought, and the response to it, affect cropping plans and profit in subsequent years via inter-year crop dynamics. This result has implications for the effectiveness of government assistance in response to drought. It also has implications for the impact of multi-year droughts. The above results provide a more complete understanding of the complex tradeoffs that producers in a stochastic and dynamic farm system face when preparing and responding to drought.

The ability of the multi-peril crop insurance program's prevented planting provision to mitigate the farm-level impacts of drought is also explored. The prevented planting provision, which covers losses attributable to an anticipated water shortage, is shown to be a cost-effective drought preparedness tool for producers, whether premiums are subsidized or not. Enrollment in the prevented planting provision effectively eliminates profit loss attributable to drought. No attempt is made, however, to determine the social efficiency or social-cost-effectiveness of the prevented planting provision.

The effect of climate change, specifically more frequent and severe drought, on optimal drought preparedness and response, and on profit loss associated with drought is also analyzed. An increase in drought frequency has little impact on the drought preparedness plan or on profit loss attributable to drought. This result does not hold, however, for an increase in drought severity (or both severity and frequency). Adjustments in the crop plan, and change in profit loss differ substantially depending upon which climate parameter changes. These insights inform discussions about the need for and the design of government assistance in a changing climate.

The last body of literature to which this dissertation contributes is mathematical modeling of stochastic and dynamic farm systems. The use of multi-stage discrete sequential stochastic programming (DSSP) to capture the dynamic and stochastic features of a farm system is illustrated. Few studies have taken advantage of multi-stage DSSP's ability to represent both intra- and inter-year dynamics. A second contribution is made by solving both a binary and continuous variables version of the model and comparing their solutions. A binary model represents the producer's decision problem more accurately than a continuous model, but it is also more difficult to solve. The ability of a continuous model to approximate the binary model's solution is therefore examined. The producer has more flexibility in the continuous model than in the binary model; therefore, the continuous model fails to identify some of the drought preparedness tools identified by the binary model.

The remainder of the dissertation is organized as follows. Chapter 2 provides an overview of relevant concepts and literature. Chapter 3 describes the study area. Chapter 4 presents the farm decision model. Chapters 5 and 6 present results and a discussion of farm-level implications. Chapter 7 summarizes research findings and draws them together in a concluding discussion of potential implications for drought-related farm programs.

2 Review of Relevant Concepts and Literature

This chapter discusses key concepts and literature relevant to the exploration of the objectives of this dissertation. Specifically, chapter 2 consists of the following sections: 2.1 Decision-making under uncertainty, 2.2 Incorporating stochasticity in linear programming models, 2.3 Economic studies of agricultural water shortage, 2.4 The multi-peril crop insurance program's prevented planting provision, and 2.5 Climate change and drought in the western United States.

2.1 Decision-Making under Uncertainty

Agricultural producers make many production decisions without knowing the outcome *a priori*. Much of the uncertainty that agricultural producers face is due to the strong influence of nature on the production of agricultural goods, and a limited ability to predict nature. In addition to their subjective beliefs about the probability of different states of nature, a producer's physical and financial resources, management objectives, and attitude towards risk also influence their decisions under uncertainty.

Economists incorporate many of these factors in mathematical models to improve their ability to mimic the complex process of decision-making under uncertainty, and thus enhance the robustness of their economic analyses. Producer characteristics are diverse, so economists typically must choose a finite number of "representative" producers to model, but model performance varies with the chosen characteristics. This fact is especially relevant for the selection of management objectives and risk preferences. This section of the literature review provides an overview of the standard approach to modeling decision-making under uncertainty, and discusses the selection of management objectives and risk preferences.

In the presence of uncertainty, a decision problem has the following elements (Hirshleifer and Riley 1992, p. 7; Mas-Colell, Whinston, and Green 1995, p. 184):

1) a set of *actions* available to the decision-maker, (x = 1,…,X),
2) a set of *states* possible in nature, (s = 1,…,S),
3) a *consequence function*, c(x,s), showing outcomes of all combinations of acts and states,
4) a *probability function*, p(s), expressing the decision-maker's beliefs about the likelihood of each state,
5) a *preference scaling function*, u(c), (also referred to as the *Bernoullian utility function*), which measures the desirability of the different possible consequences, and
6) a *von-Neumann-Morgenstern expected utility function*, U(x), which maps a preference ordering for the set of acts from the preference scaling function and probability function.

A researcher can usually identify elements 1), 2) and 3) with relative ease. The researcher cannot, however, identify, *a priori*, how a decision-maker will choose among the actions. This will depend on the remaining elements, 4), 5) and 6), which can vary significantly between individuals, even when faced with the same decision problem.

Since the true probability of the random states of nature (element 4) can never be known with certainty, individual decision-makers must form subjective probabilities. This subjective probability distribution must be elicited from the decision-maker, or assumed by the researcher. The preference scaling function (element 5) must also either be elicited from the decision-maker, or assumed by the researcher. Once elements 4) and 5) have been established, element 6), U(x), can be derived from them.

The decision-maker's expected utility function, U(x), expresses their preference for actions. Each action is associated with a set of potential consequences; each consequence results from a different state of nature, and each state of nature has a probability of occurrence. Under certainty, the decision-maker knows precisely the consequence of each action, because the state of nature has been revealed prior to the decision choice. In contrast, under uncertainty, the decision-maker does not know which state will occur, and therefore does not know for certain which consequence will be realized for each action. When choosing an action given uncertainty, the decision-maker cannot simply choose the action that is directly associated with their preferred consequence, because actions are no longer necessarily associated with a single consequence.

The "Expected Utility Rule" of von Neumann and Morgenstern provides a way to order preferences over actions when actions and consequences are not one-to-one (Hirshleifer and Riley 1992, p. 14). The Expected Utility Rule states that if utility has the expected utility form (i.e. rational preferences satisfying the continuity and independence axioms (Mas-Colell, Whinston, and Green 1995, p. 175)), and we are given the following information,

1) uncertain states of nature $(1,\ldots,s,\ldots S)$,
2) consequences of action x under each state (c_{xs}),
3) the probability of each state (p_s), and
4) the utility of each consequence ($u(c_{xs})$),

then the utility gained from action x is U(x), where:

$$U(x)= U(c_{x1}, c_{x2},\ldots,c_{xS}; p_1, p_2,\ldots p_S)= p_1u(c_{x1})+p_2u(c_{x2})+\ldots+p_Su(c_{xS}) =\sum_{s=1}^{S} p_s u(c_{xs}),$$

(Hirshleifer and Riley 1992, p. 14). Simply, the utility from action x is equal to the probability-weighted average (i.e. mathematical expectation) of the utilities of the consequences associated with action x, for all states of nature. In terms of the selection of a preferred action, the "Expected Utility Theorem" states that for preferences that admit the expected utility form, action x is strictly preferred to action y if:

$$U(x) = \sum_{s=1}^{S} p_s u(c_{xs}) \;>\; \sum_{s=1}^{S} p_s u(c_{ys}) = U(y)$$

(Mas-Colell, Whinston, and Green 1995, p. 176). The Expected Utility Rule translates the preference scaling function and the probability of states into a von-Neumann-Morgenstern expected utility function. The Expected Utility Theorem provides a rule for choosing among actions.

Economists are interested in the decision-maker's utility function, since it contains information about behavior that can be used to predict their choice of an action. Differential calculus is often used to describe the utility function, but since actions are often discrete, differential calculus cannot be used to describe the properties of U(x). Consequences, however, (usually expressed as monetary values) are often continuous; hence, economists look at the properties of the preference scaling function (Bernoullian utility function), u(c), to deduce the decision-maker's behavioral properties. From this point forward, the preference scaling function, u(c), is used to define and discuss behavioral properties, such as risk-attitude. Since U(x) is a linear combination of points on u(c), it is appropriate to use u(c) for the purpose of determining behavioral properties.

The shape of an individual's preference scaling function, and hence the utility function, is as unique as the individuals themselves. Figure 2.1 shows three shapes commonly assumed for the preference scaling function. The preference scaling function is usually assumed to be upward sloping; this implies monotonic utility, i.e. as the quantity of a desirable consequence increases, utility increases, or

$$u'(c) = \frac{\delta u(c)}{\delta c} > 0 .$$

The shape of the preference scaling function indicates the decision-maker's risk attitude. Figure 2.2 reveals that person A, represented by curve u^A, when faced with the choice between a gamble, G(c_1= -\$200, c_3= +\$200; p_1=0.5, p_3=0.5), with an expected consequence of c_2=\$0 (a fair gamble), or a guaranteed consequence of c_2=\$0, derives greater utility from the guaranteed consequence

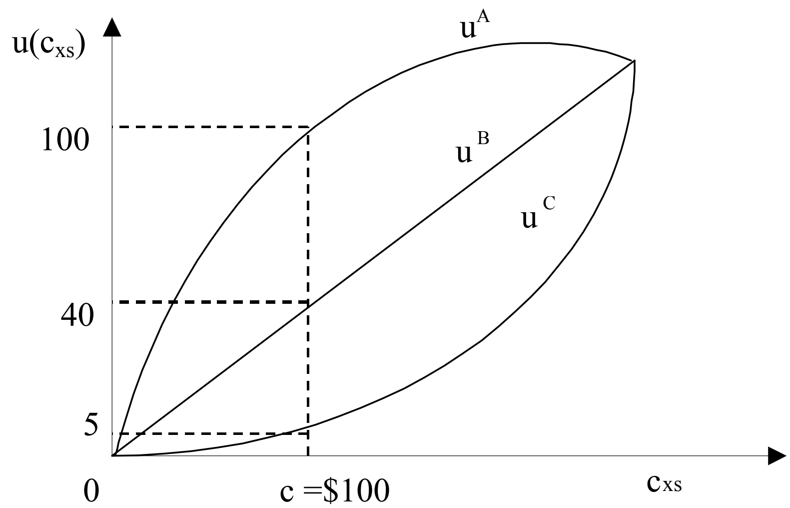


Figure 2.1. Common preference scaling functions (Hirshleifer and Riley 1992, p. 24).

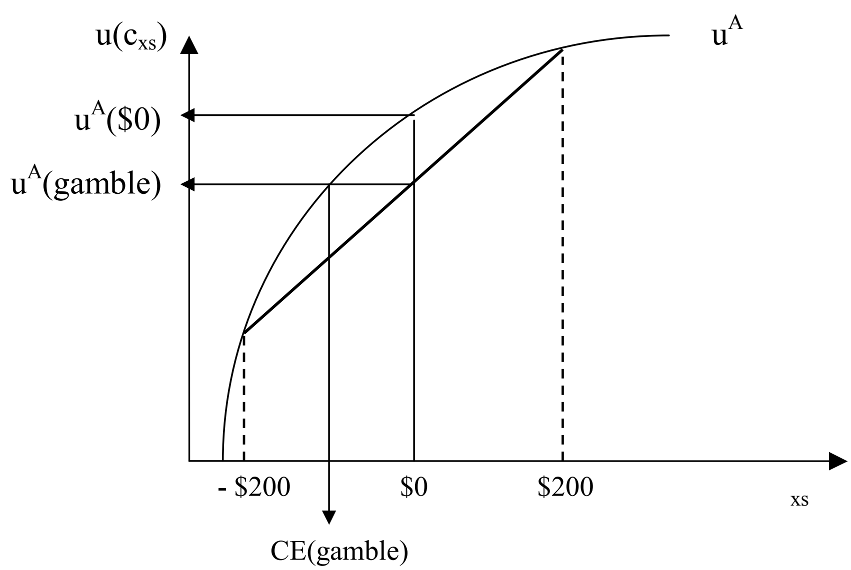


Figure 2.2. Preference scaling function or Bernoullian utility function, u(c), for a risk-averse person.

than from the gamble, even though the gamble's expected consequence is equal to the guaranteed consequence. Person A is risk-averse. They would accept a guaranteed amount that is less than the gamble's expected payout (their certainty equivalent, CE), rather than take the gamble.

Figure 2.3 reveals that person B, represented by curve u^B, when faced with the choice between a gamble with an expected consequence of c_2=\$0 (a fair gamble), and a guaranteed consequence of c_2=\$0, derives equal utility from the two choices. Person B is risk-neutral. They only care about the expected payout of a gamble, and do not care about the variance of the payout. Figure 2.4 reveals that person C, represented by curve u^C, when faced with the choice between a gamble with an expected consequence of c_2=\$0 (a fair gamble), and a guaranteed consequence of c_2=\$0, derives less utility from the guaranteed consequence than from the gamble. Person C is risk-loving. They would have to be paid a guaranteed amount that exceeds the gamble's expected payout to not take the gamble; this amount is their certainty equivalent of the gamble, or CE(gamble).

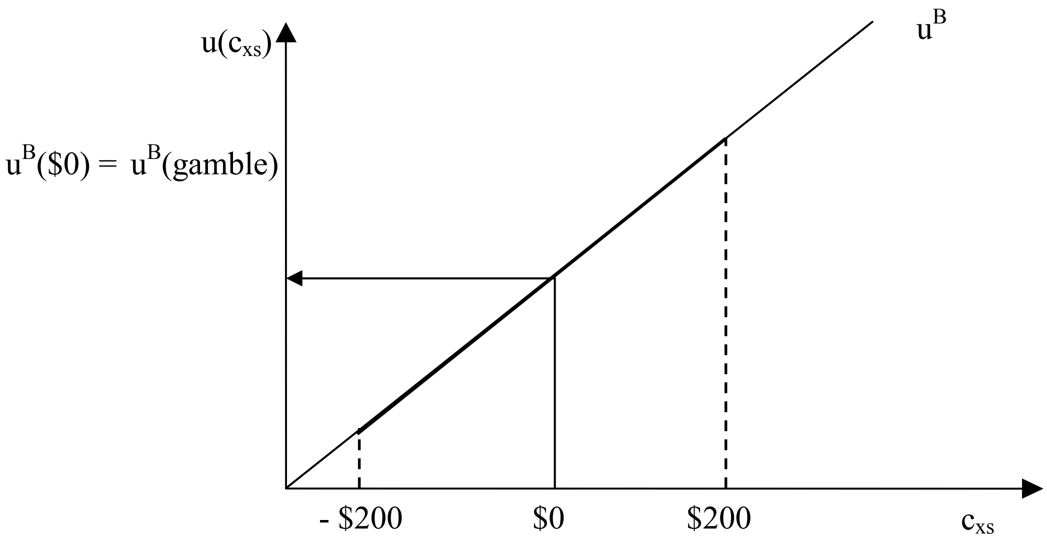


Figure 2.3. Preference scaling function, u(c), for a risk-neutral person.

Risk-preferences are expressed as the rate of change of the slope of the preference scaling function, equivalently, the second derivative of u(c), $u''(c) = \dfrac{\partial^2 u(c)}{\partial c^2}$. Strict risk aversion is expressed as the strict concavity of u(c), i.e. $u'(c) > 0,\ u''(c) < 0$. Strict concavity implies that the person's marginal utility of money is decreasing. That is, at any level of wealth, the utility gained from having an additional dollar is less than the utility lost from having one fewer dollar (Mas-Colell, Whinston, and Green 1995, p. 186). In a gamble where equal amounts of money can be lost

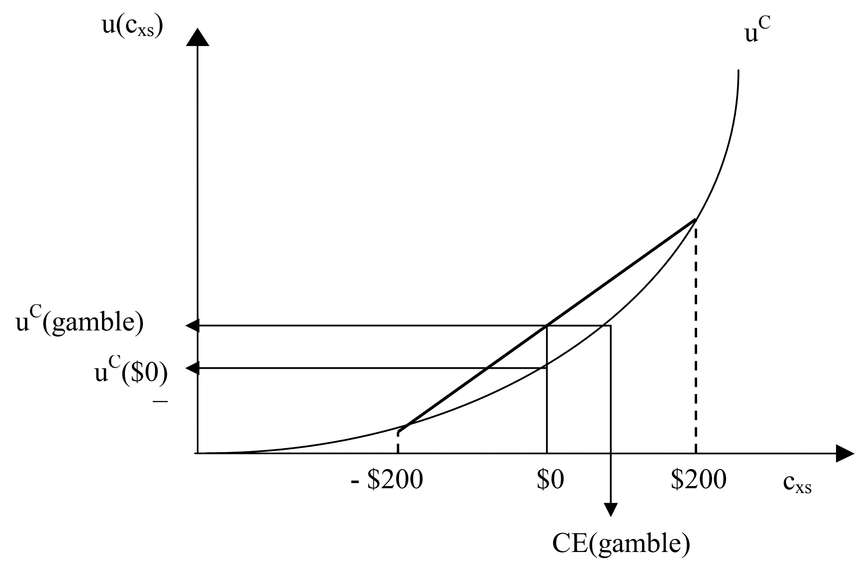


Figure 2.4. Preference scaling function, u(c), for a risk-loving person.

or won, the disutility of losing outweighs the utility of winning, so the gamble is not taken. Risk neutrality is expressed as a linear u(c), i.e. $u'(c) > 0,\ u''(c) = 0$. A risk-neutral person has a constant marginal utility of money. That is, their utility from an additional dollar is equivalent to their disutility from losing one dollar. In a gamble where equal amounts of money can be lost or won, they are indifferent between taking or not taking the gamble. Strict risk loving is expressed as the strict convexity of u(c), i.e. $u'(c) > 0,\ u''(c) > 0$. The risk-lover's marginal utility of money is increasing. That is, the utility gained from having an additional dollar is more than the disutility of losing a dollar; thus, the risk-lover chooses to take the gamble when equal amounts of money can be lost or won.

It is clear that the preference scaling function's general shape, or functional form, has important implications for the decision-maker's behavior under uncertainty. A review of the literature on decision-making under uncertainty reveals that agricultural producers are commonly assumed to be, or found through empirical analysis to be, either risk-averse or risk-neutral (Gomez-Limon, Arriaza, and Riesgo 2003; Hardaker, Huirne, and Anderson 1997, p. 101; Lin, Dean, and Moore 1974; Meyer 2002; Torkamani and Haji-Rahimi 2001). The choice between risk-averse or risk-neutral depends on the decision-making scenario, but has important implications for the structure of the decision-making objective. Specifically, when profit is the only argument in the utility function, risk-neutrality implies that the producer's objective is to maximize expected profit. Risk-aversion, in contrast, implies that the producer cares not only about expected profit, but also about the variance of profit. An expected utility maximization problem with a non-linear utility function would be developed for the risk-averse producer.

The choice of whether to model a producer as maximizing expected utility or expected profit can have significant implications for the model's solution (Isik 2002; Just 1975). A non-linear utility function often increases the complexity of analyses, particularly for mathematical programming models. This source of complexity may require simplification of other, more critical, areas of the model. Risk neutrality is assumed in this dissertation, so that the stochastic and dynamic features of the model can be enhanced. Pannell et al. (2000) suggest that the marginal benefit of accommodating risk aversion is small relative to that of improving other aspects of a farm-level mathematical programming model.

2.2 Incorporating Stochasticity in Linear Programming Models

2.2.1 Introduction to Linear Programming

Linear programming (LP) is a common tool for analyzing farm management problems. LP models can be easily constructed and manipulated to simulate many management scenarios. Equations (1) – (3) represent a generic LP model.

(1) $\underset{x}{\text{Min}} \; z = c^T x$

s.t.

(2) $Ax \leq b$

(3) $x \geq 0$

where x is a vector of decision (activity) variables, and c, A, and b are vectors and matrices (lowercase and uppercase letters, respectively) containing known constants. The elements of vector c often represent, in a farm management problem, the per-unit cost of activities in vector x. Matrix A contains technical coefficients that express, for example, resource use per unit of x. Vector b would then represent the quantity of resources available for use. Note that equation (2) can be equivalently expressed in summation notation, as follows, for resource i and activities j: $\sum_{j=1}^{n} a_{ij} x_j \leq b_i \quad i = 1, 2, ..., M$.

Assumptions underlying this general LP model limit the modeler's ability to realistically represent actual decision-making processes. The assumption of a linear objective function, for example, precludes the use of a nonlinear utility function to represent risk aversion. Nonlinear programming and linear approximation approaches, such as MOTAD, have been developed to address this limitation (Hardaker, Pandey, and Patten 1991). The assumption that all coefficients and relationships are known is also unrealistic in some cases. Mathematical programming models, including LP, are often unable to reproduce producer behavior, in part because the model does not capture all elements of the decision environment, or because the model is incorrectly parameterized. Sensitivity analysis is often used in these cases to provide a range of possible model outcomes. Alternatively, a calibration procedure known as positive mathematical programming can be used to improve a model's ability to replicate reality (Howitt 1995).

The limiting assumption of interest in this study is deterministic coefficients (c, A, and b in the equations above). Such an assumption essentially ignores that farm managers make decisions in an uncertain environment. The elements of c, A, and b often represent input and output prices, yield, and resource availability and requirements, many of which are random variables whose values are not revealed until after decisions are made. The assumption that all coefficients are both constant and known *a priori* is unrealistic, and can generate solutions that lead to suboptimal outcomes when applied in the presence of uncertainty.

Chance-constrained programming, passive programming, and stochastic programming are common approaches to relaxing the certainty assumption (i.e. incorporating stochasticity) in farm management LP models. In the next section, an overview of each approach is provided, followed by a discussion of their advantages and weaknesses. The review concludes by identifying the approach chosen for this study.

2.2.2 Chance-Constrained Programming

Chance-constrained programming (CCP) was an early attempt to introduce stochasticity into mathematical programming problems (Charnes and Cooper 1959). Inspiration for the approach was derived from the oil industry's need to optimally schedule oil production subject to stochastic demand for heating oil (Charnes, Cooper, and Symonds 1958). Industry, more specifically, sought a production schedule that would guarantee that stochastic demands for heating oil would be met with some level of probability.

CCP optimizes (i.e. maximizes or minimizes) the objective function through choice of activity levels, subject to constraints, some of which involve random variables with known distributions. The optimal activity levels must meet all deterministic constraints, as well as maintain at a prescribed level of probability the constraints that involve random variables (Charnes and Cooper 1959). The following equations represent a generic CCP model.

$$(4)\quad \min_{x}\ z = c^T x$$

s.t.

$$(5)\quad \sum_{j=1}^{n} a_{ij} x_j \le b_i \qquad i = 1, 2, ..., m$$

$$(6)\quad P\left(\sum_{j=1}^{n} a_{hj} x_j \le b_h\right) \ge p_h \qquad h = m+1, m+2, ..., M$$

$$(7)\quad x_j \ge 0$$

where j represents activities, and i and h represent resources required for the production of the activities. Subscript i represents resources that involve no uncertainty. The quantity of resource i that is available for use and the quantity required by an activity are constant and known *a priori*. Subscript h represents resources that involve some uncertainty, perhaps in the quantity available, the quantity required per unit of activity, or both. P is the probability operator, and p_h is some critical probability level pertinent to the constraint on the h^{th} resource; the decision-maker selects p_h in advance.

Constraints that strictly contain deterministic coefficients are represented by equation (5), just as they were in the LP model. Constraints containing either random right-hand side or left-hand side coefficients, or both, are represented by equation (6). Equation (6) states that the use of the h^{th} resource across all j activities must be less than the limit b_h, with a probability of at least p_h (Anderson, Dillon, and Hardaker 1977 p. 222). Right-hand side stochasticity occurs when b_h is a random variable; that is, when the quantity of resource h available for use is uncertain at the time decisions are made, but follows a known distribution. Total water supply for the growing season is an example in farm management of a right-hand side random variable. Its quantity varies annually and is rarely known at the time planting decisions are made, but historical data can be used to estimate its distribution. Dillon (1999), Maji and Heady (1978), and Keith et al. (1989) provide additional examples of right-hand side stochasticity.

Left-hand side stochasticity occurs when a_{hj} is a random variable; that is, when the quantity of resource h required per unit of activity j is uncertain at the time decisions are made, but follows a known distribution. Irrigation water required per acre of crop j is an example of a left-hand side random variable. The quantity of irrigation water required by a crop for the growing season varies with factors that are highly unpredictable at the time planting decisions are made, such as summer rainfall, air temperature, and humidity. Segarra, Kramer, and Taylor (1985), Johnson and Segarra (1995), and Wojciechowski et al. (2000) provide additional examples of left-hand side stochasticity. Most examples in the literature consider the case of a single random variable, since having multiple random variables in the same constraint may require their joint distribution.

The probabilistic structure of equation (6) must be converted to a deterministic equivalent in order for a linear programming algorithm to find a solution. Conversion involves the following steps: 1) estimate or assume the random variable's probability density function, 2) choose the desired critical probability level, p_h, at which the constraint should hold, and 3) determine the value of the stochastic coefficient (a_{hj}) or (b_h), at which the constraint will hold p_h percent of the time, using the random variable's density function. Assuming left-hand side stochasticity, the deterministic equivalent of equation (6) is represented by the following equation:

$$(6a) \quad \sum_{j=1}^{n} a_{hj}^{\alpha} x_j \le b_h \qquad h = m+1, m+2, \ldots, M$$

where, a_{hj}^{α} represents the value selected from a_{hj}'s density function, such that the constraint is guaranteed to hold p_h percent of the time. Assuming right-hand side stochasticity, the deterministic equivalent of equation (6) is represented by the following equation:

(6b) $\sum_{j=1}^{n} a_{hj} x_j \leq b_h^{\alpha} \quad h = m+1, m+2,..., M$

where b_h^{α} represents the value selected from b_h's density function, such that the constraint is guaranteed to hold p_h percent of the time. Note that equations (6) and (6a) are written such that the coefficient a_{hj} is random for every activity j. This is not always the case; a mixture of deterministic and random a_{hj} is allowed. For example, per acre yield of corn could be known and constant, while per acre yield of wheat could be a random variable.

The intuition behind CCP is relatively straightforward. If a random coefficient's value is unknown at the time a decision must be made, and the penalty of not meeting a constraint is severe, then you should assume a value for the random variable such that the model's solution, under most circumstances, will meet the constraint. The previous example of an uncertain total water supply (right-hand side) illustrates the intuition.

Suppose that the water supply's expected value is 20 inches, but that it varies from 10 to 40 inches, and follows a uniform distribution. If the random variable "water supply" (b_{water}) is replaced with its expected value (this is known as the "expected value problem" and denoted EV), the problem is equivalent to a deterministic LP model. The solution indicates optimal activity levels given a water supply of 20 inches. It does not indicate, however, the outcome of applying these activity levels when water supply is revealed to be 10 inches, rather than 20. The constraint that water use must not exceed water supply is likely violated, since the optimal crop combination given 20 inches of water almost certainly consumes more than 10 inches of water.

Suppose instead that the random variable b_{water} is replaced with the conservative value of 10 inches (conservative in the sense that according to $b_{water} \sim U[10,40]$ there is a high probability that in most years actual water supply will exceed 10 inches). The resulting optimal activity levels, when implemented in the presence of all possible realizations of water supply, would always result in the water constraint being met. Essentially, by planning to be constrained to a small quantity of a resource, the resulting optimal activity levels are such that the resource constraint is met for most realizations of the random variable. Similarly, in the case of a random left-hand side coefficient, by planning for a large quantity of resource use per unit of activity, you choose activity levels that, under most realizations of the random variable, result in the constraint being met (i.e. resource use is less than or equal to resource supply).

How far the value chosen for the random variable deviates from its expected value depends on the probability, p_h, with which the modeler wishes the constraint to be met. The closer p_h is to 1, the more extreme the chosen value will be. Calculating the appropriate value for a random variable given a pre-selected p_h involves estimating the mean and standard deviation, if the random variable is distributed normally (see Segarra, Kramer, and Taylor 1985). If the distribution is not normal, but relevant historical data are available, a value is chosen based on its percentile (see Keith et al. 1989). For example, suppose a value representing the 25th percentile of historic water supplies, call it $b_{25\%}$, is chosen. Then by definition, actual b_{water} will be less than $b_{25\%}$ 25% of the time (and planned water use will exceed actual water supply), and actual b_{water} will exceed $b_{25\%}$ 75% of the time (and planned water use will be less than actual water supply). Dillon (1999) presents a slightly different approach for determining the appropriate value for the random variable using historical data.

The simplicity of CCP is appealing. The most challenging steps are to identify the random variable's probability density function (or a set of historical realizations), choose the desired level of p_h, and select the appropriate deterministic value for the random variable. Once these tasks are completed, the problem is easily converted to its deterministic equivalent and solved with a standard LP algorithm. Major criticisms of CCP exist, however. The first criticism is that CCP deals only with random variables that appear in constraints, and not those relevant to the objective function (Cocks 1968). It is not clear whether this criticism is contradicted by the ability to construct a CCP model with the following structure (Charnes and Cooper 1963).

(8) $\underset{x}{\text{Min}}\ P(c^T x \le c^{0T} x^0)$

s.t.

(9) $\sum_{j=1}^{n} a_{ij} x_j \le b_i \qquad i = 1, 2, ..., m$

(10) $P(\sum_{j=1}^{n} a_{hj} x_j \le b_h) \ge p_h \qquad h = m+1, m+2,..., M$

(11) $x_j \ge 0$

The objective in this CCP problem is to choose activity levels that guarantee an achieved value for the objective function with some probability, and meet resource constraints with some probability (Cocks 1968).

A second criticism of CCP is the arbitrary selection of a value for p_h. In reality, the decision-maker selects a value for p_h by weighing the tradeoff between more certainty and less profit (Anderson, Dillon, and Hardaker 1977 p. 224; Hardaker, Pandey, and Patten 1991). The selection of a value for p_h should therefore be part of the optimization problem. Askew (1974), in an attempt to formulate a dynamic chance-constrained programming problem, may provide a means for incorporating the choice of p_h in the decision process. A final criticism of CCP is that it assumes that constraint violation is acceptable $(1-p_h)$% of the time, but does not indicate what to do or to expect when constraints are actually violated (Cocks 1968). Consider, for example, what might happen if a large city managed its stochastic water supply in a manner that prevented shortages 9 out of 10 years, but failed to develop a management plan for the 1 year out of 10 when a water shortage occurred. The CCP approach, while an improvement upon the deterministic LP approach, clearly results in an incomplete solution to a stochastic problem.

2.2.3 Passive Programming

It is assumed in the passive programming (PP) approach that optimization will take place under certainty at a future date. The problem in the meantime is to characterize the distribution of outcomes from which the eventual outcome will be realized (Cocks 1968). The distribution of outcomes is derived by solving a deterministic LP problem for each realization of the random variable. The general notation for a PP problem follows.

(12) $\underset{x}{\text{Min}}\ z(x,s) = c_s^T x$

s.t.

(13) $A_s x \leq b_s$

(14) $x \geq 0$

(15) $\forall\ s$

The subscript, s, identifies coefficients whose values vary depending upon the state of nature being considered. Suppose, for example, that the cost of planting an acre of corn (an element of vector c) differs between two states of nature. The appropriate value of the cost coefficient is c_1 when state of nature 1 occurs, and c_2 when state of nature 2 occurs. Similarly, coefficients in matrix A or vector b may vary with the state of nature.

Equations (12) through (14) are solved for every state of nature, s. The distributions of the optimal activity levels, $x^*(s)$, and objective values, $z(x^*(s),s)$, are then formed from the collection of s solutions (Birge and Louveaux 1997 p. 138). A decision-maker could use these distributions to inform other management decisions. The expected value of the objective function (known as the wait-and-see (WS) solution) is also of interest, and is calculated as follows (Cocks 1968): (16) $WS = E_s z(x^*(s),s)$. See Tintner (1960) for a simple applied example, and see Birge and Louveaux (1997 p. 138) for a more thorough treatment of equations (12) through (16).

The PP approach represents a decision-maker who knows the random variable's realized value at the time the decision is made, and can therefore make the decision based on perfect information. They do not know, however, the variable's value at the time they solve the PP problem. The best they can do, prior to the decision-making period, is to solve the PP problem to determine the distribution of the outcome, and use it to form an expectation.

The scenario described above is the appropriate situation in which to use the PP approach. However, decision-makers might also use the PP approach to inform their decisions when uncertainty is not resolved at the time decisions are made. The distributions derived from PP may be combined with a heuristic rule to guide decisions. Assume that a farm manager must make a decision before uncertainty is resolved. They have conducted a PP analysis of their decision; the solutions appear in Table 2.1. Suppose the manager constructs the following decision rule: implement the activity level that occurs most frequently among all the solutions. From the table of solutions, the manager would always plant 0 acres of corn and 100 acres of wheat, because it appears most frequently among the set of PP solutions. This rule obviously has no theoretical basis for being optimal, which is the criticism of using the PP approach in scenarios where uncertainty is not resolved *a priori*. It may, none-the-less, seem like a rational approach to a busy manager.

Table 2.1. A passive programming analysis of a hypothetical farm decision.

	State of Nature				
PP's solution	**Very dry**	**Dry**	**Average**	**Wet**	**Very wet**
Corn (ac)	0	0	50	75	100
Wheat (ac)	100	100	50	25	0

PP is essentially the analysis of an LP problem's sensitivity to different values of the random variable (Higle and Wallace 2003). The approach's advantage is its simplicity. PP requires the modeler to solve one LP problem for each possible value of the random variable. Once the initial LP model is developed, the PP problem only involves repeatedly changing a single value in the program and resolving it. Even if a random variable has hundreds of possible values, PP requires only additional time, and not additional programming skill.

PP is not an ideal approach to incorporating stochasticity in LP, since its assumption of perfect information at the time decisions are made is unrealistic. Rae (1971) indicates, however, that the simple PP approach can be an improvement over the expected value problem approach (EV) (defined in the previous section). An additional role for PP exists, even in a world of imperfect information. The perfect information solutions derived in PP provide a baseline to which imperfect information solutions (such as those discussed next in the stochastic programming section) can be compared. Such comparisons reveal the expected value of perfect information (Birge and Louveaux 1997 p. 137), a topic of interest to organizations who provide weather and price forecasts, for example.

2.2.4 Stochastic Programming

Stochastic programming (SP), also known as discrete stochastic programming (DSP) and discrete sequential stochastic programming (DSSP) was introduced by Cocks (1968) as a method for solving LP problems that include any number of random variables as coefficients in the constraints and/or the objective function. The ability to include random coefficients in constraints and the objective function enables a modeler to account for the timing of decisions relative to the timing of information discovery. Specifically, a modeler can represent a multi-stage problem where decisions are made both before and after random variables are realized. Decisions made before the random variables' values are revealed are known as "first-stage" activities, and denoted by a vector x. Decisions or calculations made after random variables' values are revealed are known as "second-stage" or "recourse" activities, and denoted by a vector y. The number of stages in a SP problem depends upon the number of decision/information/recourse decision cycles that occur during the decision-making process. SP can also be adapted to single-stage problems where decisions are made prior to random variables' values being revealed, but no recourse decisions are available (Cocks 1968).

An SP model consists of the following four pieces (Kaiser and Apland 1989): 1) a sequence of decision stages, 2) a set of decision variables for each stage, 3) discrete or continuous random variables, and 4) an information structure that represents the flow of information relative to the timing of decisions. SP represents the following decision process. First-stage decisions are made prior to random variables' values being revealed. After decisions are made, the random variables' values are revealed. This resolution of uncertainty prompts second-stage decisions, with which the decision-maker attempts to fix sub-optimal outcomes resulting from imperfect first-stage information. Rae (1971), in one of the first applications of discrete stochastic programming to agriculture, illustrates how SP captures this decision process.

The general goal of SP is to choose first-stage activity levels that minimize current costs (or maximize current benefits) plus the expected cost (or expected benefits) of second-stage activities. The SP solution indicates optimal first-stage activity levels, as well as optimal second-stage activity levels for each possible realization of the random variables. This approach, at least in its discrete form, is reminiscent of decision tree analysis (Hardaker, Huirne, and Anderson 1997 p. 198). SP is unique among the approaches reviewed in this dissertation because it suggests what to do after a specific state of nature is realized.

The SP model can be expressed in either the extensive form or the implicit form, both of which are presented below. A single discrete random variable and a two-stage stochastic program with recourse are assumed in the following examples for notational ease. The extensive form SP model, shown below in equations (17) through (20) (see also Birge and Louveaux 1997 p. 156), includes first-stage decision variables, indexed by activity only (e.g. x_i in the model below), and second-stage decision variables, indexed by activity and state of nature (e.g. y_{is} in the model below). This form is labeled "extensive" because a set of second-stage decision variables and constraints exists for every state of nature. Numerical examples of the extensive form model can be found in Higle and Wallace (2003) and Birge and Louveaux (1997 p. 8).

(17) $$\max_{x,\,y}\ z = -\sum_i c_i x_i + \sum_i \sum_s (r_{is} y_{is}) p_s$$

s.t.

(18) $\sum_i x_i \le L$ (land constraint)

(19) $y_{is} \le a_i x_i \quad \forall$ s and i (sales constraint)

(20) $x_i,\ y_{is} \ \ge\ 0$

where,

x_i = a first-stage decision variable for the i^{th} activity
(e.g. acres of land devoted to crop i, where i = corn, wheat)

c_i = the first-stage coefficient (known *a priori*) associated with activity x_i
(e.g. cost associated with devoting an acre of land to crop i)

y_{is} = a second-stage decision variable for the i^{th} activity when the s^{th} state of nature occurs (e.g. tons of crop i to sell when state s occurs)

s = state of nature of a random variable
(e.g. if output price is the random variable then s = low, average, high)

r_{is} = the second-stage coefficient associated with activity y_{is}
(e.g. price received per ton of crop i sold when the s^{th} state of nature occurs)

p_s = the probability of the s^{th} state of nature

L = limit on activity i (e.g. total acreage available)

a_i = coefficient linking first-stage activity levels to second stage activity levels
(e.g. per acre yield of crop i)

The objective function above demonstrates SP's goal of optimizing over both the current (first-stage) costs and the expected value of the future (second-stage) revenues. The expectation is taken over the probability distribution of the random variable. Note that while the collection of first-stage activities is $[x_1, x_2]$, the collection of second-stage activities is $[y_{1\,low}, y_{1\,avg}, y_{1\,high}, y_{2\,low}, y_{2\,avg}, y_{2\,high}]$.

Second-stage activities, y_{is}, are interpreted in this example as the tons of crop i to sell when state of nature s occurs. As the notation above indicates, constraint (19) is duplicated for every combination of crop i and state s. It is interpreted as limiting the quantity of crop i sold when state s occurs to no more than the total quantity yielded from acres planted to crop i in the first stage (x_i). The set of constraints represented by equation (19) establishes the timing of the decision problem by linking first and second-stage activities. Constraints that apply only to first-stage decision variables, such as equation (18), are not duplicated because they do not vary across states of nature. The extensive form is limited, in practice, to problems that involve few random variables and random variables with few realizations. Otherwise, the "curse of dimensionality" arises, with symptoms including cumbersome notation and myriad constraints (Anderson, Dillon, and Hardaker 1977 p. 229; Hardaker, Huirne, and Anderson 1997 p. 197).

The implicit form of SP enables modelers to compress large stochastic programming problems. The approach essentially tucks objective function terms and constraints associated with second-stage variables into a sub-problem, denoted $Q(x,\mathbf{s})$, which represents the value of the second stage for a given realization of the random vector **s**. In contrast to the previous assumption of a single random variable, s, here a vector of random variables, **s**, is assumed. Boldface notation indicates the vector is random, to differentiate it from its realization. The sub-problem, $Q(x,\mathbf{s})$, is optimized over second-stage decision variables for all individual realizations of **s** and all feasible values of first-stage activities. The goal of a single optimization of $Q(x^0,s^0)$ is to select the optimal level of second-stage activities, given the pre-selected first-stage activity level, x^0, and the pre-selected realization of **s,** s^0. This optimization is repeated for all combinations of $(x,\mathbf{s})$. The expected objective value of all sub-problems, $\mathcal{Q}(x) = \underset{\mathbf{s}}{E}\, Q(x,\mathbf{s})$, also known as the *value function* or *recourse function*, is then placed into the SP problem's original objective function. The original SP problem is finally optimized over first-stage decision variables, subject to first-stage constraints. The implicit form is represented in the equations below.

(21) $\underset{x}{\text{Min}}\ c^T x + E_{\mathbf{s}} Q(x,\mathbf{s})$

s.t.

(22) $Ax = b$

(23) $x \geq 0$

where,

(24) $Q(x,\mathbf{s}) = \text{Min}\ \mathbf{q}^T\mathbf{y}$

s.t.

(25) $\mathbf{T}x + W\mathbf{y} = \mathbf{h}$

(26) $y \geq 0$,

where $\mathbf{q}^T$, $\mathbf{h}^T$, and $\mathbf{T}$ form the vector $\mathbf{s}$, and contain the values taken by $\mathbf{q}$, $\mathbf{h}$, and $\mathbf{T}$ under each state of nature, and where W is assumed here to be constant across states of nature (fixed recourse). Birge and Louveaux (1997 p. 11) provide a numerical example of the second-stage sub-problem that demonstrates the notation used above.

The implicit form is less intuitive than the extensive form, but it reduces the volume of programming code required, and is thus a more computationally efficient approach to large SP problems (Birge and Louveaux 1997 p. 155). This is especially useful when several random variables are involved, or when random variables are continuous (see Birge and Louveaux 1997 p. 11). The extensive form problem can be solved in the same manner as a generic LP problem. The special structure of the implicit form, however, requires an alternative solution algorithm. The L-shaped method is the most frequently used approach (see Birge and Louveaux 1997 p. 156). It involves a three-step process that is repeated until an optimal solution is found. The details of this approach are omitted here, given the choice to focus on the more intuitive extensive form, rather than the implicit form.

The most significant advantage to incorporating stochasticity into an LP model via SP is that the approach captures the timing of decisions relative to the flow of information more realistically than CCP and PP. Modelers using SP are still limited to a relatively small number of stages, compared to the large number of stages in a real farm manager's decision-making process. However, Rae (1971) demonstrates that the solution obtained from a three-stage SP model of a farm manager's decision process is expected to generate 16% more profit annually than the solution obtained from an expected-value model (in which all random variables are replaced with their expected values).

One disadvantage of SP is that it becomes more computationally difficult as the number of random variables, realizations, and stages increase. SP also requires the modeler to obtain more data to sufficiently represent the random variables' realizations and probability distributions. Finally, there is no general rule for predicting the magnitude of gains from using the SP solution versus solutions obtained from less sophisticated approaches (Birge and Louveaux 1997 p. 144). It is generally believed that stochastic programming is more relevant when there is more randomness in the problem, but even this varies on a case-by-case basis. The benefit of modeling a decision-process using SP, rather than a simpler approach, cannot be known *a priori*. The modeler might therefore invest a great deal of time in developing an SP model only to discover that it produces a solution that closely resembles those obtained from simpler approaches.

2.2.5 Stochastic Dynamic Programming

Stochastic dynamic programming (SDP) is similar to stochastic programming (SP); however, the approaches have different strengths and limitations. SDP, like SP, is a mathematical optimization technique for solving multi-stage problems in which decisions are made under uncertainty. The general form of an SDP problem is as follows (Kennedy 1986, p. 52):

$$V_i\left\{x_i\right\} = \max\left[\sum_{k=1}^{m} p_i\left\{k_i\right\}\left(a_i\left\{x_i, u_i, k_i\right\} + aV_{i+1}\left\{t_i\left\{x_i, u_i, k_i\right\}\right\}\right)\right] \quad (i = n, \ldots, 1)$$

subject to

$$\sum_{\mathrm{k}=1}^{\mathrm{m}} p_i\left\{k_i\right\} = 1$$

with

$$V_{n+1}\left\{x_{n+1}\right\} = F\left\{x_{n+1}\right\}$$

where,

V_i = objective or value function in decision stage i

x_i = vector of states at stage i

(e.g. acres eligible for onions in stage i)

u_i = vector of decision variables in stage i

(e.g. acres of onions to plant in stage i)

r_i = random variable at stage i

k_i= the value of r_i

$p_i\left\{k_i\right\}$ = probability that r_i takes the value k_i

$a_i\left\{.\right\}$ = stage return function

$t_i\left\{.\right\}$ = state transformation function

$F\left\{x_{n+1}\right\}$ = terminal value function

Important characteristics of the SDP include the objective function's recursive form and the expectation taken over future returns. The recursive objective function represents the dynamic nature of the system being modeled. Decisions made in stage i affect decisions in stages i+1 through i+n. This is comparable to the dynamics captured by SP problems, in which first-stage decisions (**x**) affect second-stage decisions (**y**) (note that an SP problem can have more than two stages). The stochastic nature of the decision problem, reflected in the objective function, is attributable to random variables that, in combination with decision variables, determine returns and the state of the system in each stage. Random variables in a SDP problem are not realized prior to the decision. Hence, the objective function is the expected present value of returns from all stages. Stochastic dynamic programming is a relatively straightforward extension of dynamic programming, which is a common tool in economics; therefore, it will not be discussed further.

A brief explanation of the difference between stochastic dynamic programming and stochastic programming is warranted, however, because both approaches can be used to model multi-stage decision-making under uncertainty. Haneveld (1986, p. 2) suggests that while SDP and SP are similar in purpose, they arose separately to address fundamentally different problems, and are not equally suited for addressing the same problems. SDP stemmed from a need to cost-effectively manage dynamic systems that were only partly controllable, often over many stages. SDP is therefore best-suited to decision problems that involve few (often discrete) decision variables and many stages.

SDP is a popular approach for forestry and fishery problems, for example, in which the decision-maker chooses harvest levels throughout a long planning horizon (often twenty stages or more). SP, in contrast, resulted from an effort to incorporate random variables, such as price and yield, as parameters in LP problems. LP models often involve many (often continuous) decision variables, and relatively few stages; thus SP was developed to accommodate these features. SP is a popular approach for farm management problems, for example, in which the decision-maker chooses levels for a variety of farm activities throughout a relatively short planning horizon (often three stages or less). Both approaches unfortunately suffer the curse of dimensionality, and can therefore handle only a limited number of random variables (Featherstone, Baker, and Preckel 1993; Toft and O'Hanlon 1979).

Although SDP and SP are suited for problems with different characteristics, some decision problems can be solved using either approach. In particular, multi-stage SP models that have random variables with finite discrete distributions can often be reformulated as discrete-time SDP models with a finite number of stages (Haneveld 1986, p. 43). One advantage to using SDP rather than SP is that analytical solutions can be derived for some problems, while only numerical solutions are possible with SP. Kennedy (1986, p. 300) indicates, however, that solutions to most SDP problems are determined numerically. In this case, SP has the advantage of well-developed, commercially available solution algorithms, whereas SDP models often require problem-specific algorithms. A final distinction between the approaches is that SDP models typically assume a Markovian structure, such that actions and outcomes depend only on the current state of the system (Birge and Louveaux 1997, p. 70). That is, you do not need to know how you arrived at your current state to determine the optimal next move. SP, in contrast, can accommodate a variety of recursive structures.

2.3 Economic Studies of Agricultural Water Shortage

Many economic studies address water supply uncertainty and farm management. Example objectives include reporting producers' actual responses to water supply uncertainty (Schuck, Frasier, and Webb 2003; Zilberman et al. 2002), identifying optimal farm management in anticipation of, and response to, water supply uncertainty (Bernardo et al. 1987; Wyse 2004), estimating the economic impact of water supply uncertainty (Easterling 1993), estimating the value of improved water supply forecasts (Mjelde, Hill, and Griffiths 1998; Mjelde, Penson, and Nixon 2000; Wyse 2004), and estimating the ability of government policies or water markets to reduce the impact of water supply uncertainty (Becker 1999; Burke, Adams, and Wallender 2004; Jaeger 2004).

Several studies have surveyed agricultural producers during or after a drought to document their responses (Kromm and White 1986; Rich 1993; Schuck, Frasier, and Webb 2003; Zilberman et al. 2002). These studies consistently identify increased groundwater pumping and fallowing as primary responses to drought, and deficit irrigation, improving irrigation efficiency, or adjusting crop mixes as secondary responses. Each study solicits information from a diversity of farm systems and producers, and is therefore able to identify common themes in drought response. These studies provide an incomplete picture, however, of drought preparedness and response. First, they do not report specific response strategies for a particular farm system, or identify the degree to which alternative drought response tools are used on individual farms. Second, they do not discuss how producers prepare for drought in their year-to-year activities. Finally, they do not analyze the optimality of observed drought responses.

Studies that use simulation or optimization models complement survey-based studies by providing insights about the optimality of alternative drought preparedness and response tools for individual farm systems and producers. In contrast to survey-based studies, however, it is challenging to draw general conclusions from the model-based studies. This is because they span a wide variety of farm systems, adopt different scales of time and space, focus on different sets of drought management tools, and make a variety of assumptions about uncertainty and dynamics. Some relevant studies are summarized below to illustrate the diversity of methods, objectives, settings, and conclusions in this body of literature.

Ziari and McCarl (1995) use a two-stage single-year stochastic programming model to determine that a runoff collection impoundment is an economical source of supplemental irrigation for mixed crop producers in Texas. Iglesias et al. (2003) solves a multi-year dynamic model for several farm systems in Spain, and concludes that improvements in the inter-year management of reservoir levels and perfect water supply forecasts could mitigate the impacts of a multi-year drought. Bernardo et al. (1987) constructs a single-year model that captures intra-year irrigation dynamics, and applies it to a representative farm in Washington’s Columbia River Basin. This study finds that a surface irrigator who anticipates a water shortage should increase labor to improve irrigation efficiency, decrease the frequency and depth of individual water applications, and deficit irrigate crops during non-critical growth stages. Mejias et al. (2004), using a three-stage single-year stochastic programming model, finds that a mixed crop producer in southern Spain should shift to crops with lower water requirements in response to increases in the water price (related to water scarcity).

Tapp et al. (1998) uses a five-year stochastic budgeting model to simulate the ability of various financial and herd management strategies to mitigate the impacts of drought for a livestock system in Australia. They conclude that no strategy clearly dominates the others, and that no strategy successfully mitigates the impacts of sustained drought. Toft and O'Hanlon also consider livestock management in Australia during drought, but use an 18-month stochastic dynamic programming model, rather than simulation, and focus on herd management options only.

Kaiser et al. (1993), using a two-stage stochastic programming model, finds that a corn-soybean producer in the Midwest should make few changes to their crop mix in response to more frequent drought. Easterling (1993) also focuses on the response of crop producers in the Midwest to short-term versus sustained drought. They conclude from a multi-year simulation model that the most effective adjustments include shifting planting dates, selecting longer-season cultivars, and using furrow-dikes to capture rainfall. Finally, Weisensel et al. (1991) develop a multi-year stochastic dynamic model for dryland wheat production in western Canada. The authors compare expected net return and variance of return for a fixed wheat-fallow rotation versus a flexible rotation based on available soil moisture data. The flexible strategy generates higher expected net return, but higher variance of return as well.

The above studies reflect that the structure of a producer's decision problem and the set of relevant drought management tools vary across farm systems. The results for one farm system should therefore not be expected to transfer directly to another. The modeling methods, however, are transferable; which method is most appropriate for a chosen farm system depends largely on the chosen assumptions about uncertainty and dynamics. Four alternative sets of assumptions are common: 1) certainty with no dynamics (Adams and Cho 1998; Bernardo et al. 1987; Jaeger 2004; Michelsen and Young 1993), 2) certainty with intra- or inter-year dynamics (Garrido and Gomez-Ramos 2000; Haouari and Azaiez 2001; Iglesias, Garrido, and Gomez-Ramos 2003; Thompson and Powell 1998), 3) uncertainty with intra-year dynamics (Adams et al. 1995; Kaiser et al. 1993; Keplinger et al. 1998; Mejias, Varela-Ortega, and Flichman 2004; Taylor and Young 1995; Turner and Perry 1997), and 4) uncertainty with inter-year dynamics (and in some cases intra-year dynamics as well) (Monke 1995; Toft and O'Hanlon 1979; Weisensel, Van Kooten, and Schoney 1991).

The fourth set of assumptions most thoroughly captures the decision-making environment of a producer who faces uncertainty and a dynamic farm system. Few studies have used this set of assumptions, however, to address optimal drought preparedness and response (Antle 1983). No studies, to the author's knowledge, have used this set of assumptions in the context of an irrigated crop farm (the farm system of interest in this dissertation). Some farm systems may not involve all components of this set of assumptions, or researchers may not be interested in all components. An alternative explanation is that models that capture uncertainty and both intra- and inter-year dynamics are analytically intractable and often difficult to solve numerically. However, computer technology has advanced to the point that very large models can be solved within acceptable time limits. The role of inter-year dynamics in optimal drought preparedness and response can therefore be examined in the presence of other important characteristics of the decision environment.

2.4 The Multi-peril Crop Insurance Program's Prevented Planting Provision

The federal government actively assists agricultural producers with the management of risk, and the mitigation of severe events, such as drought. The USDA-Risk Management Agency's goal, for example, is to "promote, support and regulate sound risk management solutions to preserve and strengthen the economic stability of America's agricultural producers" (Risk Management Agency 2004b). The United States Department of Agriculture (USDA)-Farm Service Agency's goal is "to provide a safety net to help farmers produce an adequate food supply, maintain viable operations, compete for export sales of commodities in the world marketplace, and contribute to the year-round availability of a variety of low-cost, safe, and nutritious foods" (Farm Service Agency 2002).

These and other federal agencies have shown particular interest in the potential for crop insurance products to reduce economic losses associated with drought. Data suggests that existing crop insurance programs have provided significant financial support during recent drought events. The USDA's Federal Crop Insurance Corporation has, since 1989, paid insured producers a total of $462 million annually, on average, for qualifying drought losses (Office of Communications 2004). In 2003 and 2002, fifty-four percent of the $3.2 billion, and 60% of the $4.1 billion in total crop insurance indemnities paid, respectively, were attributable to drought (Office of Communications 2004). Although these transfers generally benefit the individual agricultural producers that receive them, there is much debate about the implications of these wealth transfers and other forms of government intervention for social efficiency. This aspect of farm policy is not reviewed here; however, the economics literature offers a rich discourse on the subject (e.g. Alston and Hurd 1990; Leathers and Chavas 1986; Luttrell 1989; Pasour and Rucker 2005).

Interest in crop insurance is reflected in recent government policies. Title X of the Farm Security and Rural Investment Act of 2002 (commonly referred to as the "2002 Farm Bill"), for example, includes provisions to expand existing crop insurance programs to include more crop types and locations (107th United States Congress 2002). Section 10108 initiated a feasibility study of expanding coverage to include disaster conditions caused by federal actions that restrict access to irrigation water. The potential for disruption of irrigation water supplies by federal actions increases as the list of threatened or endangered species expands. The roles for such a program will likely change through time, particularly as the effects of climate change materialize.

Research on crop insurance is robust, and includes explanatory models of crop insurance participation (Calvin 1992; Just, Calvin, and Quiggin 1999; Leathers 1994; Mahul 1999; Makki and Somwaru 2001; Sherrick et al. 2004), program design (Mahul 1999; Makki and Somwaru 2001), production and market effects of subsidized crop insurance (Glauber and Collins 2002; Hueth and Furtan 1994; Wu and Adams 2001; Young, Vandeveer, and Schnepf 2001), and the interaction or substitutability of crop insurance with other risk management tools, such as improved forecasts and disaster assistance (King and Oamek 1983; Luo, Skees, and Marchant 1994; Mjelde, Thompson, and Nixon 1996). The role of crop insurance, specifically the multi-peril crop insurance (MPCI) program's prevented plantings provision, as a drought preparedness tool is of interest here.

The USDA Risk Management Agency (RMA) has developed many insurance products to help producers better manage production and price risks. Provisions for crop insurance products are made in Title X of the Farm Bill. The federal government subsidizes many of the insurance products to encourage participation. Several insurance products, which are sold to producers through private insurance companies, are available to producers in the study area (table 2.2). Crop insurance became available in Malheur County (the county in which the study area is located) in 1990. Over $7.5 million has been paid in crop insurance indemnities to producers in the county since then. Onions, sugar beets, and wheat account for the largest portion of these indemnity payments. Twenty-eight percent of insurance claims are attributed to drought or failure of irrigation supply.

Prevented planting (PP), a provision included in basic MPCI policies for irrigated crops, is becoming an increasingly popular form of drought preparedness for producers in the study area (Agricultural Producers in the Vale Oregon Irrigation District 2003; Haight 2004). A PP payment is made when a producer provides evidence that as of the final planting date they had no reasonable expectation of receiving sufficient water to follow standard irrigation practices, due to an insurable cause of loss, such as drought (in contrast to an uninsurable cause of loss, such as infrastructure failure). The cause of loss must also affect the surrounding area and prevent other producers from planting acreage with similar characteristics (Risk Management Agency 2003). This contrasts to a traditional MPCI claim, where a crop was planted, but later failed due to unanticipated drought.

Table 2.2. Crop insurance programs available, and eligible crops, in the study area (Risk Management Agency 2004a).

Insurance Program	**Eligible Crops**
MPCI Multi-peril Crop Insurance	alfalfa seed, apples, barley, corn, dry beans, forage production, oats, onions, potatoes, processing beans, sugar beets, wheat
CRC Crop Revenue Coverage	corn, wheat
AGR Adjusted Gross Revenue	all crops
IP Income Protection	barley, wheat

The PP provision encourages producers to avoid planting when the crop is expected to fail. Producers forego spring planting costs when they expect to make a PP claim; therefore, the PP loss payment is typically a fraction of the normal MPCI payment. The percentage is set at a starting level (e.g. 45% for onions and sugar beets, 25% for potatoes, and 60% for wheat), and additional PP coverage can be purchased for some crops (Haight 2004). A PP payment is calculated as [approved yield * coverage level election* price election * share in crop * PP percentage]. Note that the first four terms in the brackets determine the normal MPCI payment. Producers cannot plant a substitute crop on the acreage submitted for a PP claim without forfeiting the payment (Haight 2004). Producers are allowed to plant some cover crops without forfeiting their PP payment, if the crop is not harvested for grain or seed and is not a normal part of a rotation program. Lastly, producers cannot rent acreage to other users if it has been submitted for a PP claim (Haight 2004). Producers in the study area indicate that the MPCI program's prevented planting provision is a useful drought preparedness tool. However, to the author's knowledge, no economic studies have examined the prevented planting provision in this role. Existing studies have focused instead on the provision's susceptibility to adverse selection and fraudulent claims (Rejesus, Escalante, and Lovell 2005; Rejesus et al. 2003).

2.5 Climate Change and Drought in the Western United States

The ability of the earth's atmosphere to trap solar radiation and increase global temperature (the so-called "greenhouse effect") has been recognized for at least 150 years. More recently, global climate change has been a topic of intense scientific and political debate. Certain evidence is unequivocal; carbon dioxide concentrations (the most abundant greenhouse gas in the earth's atmosphere) have been increasing steadily for over a century. Specifically, CO_2 levels have increased 30% since the late 1800s, and are higher now than they have been in the last 400,000 years (National Assessment Synthesis Team 2000). The decade of the 1990s was also the warmest (on a global scale) in over a century. Average annual temperature of the United States has risen almost 0.6° C (1.0° F) over the 20th century (National Assessment Synthesis Team 2000). The role that humans have played in recent global warming, and whether it is possible to offset that effect in any meaningful time scale, is still debated. The belief that global warming will continue, however, is becoming more widely accepted in the science and policy communities. It is prudent, therefore, to consider the impacts of such warming on the frequency and severity of drought in the western United States.

Several general circulation models (GCMs) have predicted U.S. average annual temperatures to increase 3 to 5° C (5 to 9° F) over the next 100 years (National Assessment Synthesis Team 2000). Atmospheric scientists anticipate numerous climatic effects to arise from these increasing temperatures. For example, precipitation, which has increased in the U.S. by 5 to 10% over the 20th century (Intergovernmental Panel on Climate Change 2001b), is predicted to continue to increase in many regions, particularly those at higher latitudes(Frederick and Gleick 1999; Gleick 2000). Two GCMs, the Canadian Climate Centre, and the Hadley Centre in the United Kingdom, have projected specific precipitation changes across the U.S. These include 25% precipitation increases in the Northeast, 10 to 30% increases in the Midwest, 20% increases in the Pacific Northwest, 10% precipitation decreases in the southern coast of Alaska, and up to 25% declines in the Oklahoma panhandle, north Texas, eastern Colorado and western Kansas (National Assessment Synthesis Team 2000). Caution should be exercised in using any of these as predictions, given the coarseness of geographical scale in existing GCMs.

Increases in precipitation, given warmer atmospheric conditions, will not necessarily mean more available water at the state or regional level. The higher evaporation rates that accompany rising temperatures are expected to result in less water available in many regions (Frederick and Gleick 1999). For example, GCMs project global average evaporation to increase 3 to 15% with doubled CO_2 levels (Gleick 2000). Simulation studies suggest that precipitation must increase by at least 10% to balance evaporative losses resulting from a 4° C temperature increase(Gleick 2000). Projections of rising evaporation rates indicate they will outpace precipitation increases, on a seasonal basis, in many regions (Gleick 2000; Intergovernmental Panel on Climate Change 1998). The greatest deficits are expected to occur in the summer, leading to decreased soil moisture levels and more frequent and severe agricultural drought (Gleick 2000; Intergovernmental Panel on Climate Change 1998).

Shifts in the form and timing of precipitation and runoff, specifically in snow-fed basins, are also likely to cause more frequent summer droughts. More precisely, rising temperatures are expected to increase the proportion of winter precipitation received as rain, with a declining proportion arriving in the form of snow (Frederick and Gleick 1999; Intergovernmental Panel on Climate Change 2001a). It is expected that snow pack levels will form much later in the winter, accumulate in much smaller quantities, and melt earlier in the season (Intergovernmental Panel on Climate Change 2001a).

These changes in snow pack and runoff are of particular concern to irrigated agriculture. For example, if the runoff season occurs primarily in winter and early spring, rather than late spring and summer, water availability for summer-irrigated crops might decline during crucial spring and summer months, causing water shortages to occur earlier in the growing season. Shifts in runoff, precipitation and evaporation patterns may also intensify interstate and international water allocation conflicts, as water managers struggle to meet obligations of compacts and court decrees given more variable water availability and timing in headwater areas. Global climate change is clearly relevant to drought in agriculture. The effect of more frequent and severe drought on farm income and optimal crop plans is investigated in chapter 5.

3 Description of the Study Area

3.1 Overview

The Vale Oregon Irrigation District (VOID) is the study area chosen for this research. VOID includes 35,000 acres of irrigable lands encompassing the towns of Harper, Little Valley, Vale, Willow Creek, and Jamieson, in Malheur County, Oregon. Vale, Oregon, with a population of 1,976, elevation of 2,244 feet, and average annual precipitation of 9.77 inches is the largest and most central town to VOID (Malheur County Oregon 2003).

3.2 Reservoirs

The Vale Oregon Irrigation District is located along the Malheur River, Willow Creek, and Bully Creek drainages in northeastern Malheur County, Oregon (figure 3.1). Neighboring irrigation districts include the Warmsprings Irrigation District, Owyhee Irrigation District, and Orchards Water Company (figure 3.2). Settlers began irrigating lands now included in VOID in 1881 (Bureau of Reclamation 1998b), which established the 1881 priority date for most of VOID's reservoir storage rights. The Vale Project was funded in 1926 through an agreement between VOID and the federal government. In addition to purchasing one-half of the storage rights to the existing Warmsprings Reservoir from the neighboring Warmsprings Irrigation District, a diversion dam, main canal, and lateral canals were to be built. The first unit of the Vale Project was open for irrigation in 1930 (Bureau of Reclamation 1998b). Two additional reservoirs were built for VOID, in 1935 and 1963.

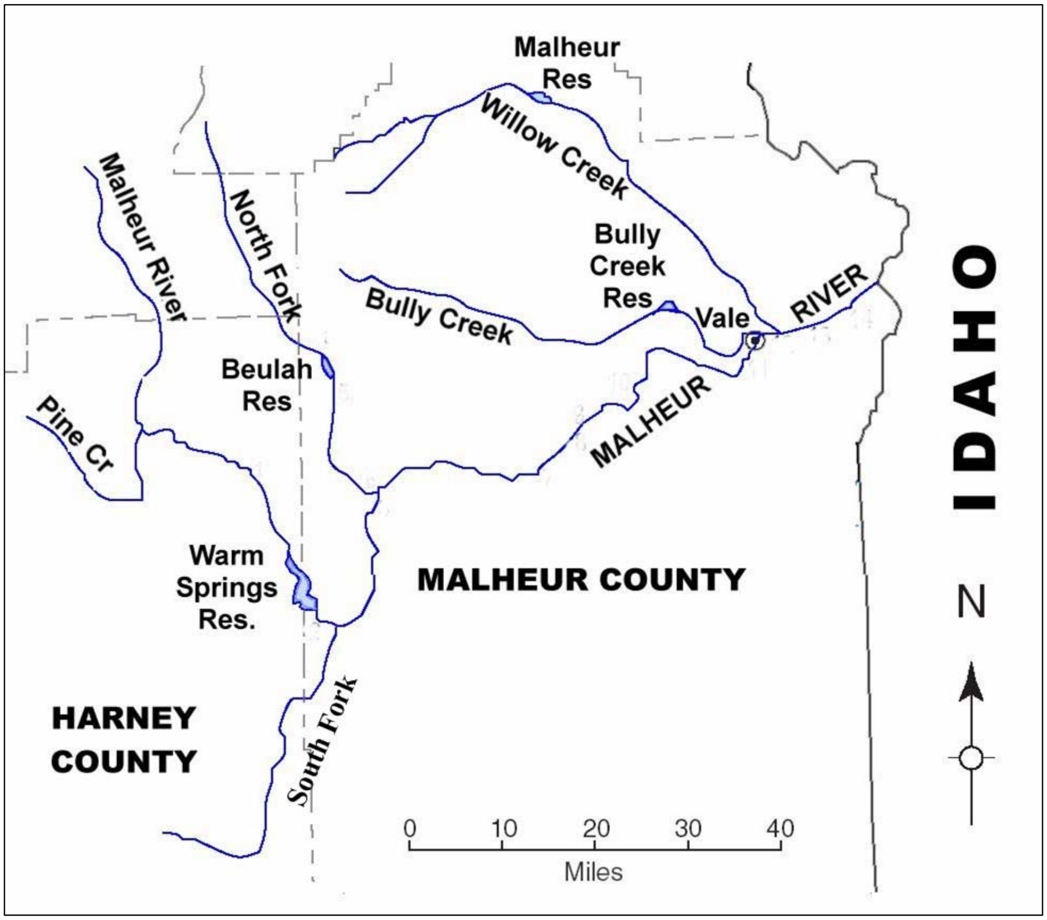


Figure 3.1. The Malheur River Basin, including Bully Creek Reservoir, Agency (Beulah) Reservoir, and Warmsprings Reservoir, which serve the Vale Oregon Irrigation District (adapted from Shock et al. 2001).

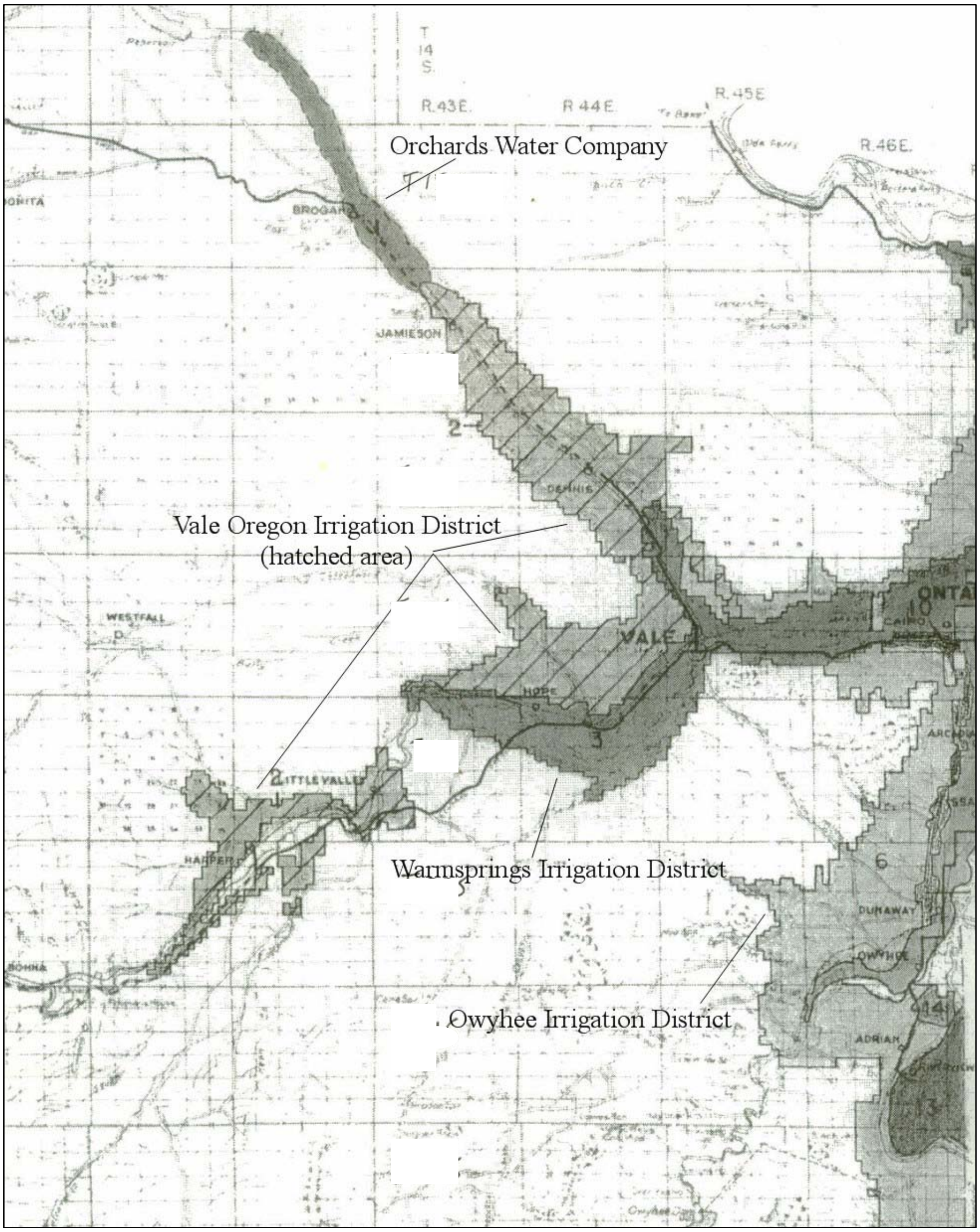


Figure 3.2. Vale Oregon Irrigation District and neighboring irrigation districts, Malheur County, Oregon (Unknown 19--).

Storage rights in Warmsprings, Beulah, and Bully Creek Reservoirs, and surface rights from the Malheur River, Willow Creek, and Bully Creek provide water for VOID (figure 3.1). The Bureau of Reclamation owns each of the reservoirs. The Warmsprings Dam and Reservoir, located on the Middle Fork of the Malheur River, 60 miles west of Vale, Oregon, collects spring snowmelt and runoff from a drainage area of 1,110 square miles, and has an active storage capacity of 191,000 acre-feet. VOID owns one-half, or 95,000 acre-feet, of this storage capacity. The Warmsprings Irrigation District owns the other one-half of the storage capacity and operates the dam on behalf of both irrigation districts (Bureau of Reclamation 1998b). The Agency Valley Dam and Beulah Reservoir, built in 1935, are located on the North Fork of the Malheur River, 18 miles north of Juntura, Oregon. Beulah Reservoir collects snowmelt and runoff from a drainage area of 444 square miles, and has an active storage capacity of 59,900 acre-feet. VOID operates the dam (Bureau of Reclamation 1998b). The Bully Creek Dam and Reservoir, built in 1963, are located on Bully Creek, 9 miles northwest of Vale, Oregon. Bully Creek Reservoir collects snowmelt and runoff from a drainage area of 550 square miles, and has an active storage capacity of 30,000 acre-feet. VOID operates the dam (Bureau of Reclamation 1998b). In addition to storing Bully Creek flows, surplus winter flows in the Malheur River are also diverted to and stored in Bully Creek Reservoir for use the following growing season.

Total reservoir storage capacity available to VOID is 184,900 acre-feet. Water is drawn from a total drainage area of 2,104 square miles to irrigate 35,000 acres. In comparison, the neighboring Owyhee Irrigation District receives its irrigation water from Owyhee Reservoir, which has an active storage capacity of 715,200 acre-feet, and collects water from a drainage area of 10,900 square miles (Bureau of Reclamation 1998a). Owyhee Reservoir serves 105,000 irrigated acres, including the Owyhee Irrigation District's 65,000 irrigated acres (Jacobs 2003).

VOID can store enough water to irrigate for 1.5 seasons provided that Warmsprings, Beulah, and Bully Creek Reservoirs fill to capacity (Ward 2004). To estimate how frequently these reservoirs are filled, the fraction of water years over a 35-year period during which the 'maximum reservoir content' exceeded 85% of the reservoir's storage capacity was calculated (Bureau of Reclamation 2004). Bully Creek Reservoir content exceeded 85% of the storage capacity during 25 out of 35 years (71.4%). Content was less than 50% of storage capacity in the years 1988, 1991, and 1992. Beulah Reservoir content exceeded 85% of storage capacity during 23 out of 35 years (65.7%). Content was less than 50% of storage capacity in the years 1988, 1991, and 1992. Warmsprings Reservoir content exceeded 85% of storage capacity during 22 out of 35 years (62.9%). During the years 1988, 1991, and 1992 Warmsprings' maximum reservoir content did not exceed 25% of storage capacity. Warmsprings Reservoir also remained at less than 50% of storage capacity in the years 1997, and 2001 to 2004. Beulah and Warmsprings Reservoirs are located only 30 miles apart; therefore, they often suffer simultaneous shortages. Table 3.1 reports the frequency of 'percent reservoir storage capacity' classes over the 35-year period.

Water stored in Warmsprings and Beulah Reservoirs must travel 65 miles east via the Malheur River before it reaches VOID's main diversion, the Harper Diversion Dam. Water is diverted there into the earthen Vale Main Canal, through which it must travel 74 miles along the western border of VOID to reach the end of the canal, near Jamieson, Oregon. The canal empties there into Willow Creek, which acts as a conduit for producers in the Willow Creek area. As water moves through the Vale Main Canal, it is diverted into numerous lateral canals and pipelines for delivery to individual VOID producers (Bureau of Reclamation 1998a). Water stored in Bully Creek Reservoir is released into Bully Creek and diverted to nearby VOID acreage. An extensive drainage system is also in place throughout VOID to manage surface and subsurface runoff, which play an important role in water allocation within VOID and between VOID and the Warmsprings Irrigation District (Bureau of Reclamation 1998a).

Table 3.1. Count and percent occurrence of five reservoir storage level classes during water years 1969-2004 at Bully Creek, Beulah, and Warmsprings Reservoirs (Bureau of Reclamation 2004).

Bully Creek Reservoir	*Storage Capacity (acft): 31,650*		
Acre-feet	% of storage capacity	# years	% occurrence
0 - 7,913	0-25%	0	0.0%
7,914 - 15,825	25.1-50%	3	8.6%
15,826 - 23,738	50.1-75%	5	14.3%
23,739 - 26,903	75.1-85%	2	5.7%
26,904 - 31,650	85.1% +	25	71.4%
Beulah Reservoir	*Storage Capacity (acft): 59,900*		
Acre-feet	% of storage capacity	# years	% occurrence
0 - 14,975	0-25%	0	0.0%
14,976 - 29,950	25.1-50%	3	8.6%
29,951 - 44,925	50.1-75%	6	17.1%
44,926 - 50,915	75.1-85%	3	8.6%
50,916 - 59,900	85.1% +	23	65.7%
Warmsprings Reservoir	*Storage Capacity (acft): 191,100*		
Acre-feet	% of storage capacity	# years	% occurrence
0 - 47,775	0-25%	3	8.6%
47,776 - 95,550	25.1-50%	5	14.3%
95,551 - 143,325	50.1-75%	4	11.4%
143,326 - 162,435	75.1-85%	1	2.9%
162,436 - 191,100	85.1% +	22	62.9%

3.3 The Distribution of Water

VOID appropriates an equal per acre water allotment to each district member. The appropriation amount is determined at the beginning of each season, and is based on many factors, including current and expected reservoir levels. Recall that all VOID water rights share the same 1881 priority date, thus all members have equal rights. Producers are allowed to apply their allotment to any of their acreage, but cannot easily transfer water to another VOID member (Jacobs 2003). Producers are assessed a fee of $80 per account plus $29 per acre, per year, regardless of the quantity of water delivered (Vale Oregon Irrigation District 2004a).

A full allotment in VOID is 3.5 acre-feet of water per acre of land (Ward 2004), although they are allowed up to 4.5 acre-feet per acre in an unrestricted water year (Jacobs 2003). Since 1992, VOID members have received a full allotment only once, in 1997. Allotment hit a record low of 0.92 acre-feet per acre in 1992 (Vale Oregon Irrigation District 2004b). Table 3.2 reports district allotments for years 1981 to 2003 (Vale Oregon Irrigation District 2004b). Interviews with producers suggest that most crops can be grown successfully with a 3 acre-feet per acre allotment. Producers received 3 or more acre-feet per acre during 11 of 23 years (48%) for the period 1981 to 2003.

Some VOID members have access to supplemental water sources. Members with canal access to Bully Creek Reservoir sometimes receive a larger allotment, because distribution from this reservoir cannot be distributed to all VOID members. A small number of producers have individual stream-flow rights to Malheur River, Willow Creek, or Bully Creek, or have access to groundwater. Twenty groundwater wells were in place at the end of the 2003 growing season (Jacobs 2003). The number of economically feasible wells is limited in VOID, due in part to deep aquifers (400 to 600 feet or more) and high electricity costs, but producers continue to search for shallow aquifers (Jacobs 2003).

Table 3.2. VOID water allotments (acre-feet per acre) for the years 1981-2003 (Vale Oregon Irrigation District 2004b).

Year	Acre-feet per acre	Year	Acre-feet per acre
2003	1.75	**1991**	1.06
2002	2.20	**1990**	2.05
2001	2.13	**1989**	2.90
2000	3.20	**1988**	1.02
1999	3.03	**1987**	2.89
1998	2.74	**1986**	3.55
1997	3.56	**1985**	3.46
1996	3.02	**1984**	3.60
1995	2.71	**1983**	3.65
1994	2.54	**1982**	3.58
1993	3.05	**1981**	3.60
1992	0.92		

3.4 Agricultural Production

Today, up to 35,000 acres of land are irrigated for agricultural purposes during the best water years. The eleven-year average of irrigated acreage for the years 1992 to 2002, including acreage irrigated but not harvested (an average of 570 acres), is 33,830 acres. The eleven-year average acreage fallowed or idled is 1,000 acres. During the extremely dry year of 1992, irrigated acreage fell to 28,100 acres, with nearly 6,800 acres fallowed. Records indicate that 216 full-time farms and 207 part-time farms operated within VOID in the year 2000, compared to 230 full-time farms and 180 part-time farms that operated within VOID in the year 1992 (Vale Oregon Irrigation District 2004b).

Soil quality in VOID is categorized into bench-land (Frohman-Virtue) and bottom-land (Powder-Turbyfill-Garbutt) (Soil Conservation Service and Oregon Agricultural Experiment Station 1979). Bottom-land has higher quality soil compared to bench-land, because it is flatter and deeper, which increases soil moisture retention. The highest quality land in VOID is a one-mile wide strip of bottom-land that buffers Willow Creek. Land west of Willow Creek, outside of the buffer area is bench-land, which tends to be hilly and have shallow soils. A similar pattern occurs along Bully Creek. Land surrounding the town of Harper has deeper soils, but it is hillier than most bottom-land. Most remaining land in VOID is bench-land (Soil Conservation Service and Oregon Agricultural Experiment Station 1979).

It is important to note that the best land in VOID occurs along its streams, and that farms located on bottom-land along streams have a higher probability of owning stream rights. This combination of having the best soils in VOID and owning supplemental water rights is likely an advantage during periods of drought. Recall, however, that land along Willow Creek is located at the end of the Vale Main Canal, making it more difficult to deliver water to the area during a drought, or at the end of the irrigation season.

Alfalfa hay and irrigated pasture account for roughly 57% of VOID's irrigated acreage. Wheat, corn, and forage for silage account for 24% of irrigated acreage. Other hay, barley, sugarbeets, dry beans, potatoes, and onions account for 16% of irrigated acreage (Vale Oregon Irrigation District 2004b). Table 3.3 reports 'harvested acreage by crop' as a percent of total harvested acreage for the period 1992 to 2002.

3.5 Irrigation Technology

Most of VOID's canals, including the Vale Main Canal, are unlined. However, canals are slowly being replaced with pipelines in an effort to reduce conveyance losses. Currently, over 130,000 feet of pipeline has been installed (Ward 2004), and 36,000 feet of additional pipeline is being installed to reduce *Escherichia coli* levels in Willow Creek. Furrow irrigation, using siphon tubes or gated pipes, is the predominant irrigation technology in the VOID. However, acreage under sprinkler irrigation (solid set, wheel line, and center pivot) grew from 4,000 acres (11.4% of district acreage) in 1992 to 5,500 acres (15.7%) in

2001 (Vale Oregon Irrigation District 2004b). The installation of additional sprinkler irrigation systems is limited, however, because most of VOID's bottom-land is too flat to generate sufficient head pressure, and thus electric pumps are required to pressurize the system (Ward 2004). Producers indicate that the cost of the infrastructure required to deliver electricity to the pressurized sprinkler systems is prohibitive.

VOID onion growers have begun adopting drip irrigation. One-hundred acres were under drip irrigation in 2002, and as of 2004 this acreage has doubled (Vale Oregon Irrigation District 2004b). Drip irrigation is used exclusively on onions in VOID because no other crop is sufficiently valuable to justify the installation and operating expenses. VOID producers are also installing reuse furrow systems to improve on-farm irrigation efficiency. Collection ponds are dug at the bottom of fields to collect surface and subsurface runoff. Pumps, filters, and pipelines then deliver the recycled water to the same field or to neighboring fields. Reuse systems reduce and alter return flows, often to the detriment of downstream producers. Warmsprings Irrigation District relies heavily on VOID's return flows, and have already reported impacts from such water conservation efforts (Ward 2004). Producers who choose not to invest in improved irrigation technology combat water shortages by allocating more labor to the management of their furrow irrigation system. However, labor is difficult to find during the irrigation season, so producers must weigh the cost of additional labor against the benefit of improved irrigation efficiency.

3.6 Water Supply Forecasts

Snowpack is the primary source of irrigation water to VOID. The transformation of winter snowpack to spring runoff is a complex process, and a major source of uncertainty for VOID managers and producers. Water supply forecasts for the VOID currently have a limited forecast horizon (predictions are typically formulated no earlier than April), and limited accuracy. An exploratory economic analysis indicates positive economic benefit to VOID from improved water supply forecasts (Wyse 2004).

3.7 Summary

The Vale Oregon Irrigation District has many characteristics that make it an appropriate empirical focus for this research: 1) VOID producers experience drought frequently (most recently a three-year drought that ended in 2004), which has resulted in application of numerous drought preparedness and response tools; 2) row-crop systems in the VOID involve both intra- and inter-year dynamics, and 3) producers have indicated a desire to enhance their ability to prepare for, and respond to drought. The model is therefore parameterized for a hypothetical irrigated row-crop farm in VOID.

Table 3.3. Harvested acres by crop as a percent of total harvested acreage, 1992-2002 (Vale Oregon Irrigation District 2004b).

Year	Harvested Acres	Water Delivered (Acft Per Acre)	Alfalfa Hay	Irrig. Pasture	Wheat	Corn	Silage
1992	28,136	0.92	28.0%	22.9%	13.2%	2.3%	10.5%
1993	33,079	3.05	25.9	23.7	9.8	7.2	10.3
1994	33,753	2.54	29.4	25.5	9.7	5.1	8.9
1995	33,589	2.71	29.9	25.7	9.8	8.1	7.6
1996	34,376	3.02	26.0	26.9	15.4	10.7	5.9
1997	34,345	3.56	27.2	26.4	15.7	10.7	5.9
1998	34,467	2.74	32.8	26.9	10.0	8.1	6.7
1999	33,850	3.03	33.0	28.5	6.1	10.3	5.5
2000	33,839	3.20	33.8	29.3	6.0	8.5	5.6
2001	34,410	2.13	38.6	29.3	4.9	6.7	5.0
2002	33,816	2.20	42.6	27.2	4.5	5.8	6.5

Table 3.3. (Cont.)

Year	Other Hay	Barley (feed)	Sugar beet	Beans (dry edible)	Onions (dry)	Potatoes (early)	Potatoes (late)
1992	4.6%	10.3%	2.9%	0.73%	0.99%	1.14%	0.40%
1993	9.0%	4.8%	2.1%	2.55%	1.24%	1.54%	0.75%
1994	4.6%	5.2%	2.3%	2.66%	1.33%	1.68%	1.17%
1995	4.6%	4.2%	2.6%	2.61%	1.12%	1.32%	1.31%
1996	2.9%	2.7%	1.9%	1.51%	1.03%	1.71%	1.64%
1997	2.6%	2.7%	1.4%	1.53%	1.01%	1.60%	1.54%
1998	3.9%	2.2%	2.4%	1.49%	0.68%	1.21%	1.70%
1999	3.7%	2.3%	2.0%	2.10%	1.29%	1.10%	1.82%
2000	6.0%	2.9%	2.6%	0.59%	1.16%	0.67%	1.45%
2001	7.5%	1.5%	2.6%	0.24%	1.34%	0.34%	1.53%
2002	6.2%	1.1%	2.1%	0.71%	1.04%	0.00%	1.90%

4 Model Description

4.1 Overview of the Model

Stochastic programming (SP) is selected to represent the decision-process of farm managers in the study area. SP is able to represent farm managers who make fall decisions about several cropping activities, given an uncertain future water supply, with explicit consideration of future spring decisions. Managers decide in the fall the number of acres to plant to winter wheat, and the number of acres to prepare for onions, potatoes, and sugar beets. The phenology of winter wheat requires it to be fall-planted, and spring labor constraints require the fall preparation of other acreage. Ideally, fall decisions would be made given perfect knowledge of the upcoming growing season's water supply. Unfortunately, only the subjective probability distribution of the future water supply is known when fall decisions are made. Fall decisions therefore represent the first stage of the SP model.

Information enters the SP model decision framework in early spring when a water supply forecast becomes available. The forecast is assumed to perfectly predict the growing season's water supply; this is not the case in reality, but is a simplifying assumption. Upon receiving these forecasts, and subject to constraints associated with their fall decisions, managers make their spring decisions. These spring decisions represent the second stage of the SP model. Managers have some recourse actions available at this time. Suppose, for example, that the spring forecast indicates a full water allotment. A manager who left a large acreage open in the previous fall could plant it to a spring-prepared and planted crop, such as corn. SP would capture the structure of this decision process much better than CCP or PP. SP is chosen over SDP because it accommodates several decision variables, and because the desired number of stages is relatively small (twelve or fewer).

Additional recourse stages exist in the manager's true decision process. These additional stages occur because the spring water supply forecast is imperfect, and as the season progresses the manager gains additional information about the seasonal water supply and responds by adjusting management activities, such as irrigation and date of harvest. In fact, the actual value of the seasonal water supply is not fully revealed until all crops have matured, since the water supply includes rainfall events that cannot be predicted beyond a few days notice. There are also other random variables that are not known *a priori* and that affect managers' optimal decision path, such as output prices and the occurrence of pests, hail, and wind.

Dozens of stages could be constructed in to simulate farm managers' decisions and flow of information over a year. Such an attempt is beyond the scope of this research. The number of stages within a crop year is limited to two (three for models that incorporate price uncertainty), and the number of random variables will generally be limited to one, water supply; price is also treated as a random variable in some models. Limiting the number of stages per year and the number of random variables allows us to expand a single-year (two-stage) model to a six-year (twelve-stage) model. Six years is chosen because the dynamic effect of a specific crop in the study area spans a six-year period. The model is described in detail below.

Many studies that use mathematical programming models represent farm decisions as continuous variables (e.g. acres planted). A continuous variables model was initially developed for this study to address questions about drought in a multi-year context. One advantage of continuous variables models is that they require a less powerful solver and less computational time. However, some inter-year crop rotation constraints can be modeled only approximately within the continuous variables specification (this is discussed in detail below). Concern about the approximate nature of crop rotations in the continuous variables model prompted the construction of an equivalent binary variables model. The availability of both a continuous and binary variables model presents an opportunity to illustrate the structure of each model, and compare their optimal solutions. This comparison provides useful insights as to the differences in outcomes between a binary and continuous model in a farm system context.

A general representation of the models is presented next, followed by an explanation of the general features. A detailed presentation and description of each model's equations then follows. In the following discussions, the binary model is typically presented first and in the most detail, followed by a brief description of any features that are unique to the continuous model. Parameter values used in the analyses are presented in the Appendices. All models are constructed in GAMS (General Algebraic Modeling System) and solved using CPLEX; the programming code is provided on an attached floppy disc.

4.1.1 The Binary Variables Model

(1) $\underset{x,y}{\text{Max}}\ E_s\Pi(x,y;s)$

$s.t.$

(2) $Ax = b$

(3) $Dy = e$

(4) $Mx + Ny = g$

(5) $x, y \geq 0$

where

s = A random vector that represents water supplies over a 6-year planning horizon. Each realization of s consists of 6 components (s1 s2 s3 s4 s5 s6), which indicate the state of nature (water supply category) revealed in each of the six years. That is, s1 represents the state of nature revealed in year 1, s2 the state of nature revealed in year 2, etc. Assuming 2 possible states of nature (Dry or Full) in each of 6 years, 64 six-year water supply scenarios are possible. Scenarios range from [Dry Dry Dry Dry Dry Dry] to [Full Full

Full Full Full Full], and every combination between. The scenario [Dry Dry Full Full Full Full] indicates (from left to right) that the state of nature revealed in year 1 is Dry, year 2 is Dry, year 3 is Full, etc. Each state of nature has a probability of occurrence within any given year, denoted pr(Dry) or pr(Full). The state of nature in any one year is assumed independent of the state of nature in any other year (based on an autocorrelation analysis of historical stream-flow above the storage reservoirs as described by Haan (2002 p. 348). Therefore, the joint probability of a particular six-year water scenario is the product of the probabilities of the states of nature that occur each year. For example, pr([Dry Dry Full Full Full Full]) = pr(Dry)*pr(Dry)*pr(Full)*pr(Full)*pr(Full)*pr(Full). Historical water allotment data and Gaussian quadrature analysis (Featherstone, Baker, and Preckel 1993; Miller and Rice 1983; Preckel and Devuyst 1992) were used to assign quantity of water and probability to each state of nature (Appendix B).

x = Vector containing fall crop decision variables for each year of the planning horizon.

Example element: $x_{3,f,c,i,s1,s2}$, which indicates for the fall of year 3, that field f is prepared for or planted to crop c, under irrigation technology i, given the states of nature revealed in past years 1 and 2. Each element of x is a binary variable, taking on a value of 0 (if the crop/irrigation combination (c,i) is not chosen for field f) or 1 (if the crop/irrigation combination (c,i) is chosen for field f). Each field may also be left "open," implying that it is neither prepared for nor planted to any crop.

y = Vector of spring crop decision variables for each year of the planning horizon.

Example element: $y_{3,f,c,i,w,s1,s2,s3}$, which indicates for the spring of year 3, that field f is planted to crop c in the spring of year 3, under irrigation technology i, and deficit irrigation category w, given the states of nature revealed in past years 1, 2, and the present year 3. Each element of y is a binary variable, taking on a value of 0 (if the crop-irrigation-deficit combination (c,i,w) is not chosen for field f) or 1 (if the crop-irrigation-deficit combination (c,i,w) is chosen for field f). Each field may also be "fallowed," in which case it is either abandoned (if prepared or planted in the previous fall), or simply never planted (if left open in the previous fall).

$\Pi(x, y; s)$ = Vector containing the profit outcome for each water scenario. An individual element of the vector is the discounted stream of profit that optimal activities *x* and *y* generate over the 6-year period in which they occur, for a particular water scenario. Terminal land rental values are also included, as a function of activities in the 6-year period. A terminal value for alfalfa acreage that remains in production after year 6 is also included.

A, D = Matrices of coefficients that describe fall and spring activities' resource use.

b, e = Vectors of resource availability, such as land and water, which vary by state of nature for some resources.

M, N = Matrices of coefficients that relate activities in different time periods to each other (intra- and inter-year rotation constraints).

g = Vector of parameters that, with *M* and *N* above, define relationships between activities in different time periods.

4.1.2 The Continuous Variables Model

The continuous variables model, in its general form, is the same as the binary variables model described above, except for the interpretation of the decision variables. The new interpretation is provided below.

x = Vector containing fall crop decision variables for each year of the planning horizon.

Example element: $x_{3,c,i,s1,s2}$, which indicates for the fall of year 3 the number of acres of crop c to prepare for or plant, under irrigation technology i, given the states of nature revealed in years 1 and 2.

y = Vector of spring crop decision variables for each year of the planning horizon.

Example element: $y_{3,c,i,w,s1,s2,s3}$, which indicates for the spring of year 3 the number of acres of crop c to plant, under irrigation technology i, and deficit irrigation category w, given the states of nature revealed in years 1, 2, and 3.

4.2 Interpreting the General Model

The above discrete stochastic sequential programming models (binary and continuous) maximize the expected stream of profit over a 6-year planning horizon. The expectation is taken over water supply, *s*, which is assumed to have a discrete probability distribution over a small number of pre-defined categories (e.g. dry and full). Choice variables are contained in the vectors *x* and *y*. Vector *x* includes fall cropping activities, which are chosen under an uncertain future water supply. Vector *y* includes spring cropping activities, which are chosen after water supply is revealed. Fall and spring activities are chosen for each year of the six-year planning horizon, for each water supply scenario, (e.g. [Full Full Full Dry Dry Dry]). Fall and spring activities are constrained by resource availability, as expressed in equations (2) and (3). Equation (4) describes dynamic interactions in the cropping system, including how fall activities restrict spring activities (intra-year dynamics), and how activities in year t restrict activities in subsequent years (inter-year dynamics).

The timing of decisions relative to the availability of water supply information is an essential feature of the DSSP model (figure 4.1). Past water supply is known in the base model, but future water supply is uncertain. Specifically, fall cropping activities (x_t) are chosen before the water supply for the upcoming growing season is known, and before the water supplies for future growing seasons are known. Water supply for the upcoming growing season is revealed in early spring, after which spring cropping activities (y_t) are chosen. Note that although the water supply for the upcoming season is revealed in the spring, the water supplies in future growing seasons remain uncertain. This sequence of events (choose x_t, water supply is revealed, choose y_t) is repeated in each year of the six-year planning horizon.

Intra- and inter-year dynamics between cropping activities require the producer to be forward-looking to make optimal decisions. Activities in the fall of year 1, for example, will constrain activities in the spring of year 1, which will potentially constrain activities throughout the remainder of the planning horizon.

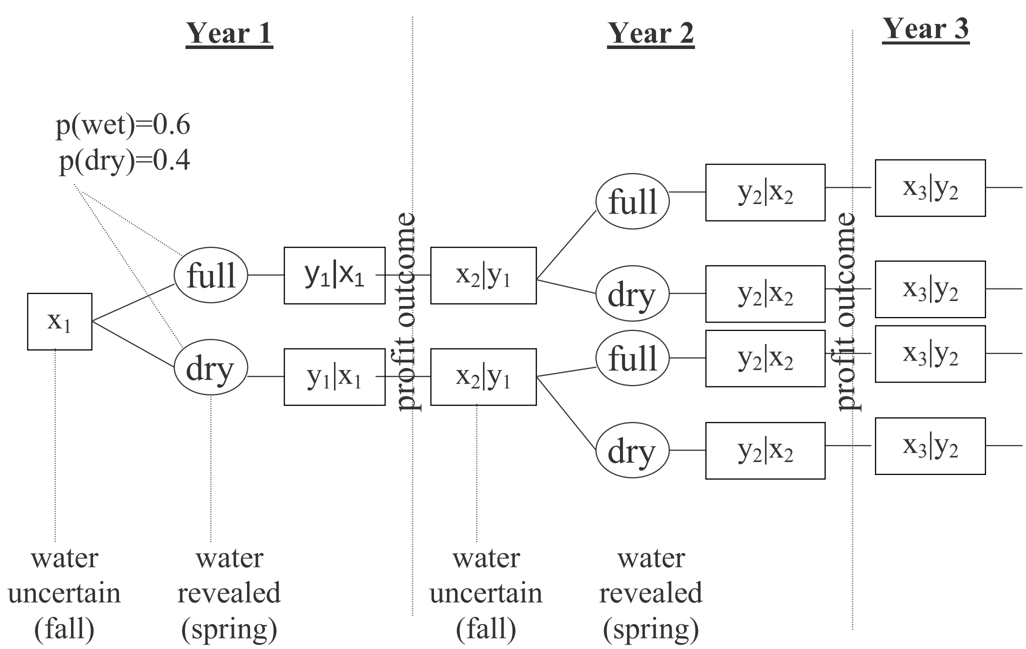


Figure 4.1. Decision tree representation of decision-making under uncertainty. Fall cropping activities (x_t) are chosen given an uncertain spring water supply. The spring water supply is then revealed (full or dry), after which spring cropping activities (y_t) are chosen.

Therefore, when selecting activities for fall of year 1, the producer must consider the activities' future impacts. Future impacts are challenging to identify, however, because future water supplies are uncertain. The following example illustrates this point.

Suppose, for simplicity, that the planning horizon is a single year, within which fall decisions are made given an uncertain water supply, and spring decisions are made given a certain water supply. When selecting fall activities, the producer must consider the impact on spring activities for two cases: 1) the spring allotment is revealed to be full, and 2) the spring is revealed to be dry. A particular set of fall activities might maximize profit in the event of a full allotment, but not a dry spring, or vice versa. In contrast, the optimal set of fall activities will, by the definition of "optimal" in this dissertation, maximize *expected* profit over both water scenarios. That is, the producer must select fall activities based on their performance in each possible water scenario, and the probability of each scenario.

A solution to this two-stage, single-year problem consists of one set of optimal fall activities, and two sets of optimal spring activities, one for a full spring allotment, and one for a dry spring. The producer implements the fall plan, and after the water supply is revealed as full or dry, the producer implements the corresponding spring plan. Suppose that the producer knows, prior to making their fall decision, that the allotment will be full. The resulting set of optimal fall activities would likely differ from the set derived under uncertainty. Note that the difference in profit between these two scenarios represents the cost of uncertainty, or equivalently, the value of perfect information.

When this model is expanded from one year to two, the producer identifies one set of optimal "fall year 1" activities, two sets of optimal "spring year 1" activities, two sets of optimal "fall year 2" activities, and four sets of optimal "spring year 2" activities (figure 4.1). The producer, in choosing their activities for fall year 1, considers that four water supply scenarios are possible over the two-year period: [Full Full], [Full Dry], [Dry Full], and [Dry Dry]. In addition to choosing a plan for fall year 1, the producer selects activities for each stage of every possible water supply scenario. In reality, the producer will update year 2 plans once the outcome of year 1 is realized, in order to make full use of information gained in year 1, and to look six years into the future before choosing a year 2 plan. The plan made for year 2 in the fall of year 1 should therefore be interpreted as an estimate of the optimal year 2 plan. Figure 4.1 illustrates the branching pattern of crop plans that arises when future water supplies are uncertain. Two states of nature and a six-year planning horizon are assumed in the empirical model, which generates 64 unique water scenarios, and potentially 64 unique six-year crop plans. It is unlikely that a producer could envision six-year crop plans for all sixty-four scenarios. It is likely, however, that a producer could clearly envision crop plans and outcomes for the near future, as well as attempt to consider the dynamic implications of those plans in the more distant future. The farther into the future the producer can envision, the closer their year 1 plans will be to the optimal.

Once a crop plan is determined for each stage (fall and spring) of each year of each water supply scenario, a discounted stream of profit is calculated for each scenario (i.e. for each branch of the decision tree). Expected profit over all possible water supply scenarios is then calculated, given each scenario's probability of occurrence. The DSSP models are presented in detail next for both the binary and continuous variables models.

4.3 Details of the Binary Variables Model

The equations of the binary variables model are presented below, followed by their interpretation.

$$(6)\quad \underset{x,y}{\text{Max}}\ E_s\Pi(x,y;s)=\sum_s \rho_s\cdot\left[\begin{array}{l}\displaystyle\sum_{t=1}^{6}\left(\frac{1}{(1+d)^t}\pi_{t,s}(x_{t,s},y_{t,s})\right)\\ \displaystyle+\sum_{t=7}^{12}\left(\frac{1}{(1+d)^t}\pi_{t,s}(y_{t-6,s},\ldots y_{6,s})\right)\end{array}\right]$$

where for t =1,...,6

$$(7)\quad \pi_{t,s}(x_{t,s},y_{t,s})=\sum_c\sum_i\sum_w\left(\begin{array}{l}\displaystyle\sum_f FAC\cdot(p_c yld_{c,i,w}y_{t,f,c,i,w,s}\\ -j_{c,i}y_{t,f,c,i,w,s}-h_{c,i}x_{t,f,c,i,s})\end{array}\right)$$

$$-fxd\cos t-r\cdot\left(\begin{array}{l}\displaystyle\sum_c\sum_i\sum_w\left(\sum_f FAC\cdot(j_{c,i}y_{t,f,c,i,w,s}+h_{c,i}x_{t,f,c,i,s})\right)\\ +fxd\cos t-\pi_{t-1,s}(x_{t-1,s},y_{t-1,s})\end{array}\right)$$

and

$$(8)\quad yld_{c,i,w}=\max yld_{c,i}\cdot\left[1-\left(ky_c\cdot\left(1-\frac{w\cdot(ET\max_c-Ppt)+Ppt}{ET\max_c}\right)\right)\right]$$

where for t =7,...,12

$$(9)\quad \pi_{t,s}(y_{t-6,\mathbf{s}},\ldots y_{6,s})=RRate_{onion}\cdot EligOnion_{t,s}(y_{t-6,s},\ldots y_{6,s})$$

$$+RRate_{other}\cdot EligOther_{t,s}(y_{t-6,s},\ldots y_{6,s})$$

$$+\left(\sum_i NetRv_{alf,i,d1}\cdot EligAlf_{t,i,s}(y_{6,s})\right)-fxd\cos t$$

$$-r\cdot\left(\sum_i\left(j_{alf,i}\cdot EligAlf_{t,i,s}(y_{6,s})\right)+fxd\cos t-\pi_{t-1,s}(y_{t-6,s},\ldots y_{6,s})\right)$$

subject to

$$(10)\quad \sum_c\sum_i\sum_w\sum_f w\cdot\left(\frac{ET\max_c-Ppt}{IrrEffic_i}\right)\cdot FAC\cdot y_{t,f,c,i,w,s}$$

$$\le Water_{t,s}\cdot TotAcres \qquad \forall\ \text{t}, s$$

$$(11)\quad x_{t,f,c,i,s}=0 \qquad \text{for some t,c,i,s}\ \forall\ \text{f}$$

$$(12)\quad \text{y}_{\text{t,f,c,i,w,s}}=0 \qquad \text{for some t,c,i,w,s} \qquad \forall\ \text{f}$$

$$(13)\quad x_{t,f,c,i,s},y_{t,f,c,i,w,s}=0 \text{ or } 1 \qquad \forall\ \text{t,f,c,i,w,s}$$

$$(14)\quad \sum_i x_{1,f,wheat,i}+H6_{f,wheat}+H6_{f,barley}\le 1 \qquad \forall\ \text{f}$$

$$(15)\quad \sum_i x_{1,f,sugbt,i} + H6_{f,sugbt} + H5_{f,sugbt} + H4_{f,sugbt} + H3_{f,sugbt} \le 1 \qquad \forall\, f$$

$$(16)\quad \sum_i x_{1,f,onion,i} + H6_{f,onion} + H5_{f,onion} + H4_{f,onion} + H3_{f,onion} + H2_{f,onion} \le 1 \qquad \forall\, f$$

$$(17)\quad \sum_i x_{1,f,potato,i} + H6_{f,potato} + H5_{f,potato} + H4_{f,potato} + H3_{f,potato} + H2_{f,potato} \le 1 \qquad \forall\, f$$

$$(18)\quad \sum_i \sum_f x_{1,f,potato,i} \le PotatoContract$$

$$(19)\quad \sum_i x_{1,f,alf2,i} = H6_{f,alf1} \qquad \forall\, f,i$$

$$(20)\quad \sum_i x_{1,f,alf3,i} = H6_{f,alf2} \qquad \forall\, f,i$$

$$(21)\quad \sum_i x_{1,f,alf4,i} = H6_{f,alf3} \qquad \forall\, f,i$$

$$(22)\quad \sum_c \sum_i x_{1,f,c,i} + open_{f,1} = 1 \qquad \forall\, f$$

$$(23)\quad \sum_w y_{1,f,fall,i,w,s} \le x_{1,f,fall,i} \qquad \forall\, f,fall,i,s$$

$$(24)\quad \sum_w y_{1,f,alf2,i,w,s} = x_{1,f,alf2,i} \qquad \forall\, f,i,s$$

$$(25)\quad \sum_w y_{1,f,alf3,i,w,s} = x_{1,f,alf3,i} \qquad \forall\, f,i,s$$

$$(26)\quad \sum_w y_{1,f,alf4,i,w,s} = x_{1,f,alf4,i} \qquad \forall\, f,i,s$$

$$(27)\quad \sum_i \sum_w y_{1,f,gcorn,i,w,s} + H6_{f,gcorn} + H6_{f,scorn} + H5_{f,gcorn} + H5_{f,scorn} \le 2 \qquad \forall\, f,s$$

$$(28)\quad \sum_i \sum_w y_{1,f,scorn,i,w,s} + H6_{f,gcorn} + H6_{f,scorn} + H5_{f,gcorn} + H5_{f,scorn} \le 2 \qquad \forall\, f,s$$

$$(29)\quad \sum_i \sum_w y_{1,f,barley,i,w,s} + H6_{f,barley} + H6_{f,wheat} \le 1 \qquad \forall\, f,s$$

$$(30)\quad \sum_c \sum_i \sum_w y_{1,f,c,i,w,s} = 1 \qquad \forall\, f,s$$

$$(31)\quad \sum_i x_{2,f,wheat,i,s} + \sum_i \sum_w y_{1,f,wheat,i,w,s} + \sum_i \sum_w y_{1,f,barley,i,w,s} \le 1 \qquad \forall\, f,s$$

(32) $$\sum_i x_{2,f,sugbt,i,s} + \sum_i \sum_w y_{1,f,sugbt,i,w,s} + H6_{f,sugbt} + H5_{f,sugbt} + H4_{f,sugbt} \le 1 \qquad \forall \text{ f,s}$$

(33) $$\sum_i x_{2,f,onion,i,s} + \sum_i \sum_w y_{1,f,onion,i,w,s} + H6_{f,onion} + H5_{f,onion} + H4_{f,onion} + H3_{f,onion} \le 1 \qquad \forall \text{ f,s}$$

(34) $$\sum_i x_{2,f,potato,i,s} + \sum_i \sum_w y_{1,f,potato,i,w,s} + H6_{f,potato} + H5_{f,potato} + H4_{f,potato} + H3_{f,potato} \le 1 \qquad \forall \text{ f,s}$$

(35) $$\sum_f \sum_i x_{2,f,potato,i,s} \le PotatoContract \qquad \forall \text{ s}$$

(36) $$\sum_i x_{2,f,alf2,i,s} = \sum_i \sum_w y_{1,f,alf1,i,w,s} \qquad \forall \text{ f,s}$$

(37) $$\sum_i x_{2,f,alf3,i,s} = \sum_i \sum_w y_{1,f,alf2,i,w,s} \qquad \forall \text{ f,s}$$

(38) $$\sum_i x_{2,f,alf4,i,s} = \sum_i \sum_w y_{1,f,alf3,i,w,s} \qquad \forall \text{ f,s}$$

(39) $$\sum_c \sum_i x_{2,f,c,i,s} + open_{f,2,s} = 1 \qquad \forall \text{ f,s}$$

(40) $$\sum_w y_{2,f,fall,i,w,s} \le x_{2,f,fall,i,s} \qquad \forall \text{ f,fall,i,s}$$

(41) $$\sum_w y_{2,f,alf2,i,w,s} = x_{2,f,alf2,i,s} \qquad \forall \text{ f,i,s}$$

(42) $$\sum_w y_{2,f,alf3,i,w,s} = x_{2,f,alf3,i,s} \qquad \forall \text{ f,i,s}$$

(43) $$\sum_w y_{2,f,alf4,i,w,s} = x_{2,f,alf4,i,s} \qquad \forall \text{ f,i,s}$$

(44) $$\sum_i \sum_w y_{2,f,gcorn,i,w,s} + \sum_i \sum_w y_{1,f,gcorn,i,w,s} + \sum_i \sum_w y_{1,f,scorn,i,w,s} + H6_{f,gcorn} + H6_{f,scorn} \le 2 \qquad \forall \text{ f,s}$$

(45) $$\sum_i \sum_w y_{2,f,scorn,i,w,s} + \sum_i \sum_w y_{1,f,gcorn,i,w,s} + \sum_i \sum_w y_{1,f,scorn,i,w,s} + H6_{f,gcorn} + H6_{f,scorn} \le 2 \qquad \forall \text{ f,s}$$

(46) $$\sum_i \sum_w y_{2,f,barley,i,w,s} + \sum_i \sum_w y_{1,f,barley,i,w,s} + \sum_i \sum_w y_{1,f,wheat,i,w,s} \le 1 \qquad \forall \text{ f,s}$$

(47) $$\sum_c \sum_i \sum_w y_{2,f,c,i,w,s} = 1 \qquad \forall \text{ f,s}$$

where,

t = a crop year within the 6-year planning horizon, with possible values of 1 through 6, or within the 6-year period following the planning horizon, with possible values of 7 through 12.

f = the field in which the cropping activity takes place {F1,…, F10}.

c = the crop {onion, potato, sugar beet, wheat, barley, grain corn, silage corn, alfalfa (1^{st} through 4^{th} year), fallow, and open}

i = the irrigation technology {furrow, reuse furrow, solid set, wheel line, center pivot, drip}

w = the deficit irrigation level {0.0, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0}

ρ_s = probability of the 6-year water supply scenario s

r = interest rate on operating loans and savings

d = discount rate

FAC = number of acres per field (fields assumed to be equal size)

p_c = price received per unit of crop c

$yld_{c,i,w}$ = yield per acre of crop c, under irrigation technology i, and deficit irrigation level w

$j_{c,i}$ = cost of spring planting per acre of crop c, under irrigation technology i.

h_c = cost of fall preparation or planting per acre of crop c

fxdcost = fixed cost per acre of land owned, such as a water district fee per acre and land taxes

$maxyld_{c,i}$ = maximum yield for crop c, under irrigation technology i, given no water deficit

ky_c = yield response coefficient for crop c, which reflects sensitivity to water stress

$ETmax_c$ = gross water requirement of crop c over the growing season to achieve maximum yield

Ppt = precipitation received during the growing season, which reduces irrigation requirements

IrrigEffic = the proportion of water delivered to the field that reaches the crop root zone

Water = per acre water allotment for the growing season

TotAcres = total number of acres available for cropping activities

$RRate_{onion}$ = rental rate of an acre eligible for onions (i.e. an acre not planted to onions in previous 5 years)

$RRate_{other}$ = rental rate of an acre not eligible for onions

$EligOnion_{t,s}$ = acres eligible to be rented for onions in period t of scenario s

$EligAlf_{t,i,s}$ = acres of alfalfa with productive lifespan remaining in years 7 through 9 for scenario s; acres inherit the irrigation technology used in year 6

$EligOther_{t,s}$ = acres eligible to be rented for crops other than onions in period t of scenario s; a function of $EligOnion_{t,s}$ and $EligAlf_{t,i,s}$.

$NetRv_{alf,i,d1}$ = net revenue from alfalfa under irrigation technology i, assuming no deficit irrigation (w =d1)

$H1_{f,c}$ = the crop c to which field f was planted six years prior to the first year of the planning horizon (i.e. planted in the first year of the previous (historical) planning horizon) (=0 if not planted, or 1 if planted)

$H2_{f,c}$ = the crop c to which field f was planted five years prior to the first year of the planning horizon (=0 if not planted, or 1 if planted)

$H3_{f,c}$ = the crop c to which field f was planted four years prior to the first year of the planning horizon (=0 if not planted, or 1 if planted)

$H4_{f,c}$ = the crop c to which field f was planted three years prior to the first year of the planning horizon (=0 if not planted, or 1 if planted)

$H5_{f,c}$ = the crop c to which field f was planted two years prior to the first year of the planning horizon (=0 if not planted, or 1 if planted)

$H6_{f,c}$ = the crop c to which field f was planted one year prior to the first year of the planning horizon (=0 if not planted, or 1 if planted)

PotatoContract = a fixed acreage of potatoes (expressed as number of fields) contracted in advance with local processors

$open_{f,t}$ = field f is left unprepared and unplanted in the fall of year t (=0 if not left open, or 1 if left open). This contrasts to "fallow," which indicates that a field is either abandoned (if prepared or planted in the previous fall), or not planted in the spring (if left open in the previous fall).

The producer's objective (equation 6) is to maximize the expected discounted stream of profit from the 6-year planning horizon through the selection of fall and spring crop activities (*x* and *y*, respectively). Decisions made in "crop year" t consist of fall decisions ($x_{t,f,c,i,s}$) and spring decisions ($y_{t,f,c,i,w,s}$). Crops that are either fall-planted or require fall bed-preparation require the following fall decisions: 1) number of fields to plant or prepare, and 2) an associated irrigation technology, i, for each field. Spring decisions for each crop, c, include the following: 1) number of fields to keep (if c is a fall-planted crop) or number of fields to plant (if c is spring-planted), 2) an irrigation technology, i, for each field (note: for some crops, decisions made in the preceding fall impose an irrigation technology on the spring decision), and 3) a deficit irrigation level, w, for each field. The optimal choice of *x* and *y* depends on past, current, and expected future water supplies, denoted by s.

Economic profit for a particular crop year of the planning horizon, given water supply scenario, s, is described in (7). Crop mix, output price, number of acres planted, yield per acre, and cost of spring and fall activities partly determine profit. Fixed costs (which include land taxes and a water district charge), and the opportunity cost of money and time also influence profit. A 7% interest rate (r) is charged for short-term operating loans (Stanger 2005, personal communication). The opportunity cost of investing equity funds in the farm is also assumed to be 7%. It has been argued that the rate charged for equity funds should be less than the rate charged for borrowed funds, because the commercial lending rate includes fees that are not relevant to equity funds (American Agricultural Economics Association Task Force 1998, p33). However, it is not possible to accommodate a separate interest rate for each source of funds in this model. Time preferences are captured with a 5% discount rate (d). This rate strikes a balance between a conservative discount rate of 3% (the average real return on a risk-free asset (American Agricultural Economics Association Task Force 1998, p33)), and a higher discount rate (7%) that is based on the assumed interest rate. The effect of choosing a lower versus higher discount rate on the model's solution is discussed in chapter 5.

The constant, FAC, which represents the size of each field and appears first in the profit calculation, is necessary when *x* and *y* are binary variables. For example, $\sum_{f} y_{1,f,c,i,w,s1}$ calculates the number of fields planted to crop c under irrigation technology i and deficit irrigation level w in the spring of year 1 for water scenario s1. This integer has to be multiplied by the acres per field (FAC) before profit is calculated, because the revenue and cost data are per acre, not per field.

Yield for crop c, under irrigation technology i and deficit irrigation level w, is calculated in equation 8, which is a linear yield response function popularized by Doorenbos and Kassam (1979). Water is assumed to be the only limiting input to crop yield. The degree to which actual crop yield ($yld_{c,i,w}$) deviates from maximum yield ($maxyld_{c,i}$) in a particular year is a function of the crop's sensitivity to water stress (indicated by the empirically-based coefficient ky_c), precipitation received during the growing season (Ppt), and the proportion (w) of the crop's maximum irrigation water requirement ($ETmax_c$-Ppt) actually provided. This formulation of the yield response function assumes water deficits occur at an equal proportion across the entire growing season. It is preferable to model strategic deficit irrigation, in which crops are deficit irrigated during their least-sensitive growth stages. Data are insufficient, unfortunately, to model this approach. The season-long deficit approach likely overestimates yield losses associated with a particular deficit level. Thus the model is likely to choose deficit irrigation as an optimal strategy less frequently than a model that assumes strategic deficit irrigation.

Terminal values are introduced in the model via equation 9. Terminal values are needed to capture the following two sources of future profit: 1) alfalfa planted or maintained in year 6 that has productive value in years 7 through 9, and 2) the rental value of land in years 7 through 12. Decisions made in years 1 through 6 impact the flow of profit from years 7 through 12; equation 9 is an attempt to incorporate this dynamic relationship into the decision problem.

Equations (10) through (45) are the detailed representation of the general constraints presented in section 4.1, specifically equations (2) through (5). Equation 10 constrains the sum of water use across all fields, accounting for the application efficiency of various irrigation technologies, to no more than the farm's total water allotment. Total water allotted equals the per acre water allotment (set by the irrigation district) multiplied by total acres owned or leased. This equation must be met in every year of every water supply scenario.

Equations 11 and 12 prevent crop-irrigation-deficit combinations that are not observed in the area from entering the solution. Cost and yield data are not available for combinations not observed in the area, so they are not included in the model. The GAMS language uses set notation to reduce the volume of required code. A by-product of this notation, however, is that cropping activities not currently practiced in the area are created through the set notation. Suppose, for example, that set c = {onions, corn} and set i = {drip, center pivot}. Set notation allows the modeler to specify one equation that applies to every (c, i) combination, rather than specifying one equation for each combination. Suppose, however, that not all (c, i) combinations occur in the study area; for example, (corn, drip) does not occur in the Vale Oregon Irrigation District. Equations 11 and 12 prevent this combination from entering the solution. Equation 13 states that cropping activities can take on binary values only. That is, a cropping activity can either be implemented in a particular field (i.e. take on the value 1), or not implemented (i.e. take on the value 0). This is in contrast to a continuous definition of cropping activities, in which the activity variable could take on any continuous value representing the number of acres on which the activity is implemented.

Equations 14 through 21 constrain the scope of specific crop activities in the fall of year 1 to reflect agronomic rules that prevent pests and diseases. These rules, derived from conversations with producers, represent agronomic guidelines that they adhere to quite rigidly. It is beyond the scope of this study to test the economic optimality of these rules. Biological response functions that capture pest and disease dynamics are not readily available, and are therefore not directly included in the economic decision model. These functions are captured through crop rotation constraints instead.

Interpretation of a few equations will help elucidate the nature of the agronomic constraints. Equation 14 prevents the planting of small grains (wheat and barley) on the same acreage in two consecutive years. It specifically states that field f can be planted to wheat in year 1 if it was not planted to wheat or barley in year 6 of the historic period (i.e. H6). The historic period consists of the six years that immediately precede the current planning horizon; historic crop activities are exogenous to the decision model. Equation 14 states, algebraically, that the sum of the listed activities (each of which can take the value of 0 or 1) cannot exceed 1. Equations 15 through 17 are the equivalent to (14) for other crops. Note that sugar beets, onions, and potatoes require four to five years between plantings to avoid pests and diseases. These agronomic practices create inter-year dynamics.

Equation 18 states, for year 1, that the number of fields allocated to potatoes cannot exceed the "PotatoContract," regardless of the water scenario. Potatoes in the study area are grown exclusively under contract with local processors, so producers are constrained to the quantity that the processor requests. A relatively small portion of onions and sugar beets are also grown under contract. It was decided, however, to exclude this option from the model. Equations 19 through 21 require the producer to maintain alfalfa that is one or more years old through its fourth year of production. The producer does, however, have an opportunity to abandon newly planted alfalfa in its first spring. Alfalfa is used in crop rotations to enhance soil quality; equations 19 through 21 ensure that alfalfa is left in place sufficiently long to accomplish this. Equation 22 forces the producer to make a fall decision for each field in year 1; they can choose to prepare, plant, or leave each field open.

Equations 23 through 29 constrain spring crop activities in year 1. Equation 23 limits the spring acreage of each fall-planted or prepared crop to no more than the number of fields planted or prepared in the preceding fall. Winter wheat acreage, for example, is planted exclusively in the fall; therefore, wheat acreage cannot be increased in the spring. Onion acreage, which is prepared in the fall, cannot typically be increased in the spring due to adverse field conditions. Equation 23 therefore generates intra-year dynamics. Equations 24 through 26 simply transfer fall alfalfa acreage to spring alfalfa acreage, thus preventing the abandonment of alfalfa stands that are one or more years old.

Equation 27 states that corn (grain or silage) cannot be planted in the same field more than two consecutive years. Algebraically, field f can be planted to grain corn in year 1 if it was planted to grain or silage corn in year H6 but not year H5, or if it was planted to corn in year H5 but not year H6. Equation 28 presents the same constraint for silage corn. Equation 30 must accompany equations 27 and 28 for them to perform correctly. It states that each field can be planted in the spring to only one crop-irrigation-deficit combination; fallowing is included in the list of spring crops. Equations 27 and 28 each sum over several corn-irrigation-deficit combinations for year 1, and the sums are allowed to equal 2; thus, without equation 30, one field could be planted to two different combinations in the same year. Equation 29 expresses the agronomic constraint for spring-planted barley. The equations explained above are defined for year 1 only. Equations 31 through 47 essentially repeat this block for year 2. Blocks for years 3, 4, 5, and 6 are similar in content, and therefore not presented here.

Care must be taken in constructing the above constraints, due to the stochastic water supply. First, all constraints must be met in every water supply scenario. The water constraint in equation 10, for example, must be met in the event of a full or dry spring. Additionally, constraints must be constructed to properly account for past water supply conditions. The number of fields planted to onions in year 4 of water scenario [Full Dry Full Full ___ ___], for example, cannot exceed the number of fields that remain eligible for onions, which is determined by cropping activities during the three preceding years, i.e. activities in scenario [Full Dry Full ___ ___ ___]. Use of the subscripts s1 through s6 ensures that current activities are constrained by their respective water supply histories.

4.4 Details of the Continuous Variables Model

Equations of the continuous variables model are presented next, followed by their interpretation. Although the model is similar in general structure to the binary variables model, variables differ slightly in their subscripts and definition.

$$(6)\ \underset{x,y}{\text{Max}}\ E_s\Pi(x,y;s)=\sum_s \rho_s \cdot \left[\begin{array}{l} \displaystyle\sum_{t=1}^{6}\left(\frac{1}{(1+d)^t}\pi_{t,s}(x_{t,s},y_{t,s})\right) \\ \displaystyle +\sum_{t=7}^{12}\left(\frac{1}{(1+d)^t}\pi_{t,s}(y_{t-6,s},\ldots y_{6,s})\right) \end{array}\right]$$

where for t =1,...,6

(7) $$\pi_{t,s}(x_{t,s}, y_{t,s}) = \sum_c \sum_i \sum_w \left(p_c y_{t,c,i,w,s} yld_{c,i,w} - j_{c,i} y_{t,c,i,w,s} - h_{c,i} x_{t,c,i,s} \right) - fxd\cos t - r \cdot \begin{pmatrix} \sum_c \sum_i \sum_w \left(j_{c,i} y_{t,c,i,w,s} + h_{c,i} x_{t,c,i,s} \right) \\ + fxd\cos t - \pi_{t-1,s}(x_{t-1,s}, y_{t-1,s}) \end{pmatrix}$$

and

(8) $$yld_{c,i,w} = \max yld_{c,i} \cdot \left[1 - \left(ky_c \cdot \left(1 - \frac{w \cdot (ET\max_c - Ppt) + Ppt}{ET\max_c} \right) \right) \right]$$

where for t =7,...,12

(9) $$\pi_{t,s}(y_{t-6,s}, \ldots y_{6,s}) = RRate_{onion} \cdot EligOnion_{t,s}(y_{t-6,s}, \ldots y_{6,s}) + RRate_{other} \cdot EligOther_{t,s}(y_{t-6,s}, \ldots y_{6,s}) + \left(\sum_i NetRv_{alf,i,d1} \cdot EligAlf_{t,i,s}(y_{6,s}) \right) - fxd\cos t - r \cdot \left(\sum_i \left(j_{alf,i} \cdot EligAlf_{t,i,s}(y_{6,s}) \right) + fxd\cos t - \pi_{t-1,s}(y_{t-6,s}, \ldots y_{6,s}) \right)$$

subject to

(10) $$\sum_c \sum_i \sum_w w \cdot \left(\frac{ET\max_c - Ppt}{IrrEffic_i} \right) \cdot y_{t,c,i,w,s} \le Water_{t,s} \cdot TotAcres \qquad \forall\ t,s$$

(11) $x_{t,c,i,s} = 0$ for some t,c,i,s

(12) $\mathrm{y}_{t,c,i,w,s} = 0$ for some t,c,i,w,s

(13) $x_{t,c,i,s}, y_{t,c,i,w,s} \ge 0$ $\forall$ t,c,i,w,s

(14) $\sum_i x_{1,wheat,i,s} \le TotAcres - H6_{wheat} - H6_{barley}$ $\forall$ s

(15) $\sum_i x_{1,sugbt,i,s} \le TotAcres - H6_{sugbt} - H5_{sugbt} - H4_{sugbt} - H3_{sugbt}$ $\forall$ s

(16) $\sum_i x_{1,onion,i,s} \le TotAcres - H6_{onion} - H5_{onion} - H4_{onion} - H3_{onion} - H2_{onion}$ $\forall$ s

(17) $\sum_i x_{1,potato,i,s} \le TotAcres - H6_{potato} - H5_{potato} - H4_{potato} - H3_{potato} - H2_{potato}$ $\forall$ s

(18) $\sum_i x_{1,potato,i,s} \le PotatoContract$ $\forall$ s

(19) $\sum_i x_{1,alf2,i,s} = H6_{alf1}$ $\forall$ i,s

(20) $\sum_{i} x_{1,alf3,i,s} = H6_{alf2}$ $\forall$ i,s

(21) $\sum_{i} x_{1,alf4,i,s} = H6_{alf3}$ $\forall$ i,s

(22) $\sum_{c}\sum_{i} x_{1,c,i,s} + open_1 = TotAcres$ $\forall$ s

(23) $\sum_{w} y_{1,fall,i,w,s} \le x_{1,fall,i,s}$ $\forall$ fall,i,s

(24) $\sum_{w} y_{1,alf2,i,w,s} = x_{1,alf2,i,s}$ $\forall$ i,s

(25) $\sum_{w} y_{1,alf3,i,w,s} = x_{1,alf3,i,s}$ $\forall$ i,s

(26) $\sum_{w} y_{1,alf4,i,w,s} = x_{1,alf4,i,s}$ $\forall$ i,s

(27) $\sum_{i}\sum_{w} y_{1,gcorn,i,w,s} + \sum_{i}\sum_{w} y_{1,scorn,i,w,s} + H6_{gcorn} + H6_{scorn}$

$+H5_{gcorn} + H5_{scorn} \le 2 * TotAcres$ $\forall$ s

(28) $\sum_{i}\sum_{w} y_{1,barley,i,w,s} + \sum_{i}\sum_{w} y_{1,wheat,i,w,s} \le TotAcres$

$-H6_{barley} - H6_{wheat}$ $\forall$ s

(29) $\sum_{c}\sum_{i}\sum_{w} y_{1,c,i,w,s} = TotAcres$ $\forall$ s

(30) $\sum_{i} x_{2,wheat,i,s} \le TotAcres - \sum_{i}\sum_{w} y_{1,wheat,i,w,s} - \sum_{i}\sum_{w} y_{1,barley,i,w,s}$ $\forall$ s

(31) $\sum_{i} x_{2,sugbt,i,s} \le TotAcres - \sum_{i}\sum_{w} y_{1,sugbt,i,w,s} - H6_{sugbt}$

$-H5_{sugbt} - H4_{sugbt}$ $\forall$ s

(32) $\sum_{i} x_{2,onion,i,s} \le TotAcres - \sum_{i}\sum_{w} y_{1,onion,i,w,s} - H6_{onion} - H5_{onion}$

$-H4_{onion} - H3_{onion}$ $\forall$ s

(33) $\sum_{i} x_{2,potato,i,s} \le TotAcres - \sum_{i}\sum_{w} y_{1,potato,i,w,s} - H6_{potato}$

$-H5_{potato} - H4_{potato} - H3_{potato}$ $\forall$ s

(34) $\sum_{i} x_{2,potato,i,s} \le PotatoContract$ $\forall$ s

(35) $\sum_{i} x_{2,alf2,i,s} = \sum_{i}\sum_{w} y_{1,alf1,i,w,s}$ $\forall$ s

(36) $\sum_{i} x_{2,alf3,i,s} = \sum_{i}\sum_{w} y_{1,alf2,i,w,s}$ $\forall$ s

(37) $\sum_i x_{2,alf4,i,s} = \sum_i \sum_w y_{1,alf3,i,w,s}$ $\forall$ s

(38) $\sum_c \sum_i x_{2,c,i,s} + open_{2,s} = TotAcres$ $\forall$ s

(39) $\sum_w y_{2,fall,i,w,s} \le x_{2,fall,i,s}$ $\forall$ fall,i,s

(40) $\sum_w y_{2,alf2,i,w,s} = x_{2,alf2,i,s}$ $\forall$ i,s

(41) $\sum_w y_{2,alf3,i,w,s} = x_{2,alf3,i,s}$ $\forall$ i,s

(42) $\sum_w y_{2,alf4,i,w,s} = x_{2,alf4,i,s}$ $\forall$ i,s

(43) $$\sum_i \sum_w y_{2,gcorn,i,w,s} + \sum_i \sum_w y_{2,scorn,i,w,s} + \sum_i \sum_w y_{1,gcorn,i,w,s} + \sum_i \sum_w y_{1,scorn,i,w,s} + H6_{gcorn} + H6_{scorn} \le 2 * TotAcres$$ $\forall$ s

(44) $$\sum_i \sum_w y_{2,barley,i,w,s} + \sum_i \sum_w y_{2,wheat,i,w,s} \le TotAcres - \sum_i \sum_w y_{1,barley,i,w,s} + \sum_i \sum_w y_{1,wheat,i,w,s}$$ $\forall$ s

(45) $\sum_c \sum_i \sum_w y_{2,c,i,w,s} = TotAcres$ $\forall$ s

where,

t = a crop year within the 6-year planning horizon, with possible values of 1 through 6, or within the 6-year period following the planning horizon, with possible values of 7 through 12.

c = the crop {onion, potato, sugar beet, wheat, barley, grain corn, silage corn, alfalfa (1^{st} through 4^{th} year), fallow}

i = the irrigation technology {furrow, reuse furrow, solid set, wheeline, center pivot, drip}

w = the deficit irrigation level {0.0, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0}

ρ_s = probability of the 6-year water supply scenario s

r = interest rate on operating loans and savings

d = discount rate

p_c = price received per unit of crop c

$yld_{c,i,w}$ = yield per acre of crop c, under irrigation technology i, and deficit irrigation level w

$j_{c,i}$ = cost of spring planting per acre of crop c, under irrigation technology i.

h_c = cost of fall preparation or planting per acre of crop c

fxdcost = fixed cost per acre of land owned, such as a water district fee per acre and land taxes

$maxyld_{c,i}$ = maximum yield for crop c, under irrigation technology i, given no water deficit

ky_c = yield response coefficient for crop c, which reflects sensitivity to water stress

$ETmax_c$ = gross water requirement of crop c over the growing season to achieve maximum yield

Ppt = precipitation received during the growing season, which reduces irrigation requirements

IrrigEffic = the proportion of water delivered to the field that reaches the crop root zone

Water = per acre water allotment for the growing season

TotAcres = total number of acres available for cropping activities

$RRate_{onion}$ = rental rate of an acre eligible for onions (i.e. an acre not planted to onions in previous 5 years)

$RRate_{other}$ = rental rate of an acre not eligible for onions

$EligOnion_{t,s}$ = acres eligible for onions in period t of scenario s

$EligAlf_{t,i,s}$ = acres of alfalfa with productive lifespan remaining in years 7 through 9 for scenario **s**; acres inherit the irrigation technology used in year 6, for simplicity

$EligOther_{t,s}$ = acres eligible for crops other than onions in period t of scenario s; a function of $EligOnion_{t,s}$ and $EligAlf_{t,i,s}$

$NetRv_{alf,i,d1}$ = net revenue from alfalfa under irrigation technology i, assuming no deficit irrigation (w =d1)

$H1_c$ = acres of crop c planted six years prior to the first year of the planning horizon (i.e. planted in the first year of the previous (historical) planning horizon)

$H2_c$ = acres of crop c planted five years prior to the first year of the planning horizon

$H3_c$ = acres of crop c planted four years prior to the first year of the planning horizon

$H4_c$ = acres of crop c planted three years prior to the first year of the planning horizon

$H5_5$ = acres of crop c planted two years prior to the first year of the planning horizon

$H6_c$ = acres of crop c planted one year prior to the first year of the planning horizon

PotatoContract = a fixed acreage of potatoes contracted in advance with local processors

$open_t$ = acres to leave unprepared and unplanted in the fall of year t

Interpretation of the continuous variables model's equations is similar to that of the binary variables model. One difference is the lack of subscript f on the *x* and *y* decision variables, which changes *x* and *y* from binary variables to continuous variables, measured in acres rather than fields. Another difference is the manner in which agronomic constraints are specified. Interpretation of a few equations will illustrate how they differ from the binary model. Equation 14 prevents the planting of wheat on acreage that was planted to wheat or barley in the previous year. The constraint specifically defines acres eligible for wheat this year as total farm acreage less acres planted to wheat or barley last year. This form of the constraint cannot guarantee that a particular field will not be planted to small grains in two consecutive years, because the continuous model does not track crop history on a field-by-field basis. However, it does guarantee at the farm-level that acres allocated to wheat do not exceed eligible acres. The binary variables model avoids this spatial ambiguity by tracking each field's crop history.

Equation 27 attempts to capture the agronomic constraint for grain and silage corn, which stipulates that acreage should not be planted to corn more than two consecutive years. It is difficult to represent this constraint, however, without tracking the crop history of individual fields; equation 27 therefore only approximates it. Equation 27 states that over a three-year period the sum of acreage planted to grain corn or silage corn cannot exceed twice the total acreage. The constraint works well if it is assumed that the producer avoids planting corn on the same acreage in two consecutive years. The illustrations below clarify the constraint. Suppose in year 1 and 2 that all 350 acres are planted to corn. Equation 27 states that acres planted to corn in years 1, 2, and 3 cannot exceed two times the total farm acreage (350 acres), which implies that 0 acres are eligible for corn in year 3 for this example. This coincides with the agronomic practice; corn was planted in two consecutive years on all 350 acres, therefore, zero acres are eligible in year 3.

Corn = 350 acres	Corn = 350 acres	Corn ≤ 700 – 350 – 350 ≤ 0 acres
Year 1	Year 2	Year 3

Consider a second example in which the constraint also functions well.

Corn = 150 acres	Corn = 350 acres	Corn ≤ 700 – 350 – 150 ≤ 200 acres
Year 1	Year 2	Year 3

Corn was planted for two consecutive years (years 1 and 2) on 150 acres. However, 200 acres were planted to corn only in year 2, thus 200 acres are eligible for corn in year 3. Consider a final example, in which the constraint does not capture the agronomic practice exactly.

Year 1	Year 2	Year 3
Corn = 200 acres	Corn = 200 acres	Corn ≤ 700 – 200 – 200 ≤ 300 acres

It is not clear in the third example whether corn in year 2 was planted on the same acres as corn in year 1. The overlap is, at a minimum, 50 acres, but could be as large as 200 acres. Equation 27 assumes that the minimum possible overlap (50 acres) occurred in year 2, such that 300 acres are eligible for corn in year 3. In reality, the producer may have overlapped the entire 200 acres, which leaves only 150 acres eligible in year 3. This example highlights the limitations of using a continuous variables model to represent agronomic practices that operate on discrete fields. The binary variables model, in contrast, represents the agronomic practice precisely. The solutions to the continuous and binary models share similar characteristics, however, including the relative acreage of corn versus other crops. This suggests that the continuous variables version of the corn constraint does not lead to serious errors in the solution. The remaining equations are sufficiently similar in interpretation to those in the binary model, so they will not be discussed further.

4.5 Alternative Versions of the Binary Variables Model

The binary variables model is used in section 5.1 to establish the "base case" solution. In sections 5.1 through 5.8, the binary variables model is modified to conduct sensitivity analyses and facilitate interpretation of the base case solution. Section 5.2 focuses on sensitivity to the discount and interest rates. Section 5.3 treats the water supply as certain to explore differences between optimal drought preparedness and response under certainty and uncertainty. Section 5.4 discusses the importance of inter-year crop dynamics. Section 5.5 introduces crop history by setting parameters H1 through H6 to non-zero values. Section 5.6 introduces price uncertainty in addition to water supply uncertainty. Section 5.7 introduces a crop insurance product known as prevented planting provisions. Section 5.8 resumes water supply uncertainty, but examines the impact of increased drought frequency and severity. Lastly, the continuous variables model's solution is presented in section 5.9, and compared with the base case solution. For most sections, only small modifications of the base case model are made (e.g. parameter values are changed). It suffices in these cases to explain the modification briefly at the beginning of the respective section in chapter 5. Sections 5.3, 5.6, and 5.7, in contrast, require changes in the model structure that are sufficient to require more thorough descriptions. These are presented next.

4.5.1 Water Supply Certainty

A deterministic version of the base case model is constructed to tease out uncertainty's role in optimal preparedness and response. The deterministic model assumes that the water supplies for all six years of the planning horizon are known in the fall of year 1. A specific water supply scenario is therefore assigned *a priori* (e.g. 24 acre-inches per acre in each of the six years), and the model chooses fall and spring activities for years 1 through 6 to maximize the stream of discounted profit. This model could be used to conduct a passive programming analysis of the effects of water supply on production (see section 2.2.3). The general model is as follows:

(1) $\underset{x,y}{\text{Max}}\ \Pi(x, y)$

$s.t.$

(2) $Ax = b$

(3) $Dy = e$

(4) $Mx + Ny = g$

(5) $x, y \geq 0$

where all notation referring to states of nature is removed, and some definitions simplify as follows:

x = Vector containing fall crop decision variables for each year of the planning horizon.

Example element: $x_{3,f,c,i,}$ which indicates for the fall of year 3, that field f is prepared for or planted to crop c, under irrigation technology i. Each element of x is a binary variable, taking on a value of 0 or 1.

y = Vector of spring crop decision variables for each year of the planning horizon.

Example element: $y_{3,f,c,i,w}$, which indicates for the spring of year 3, that field f is planted to crop c in the spring of year 3, under irrigation technology i, and deficit irrigation category w. Each element of y is a binary variable, taking on a value of 0 or 1.

$\Pi(x, y)$ = The discounted stream of profit that optimal activities *x* and *y* generate over the 6-year period in which they occur, assuming that the water supply for each of the six years is known *a priori*.

4.5.2 Price Uncertainty

The base case model must be modified significantly to accommodate uncertainty of prices. Price uncertainty is represented by three price categories (Appendix B.3), and is resolved after both fall and spring decisions are made. A third stage is therefore added to the model, during which the producer learns which price will be received. The producer has no recourse after the price is revealed.

All crops that are grown are assumed to be sold at the market price. Marketing strategies were beyond the scope of this study. The general price uncertainty model is presented next, followed by details of the model.

4.5.2.1 THE GENERAL PRICE UNCERTAINTY MODEL

$$(1)\quad \underset{x,y}{\text{Max}}\ E_{s,ss}\Pi(x,y,z;s,ss)$$

$$s.t.$$

$$(2)\qquad Ax = b$$

$$(3)\qquad Dy = e$$

$$(4)\qquad Mx + Ny + Rz = g$$

$$(5)\qquad x, y, z \geq 0$$

where

s = A random vector that represents water supplies over a 3-year planning horizon. Each realization of *s* consists of 3 components (s1 s2 s3), which indicate the state of nature (water supply category) revealed in each of the three years. That is, s1 represents the state of nature revealed in year 1, s2 the state of nature revealed in year 2, etc.

ss = A random vector that represents the price of onions in each of the 3 years of the planning horizon.

Assuming 2 possible states of the water supply (Dry or Full) and 3 possible states of the onion price (Lo, Med, Hi) in each of 3 years, 216 three-year scenarios are possible. Scenarios range from [Dry Lo Dry Lo Dry Lo] to [Full Hi Full Hi Full Hi], and every combination between. The scenario [Dry Lo Full Med Full Hi] indicates (from left to right) that the water supply in year 1 was Dry, the onion price in year 1 was Lo, the water supply in year 2 was Dry, the onion price in year 2 was Med, the water supply in year 3 was Full, and the onion price in year 3 was Hi. Each state of nature has a probability of occurrence within any given year, denoted pr(Dry) or pr(Full), and prp(Lo), prp(Med), or prp(Hi). The state of nature in any one year is assumed independent of the state of nature in any other year. Therefore, the joint probability of a particular three-year scenario is the product of the probabilities of the states of nature that occur each year. For example, pr([Dry Lo Full Med Full Hi]) = pr(Dry)*prp(Lo)*pr(Full)*prp(Med)*pr(Full)*prp(Hi). Historical water allotment and onion price data and Gaussian quadrature analysis (Featherstone, Baker, and Preckel 1993; Miller and Rice 1983; Preckel and Devuyst 1992) were used to assign a value and a probability to each state of nature (Appendix B).

x = Vector containing fall crop decision variables for each year of the planning horizon.

Example element: $x_{3,f,c,i,s1,ss1,s2}$, which indicates for the fall of year 3, that field f is prepared for or planted to crop c, under irrigation technology i, given the states of nature revealed in past years 1 and 2. Each element of x is a binary variable, taking on a value of 0 (if the crop/irrigation combination (c,i) is not chosen for field f) or 1 (if the crop/irrigation combination (c,i) is chosen for field f).

y = Vector of spring crop decision variables for each year of the planning horizon.

Example element: $y_{3,f,c,i,w,s1,ss1,s2,ss2,s3}$, which indicates for the spring of year 3, that field f is planted to crop c in the spring of year 3, under irrigation technology i, and deficit irrigation category w, given the states of nature revealed in past years 1, 2, and the present year 3. Each element of y is a binary variable, taking on a value of 0 (if the crop-irrigation-deficit combination (c,i,w) is not chosen for field f) or 1 (if the crop-irrigation-deficit combination (c,i,w) is chosen for field f).

z = Vector of variables that represents the crops sold at the market price for each year of the planning horizon.

Example element: $z_{3,f,c,i,w,s1,ss1,s2,ss2,s3,ss3}$, which indicates for the post-harvest of year 3, that field f, which is planted to crop c in the spring of year 3, under irrigation technology i, and deficit irrigation category w, given the states of nature revealed in past years 1, 2, and the present year 3, is sold at market price ss. Each element of z is a binary variable, taking on a value of 0 (if the crop-irrigation-deficit combination (c,i,w) on field f is not sold) or 1 (if the crop-irrigation-deficit combination (c,i,w) on field f is sold).

$\Pi(x, y, z; s, ss)$ = Vector containing the profit outcome for each scenario. An individual element of the vector is the discounted stream of profit that optimal activities *x*, *y,* and *z* generate over the 3-year period in which they occur, for a particular scenario. Terminal land rental values are also included, as a function of activities in the 3-year period. A terminal value for alfalfa acreage that remains in production after year 3 is also included.

A, D = Matrices of coefficients that describe fall and spring activities' resource use.

b, e = Vectors of resource availability, such as land and water, which vary by state of nature for some resources.

M, N = Matrices of coefficients that relate activities in different time periods to each other (intra- and inter-year constraints).

g = Vector of parameters that, with *M* and *N* above, define relationships between activities in different time periods.

The above binary discrete stochastic sequential programming model maximizes the expected stream of profit over a 3-year planning horizon. The planning horizon is shortened from six to three years because the programming software, GAMS, can only accommodate ten subscripts on decision variables. A six-year horizon requires sixteen subscripts. The expectation is taken over the joint probability of water supply, *s*, and onion price, *ss*, which are assumed to have independent discrete probability distributions over a small number of pre-defined categories (e.g. dry and full; lo, med, and hi).

Choice variables are contained in the vectors *x*, *y* and *z*. Vector *x* includes fall cropping activities, which are chosen under an uncertain future water supply and onion price. Vector *y* includes spring cropping activities, which are chosen after water supply is revealed, but before onion price is revealed. Vector *z* includes post-harvest sales activities, which take place after the price is revealed. It is assumed, however, that all crops grown are sold. The producer therefore has no recourse after price is revealed; this is in contrast to the recourse options available after the water supply is revealed (e.g. fallowing, spring-planted crops, deficit irrigation). Fall, spring, and post-harvest activities are chosen for each year of the three-year planning horizon, for each water supply scenario, (e.g. [Full Lo Full Hi Dry Med]). Fall and spring activities are constrained by resource availability, as expressed in equations (2) and (3). Equation (4) describes dynamic interactions in the cropping system, including how fall activities restrict spring activities, and how spring activities restrict post-harvest activities (intra-year dynamics), and how activities in year t restrict activities in subsequent years (inter-year dynamics). The timing of decisions relative to the availability of water supply information is presented in figure 4.2. Past water supplies and onion prices are known, but future water supplies and onion prices are uncertain.

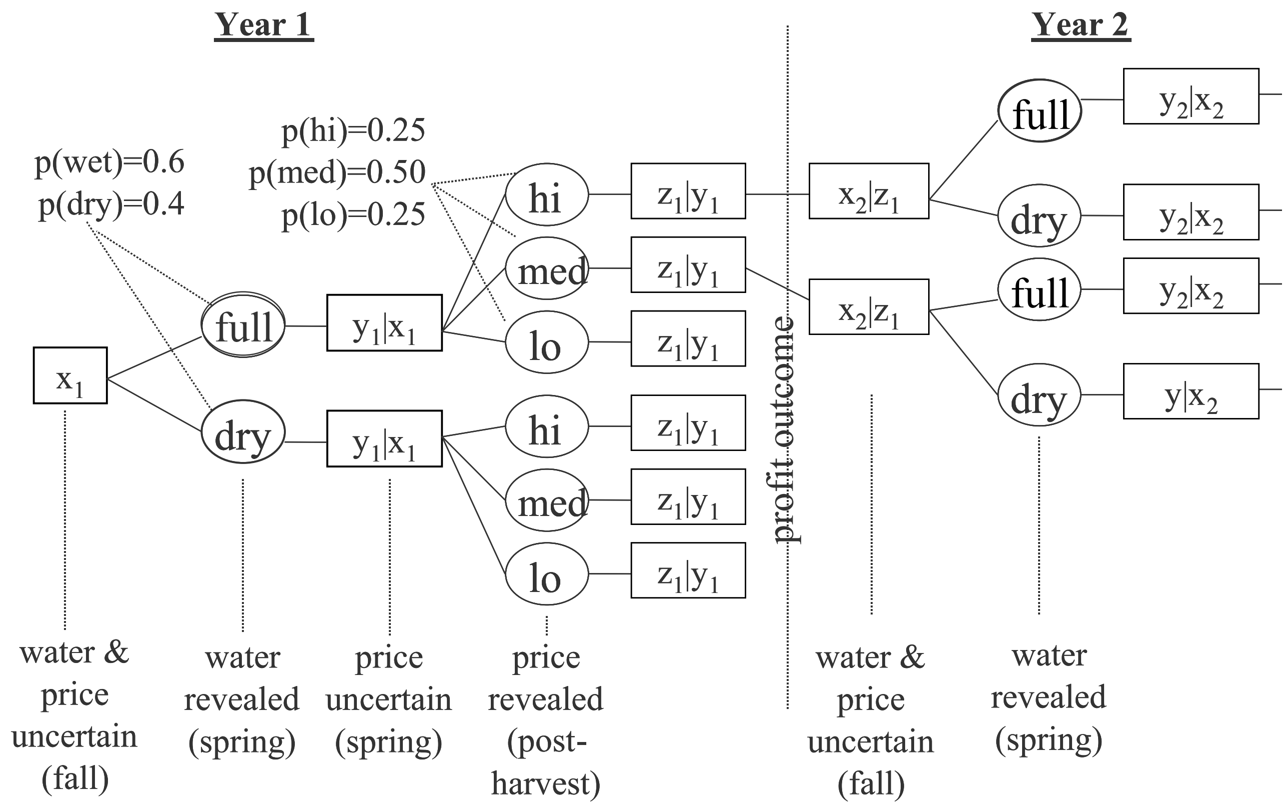


Figure 4.2. Decision tree representation of decision-making under water and price uncertainty. Fall cropping activities (x_t) are chosen given an uncertain spring water supply and post-harvest onion price. The spring water supply is then revealed (full or dry), after which spring cropping activities (y_t) are chosen under uncertain onion price. The onion price is then revealed (hi, med, or lo), after which post-harvest sales activities (z_t) are chosen. This sequence continues for all three years of the planning horizon.

4.5.2.2 DETAILS OF THE PRICE UNCERTAINTY MODEL

$$(6)\ \underset{x,y}{\text{Max}}\ E_{s,ss}\Pi(x,y;s,ss)=\sum_{s}\sum_{ss}\rho_s\rho_{ss}\cdot\left[\begin{array}{l}\sum_{t=1}^{3}\left(\frac{1}{(1+d)^t}\pi_{t,s,ss}(x_{t,s,ss},y_{t,s,ss},z_{t,s,ss})\right)\\+\sum_{t=4}^{9}\left(\frac{1}{(1+d)^t}\pi_{t,s,ss}(y_{t-3,s,ss},\ldots y_{3,s,ss})\right)\end{array}\right]$$

where for t =1, 2, 3

$$(7)\quad \pi_{t,s,ss}(x_{t,s,ss},y_{t,s,ss},z_{t,s,ss})=\sum_{c}\sum_{i}\sum_{w}\left(\begin{array}{l}\sum_{f}FAC\cdot(p_{c,ss}yld_{c,i,w}z_{t,f,c,i,w,s,ss}\\-j_{c,i}y_{t,f,c,i,w,s,ss}-h_{c,i}x_{t,f,c,i,s,ss})\end{array}\right)$$

$$-fxd\cos t-r\cdot\left(\begin{array}{l}\sum_{c}\sum_{i}\sum_{w}\left(\sum_{f}FAC\cdot(j_{c,i}y_{t,f,c,i,w,s,ss}+h_{c,i}x_{t,f,c,i,s,ss})\right)\\+fxd\cos t-\pi_{t-1,s,ss}(x_{t-1,s,ss},y_{t-1,s,ss},z_{t-1,s,ss})\end{array}\right)$$

and

$$(8)\qquad yld_{c,i,w}=\max yld_{c,i}\cdot\left[1-\left(ky_c\cdot\left(1-\frac{w\cdot(ET\max_c-Ppt)+Ppt}{ET\max_c}\right)\right)\right]$$

where for t =4,...,9

$$(9)\quad \pi_{t,s,ss}(y_{t-3,s,ss},\ldots y_{3,s,ss})=RRate_{onion}\cdot EligOnion_{t,s}(y_{t-3,s,ss},\ldots y_{3,s,ss})$$

$$+RRate_{other}\cdot EligOther_{t,s,ss}(y_{t-6,s,ss},\ldots y_{6,s,ss})$$

$$+\left(\sum_{i}NetRv_{alf,i,d1}\cdot EligAlf_{t,i,s,ss}(y_{3,s,ss})\right)-fxd\cos t$$

$$-r\cdot\left(\begin{array}{l}\sum_{i}\left(j_{alf,i}\cdot EligAlf_{t,i,s,ss}(y_{3,s,ss})\right)+fxd\cos t\\-\pi_{t-1,s,ss}(y_{t-3,s,ss},\ldots y_{3,s,ss})\end{array}\right)$$

subject to

$$(10)\ \sum_{c}\sum_{i}\sum_{w}\sum_{f}w\cdot\left(\frac{ET\max_c-Ppt}{IrrEffic_i}\right)\cdot FAC\cdot y_{t,f,c,i,w,s,ss}$$

$$\leq Water_{t,s}\cdot TotAcres\qquad\forall\ \text{t},s,ss$$

(11) $x_{t,f,c,i,s,ss}=0$ for some t,c,i,s,ss $\forall$ f

(12) $\text{y}_{\text{t,f,c,i,w,s,ss}}=0$ for some t,c,i,w,s,ss $\forall$ f

(13) $x_{t,f,c,i,s,ss},y_{t,f,c,i,w,s,ss},z_{t,f,c,i,w,s,ss}=0$ or 1 $\forall$ t,f,c,i,w,s,ss

(14) $$\sum_i x_{1,f,wheat,i} + H6_{f,wheat} + H6_{f,barley} \leq 1 \qquad \forall\ f$$

(15) $$\sum_i x_{1,f,sugbt,i} + H6_{f,sugbt} + H5_{f,sugbt} + H4_{f,sugbt} + H3_{f,sugbt} \leq 1 \qquad \forall\ f$$

(16) $$\sum_i x_{1,f,onion,i} + H6_{f,onion} + H5_{f,onion} + H4_{f,onion} + H3_{f,onion} + H2_{f,onion} \leq 1 \qquad \forall\ f$$

(17) $$\sum_i x_{1,f,potato,i} + H6_{f,potato} + H5_{f,potato} + H4_{f,potato} + H3_{f,potato} + H2_{f,potato} \leq 1 \qquad \forall\ f$$

(18) $$\sum_i \sum_f x_{1,f,potato,i} \leq PotatoContract$$

(19) $$\sum_i x_{1,f,alf2,i} = H6_{f,alf1} \qquad \forall\ f,i$$

(20) $$\sum_i x_{1,f,alf3,i} = H6_{f,alf2} \qquad \forall\ f,i$$

(21) $$\sum_i x_{1,f,alf4,i} = H6_{f,alf3} \qquad \forall\ f,i$$

(22) $$\sum_c \sum_i x_{1,f,c,i} + open_{f,1} = 1 \qquad \forall\ f$$

(23) $$\sum_w y_{1,f,fall,i,w,s} \leq x_{1,f,fall,i} \qquad \forall\ f,fall,i,s$$

(24) $$\sum_w y_{1,f,alf2,i,w,s} = x_{1,f,alf2,i} \qquad \forall\ f,i,s$$

(25) $$\sum_w y_{1,f,alf3,i,w,s} = x_{1,f,alf3,i} \qquad \forall\ f,i,s$$

(26) $$\sum_w y_{1,f,alf4,i,w,s} = x_{1,f,alf4,i} \qquad \forall\ f,i,s$$

(27) $$\sum_i \sum_w y_{1,f,gcorn,i,w,s} + H6_{f,gcorn} + H6_{f,scorn} + H5_{f,gcorn} + H5_{f,scorn} \leq 2 \qquad \forall\ f,s$$

(28) $$\sum_i \sum_w y_{1,f,scorn,i,w,s} + H6_{f,gcorn} + H6_{f,scorn} + H5_{f,gcorn} + H5_{f,scorn} \leq 2 \qquad \forall\ f,s$$

(29) $$\sum_i \sum_w y_{1,f,barley,i,w,s} + H6_{f,barley} + H6_{f,wheat} \leq 1 \qquad \forall\ f,s$$

(30) $$\sum_c \sum_i \sum_w y_{1,f,c,i,w,s} = 1 \qquad \forall\ f,s$$

(31) $z_{1,f,c,i,w,s,ss} = y_{1,f,c,i,w,s}$ $\forall$ f,c,i,w,s,ss

(32) $\sum_i x_{2,f,wheat,i,s,ss} + \sum_i \sum_w y_{1,f,wheat,i,w,s} + \sum_i \sum_w y_{1,f,barley,i,w,s} \leq 1$ $\forall$ f,s,ss

(33) $\sum_i x_{2,f,sugbt,i,s,ss} + \sum_i \sum_w y_{1,f,sugbt,i,w,s} + H6_{f,sugbt}$

$+ H5_{f,sugbt} + H4_{f,sugbt} \leq 1$ $\forall$ f,s,ss

(34) $\sum_i x_{2,f,onion,i,s,ss} + \sum_i \sum_w y_{1,f,onion,i,w,s} + H6_{f,onion} + H5_{f,onion}$

$+ H4_{f,onion} + H3_{f,onion} \leq 1$ $\forall$ f,s,ss

(35) $\sum_i x_{2,f,potato,i,s,ss} + \sum_i \sum_w y_{1,f,potato,i,w,s} + H6_{f,potato} + H5_{f,potato}$

$+ H4_{f,potato} + H3_{f,potato} \leq 1$ $\forall$ f,s,ss

(36) $\sum_f \sum_i x_{2,f,potato,i,s,ss} \leq PotatoContract$ $\forall$ s,ss

(37) $\sum_i x_{2,f,alf2,i,s,ss} = \sum_i \sum_w y_{1,f,alf1,i,w,s}$ $\forall$ f,s,ss

(38) $\sum_i x_{2,f,alf3,i,s,ss} = \sum_i \sum_w y_{1,f,alf2,i,w,s}$ $\forall$ f,s,ss

(39) $\sum_i x_{2,f,alf4,i,s,ss} = \sum_i \sum_w y_{1,f,alf3,i,w,s}$ $\forall$ f,s,ss

(40) $\sum_c \sum_i x_{2,f,c,i,s,ss} + open_{f,2,s,ss} = 1$ $\forall$ f,s,ss

(41) $\sum_w y_{2,f,fall,i,w,s,ss} \leq x_{2,f,fall,i,s,ss}$ $\forall$ f,fall,i,s,ss

(42) $\sum_w y_{2,f,alf2,i,w,s,ss} = x_{2,f,alf2,i,s,ss}$ $\forall$ f,i,s,ss

(43) $\sum_w y_{2,f,alf3,i,w,s,ss} = x_{2,f,alf3,i,s,ss}$ $\forall$ f,i,s,ss

(44) $\sum_w y_{2,f,alf4,i,w,s,ss} = x_{2,f,alf4,i,s,ss}$ $\forall$ f,i,s,ss

(45) $\sum_i \sum_w y_{2,f,gcorn,i,w,s,ss} + \sum_i \sum_w y_{1,f,gcorn,i,w,s} + \sum_i \sum_w y_{1,f,scorn,i,w,s}$

$+ H6_{f,gcorn} + H6_{f,scorn} \leq 2$ $\forall$ f,s,ss

(47) $\sum_i \sum_w y_{2,f,scorn,i,w,s,ss} + \sum_i \sum_w y_{1,f,gcorn,i,w,s} + \sum_i \sum_w y_{1,f,scorn,i,w,s}$

$+ H6_{f,gcorn} + H6_{f,scorn} \leq 2$ $\forall$ f,s,ss

(48) $$\sum_{i}\sum_{w} y_{2,f,barley,i,w,s,ss} + \sum_{i}\sum_{w} y_{1,f,barley,i,w,s} + \sum_{i}\sum_{w} y_{1,f,wheat,i,w,s} \leq 1 \qquad \forall \text{ f,s,ss}$$

(49) $$\sum_{c}\sum_{i}\sum_{w} y_{2,f,c,i,w,s,ss} = 1 \qquad \forall \text{ f,s,ss}$$

(50) $$z_{2,f,c,i,w,s,ss} = y_{2,f,c,i,w,s,ss} \qquad \forall \text{ f,c,i,w,s,ss}$$

where,

t = a crop year within the 3-year planning horizon, with possible values of 1 through 3, or within the 6-year period following the planning horizon, with possible values of 4 through 9.

f = the field in which the cropping activity takes place {F1,…, F10}.

c = the crop {onion, potato, sugar beet, wheat, barley, grain corn, silage corn, alfalfa (1^{st} through 4^{th} year), fallow}

i = the irrigation technology {furrow, reuse furrow, solid set, wheeline, center pivot, drip}

w = the deficit irrigation level {0.0, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0}

ρ_s = probability of the 3-year water supply scenario s

ρ_{ss} = probability of the 3-year price scenario ss

r = interest rate on operating loans and savings

d = discount rate

FAC = number of acres per field (fields assumed to be equal size)

$p_{c,ss}$ = price received per unit of crop c in price scenario ss

$yld_{c,i,w}$ = yield per acre of crop c, under irrigation technology i, and deficit irrigation level w

$j_{c,i}$ = cost of spring planting per acre of crop c, under irrigation technology i.

h_c = cost of fall preparation or planting per acre of crop c

fxdcost = fixed cost per acre of land owned, such as a water district fee per acre and land taxes

$maxyld_{c,i}$ = maximum yield for crop c, under irrigation technology i, given no water deficit

ky_c = yield response coefficient for crop c, which reflects sensitivity to water stress

$ETmax_c$ = gross water requirement of crop c over the growing season to achieve maximum yield

Ppt = precipitation received during the growing season, which reduces irrigation requirements

IrrigEffic = the proportion of water delivered to the field that reaches the crop root zone

Water = per acre water allotment for the growing season

TotAcres = total number of acres available for cropping activities

$RRate_{onion}$ = rental rate of an acre eligible for onions (i.e. an acre not planted to onions in previous 5 years)

$RRate_{other}$ = rental rate of an acre not eligible for onions

$EligOnion_{t,s,ss}$ = acres eligible for onions in period t of scenario s,ss

$EligAlf_{t,i,s,ss}$ = acres of alfalfa with productive lifespan remaining in years 4 through 6 for scenario s,ss; acres inherit the irrigation technology used in year 3, for simplicity

$EligOther_{t,s,ss}$ = acres eligible for crops other than onions in period t of scenario s,ss; a function of $EligOnion_{t,s,ss}$ and $EligAlf_{t,i,s,ss}$

$NetRv_{alf,i,d1}$ = net revenue from alfalfa under irrigation technology i, assuming no deficit irrigation (w =d1)

$H1_{f,c}$ = the crop c to which field f was planted six years prior to the first year of the planning horizon (i.e. planted in the first year of the previous (historical) planning horizon) (=0 if not planted, or 1 if planted)

$H2_{f,c}$ = the crop c to which field f was planted five years prior to the first year of the planning horizon (=0 if not planted, or 1 if planted)

$H3_{f,c}$ = the crop c to which field f was planted four years prior to the first year of the planning horizon (=0 if not planted, or 1 if planted)

$H4_{f,c}$ = the crop c to which field f was planted three years prior to the first year of the planning horizon (=0 if not planted, or 1 if planted)

$H5_{f,c}$ = the crop c to which field f was planted two years prior to the first year of the planning horizon (=0 if not planted, or 1 if planted)

$H6_{f,c}$ = the crop c to which field f was planted one year prior to the first year of the planning horizon (=0 if not planted, or 1 if planted)

PotatoContract = a fixed acreage of potatoes (expressed as number of fields) contracted in advance with local processors

$open_{f,t}$ = leave field f unprepared and unplanted in the fall of year t (=0 if not left open, or 1 if left open)

The producer's objective (equation 6) is to maximize the expected discounted stream of profit from the 3-year planning horizon through the selection of fall, spring, and post-harvest crop activities (*x*, *y*, and *z* respectively). Decisions made in "crop year" t consist of fall decisions ($x_{t,f,c,i,s,ss}$), spring decisions ($y_{t,f,c,i,w,s,ss}$), and post-harvest decisions ($z_{t,f,c,i,w,s,ss}$). Crops that are either fall-planted or require fall bed-preparation require the following fall decisions: 1) number of fields to plant or prepare, and 2) an associated irrigation technology, i, for each field. Spring decisions for each crop, c, include the following: 1) number of fields to keep (if c is a fall-planted crop) or number of fields to plant (if c is spring-planted), 2) an irrigation technology, i, for each field (note: for some crops, decisions made in the preceding fall impose an irrigation technology on the spring decision), and 3) a deficit irrigation level, w, for each field. Post-harvest decisions are not actually decisions; all spring-grown crops are simply sold at the revealed market prices (equations 31 and 50 above).

All crops' prices are revealed post-harvest; however, onions are the only crop to which different prices are assigned for the alternative states of nature. This implies price certainty for all other crops. The optimal choice of x, y, and z depends on past, current, and expected future water supplies and onion prices, denoted by s and ss, respectively. Interpretation of the price uncertainty model is otherwise similar to that of the binary variables model.

4.5.3 Prevented Planting Provisions

The base case model is modified to accommodate prevented planting provisions primarily by adding new cropping activities to the existing set. The new activities reflect the producer's option to purchase alternative levels of multi-peril crop insurance (each with a prevented planting provision) for onions, potatoes, sugar beets, and wheat. Insurance can be purchased on a field-by-field basis. Crop insurance policies are purchased in the fall. If the water supply is revealed dry, the producer then chooses whether to abandon the crop and receive a prevented planting payment, or to plant the crop. Claims for post-planting disasters, such as hail, pests, freeze, or abnormally high temperatures are not modeled. Crop insurance is also not offered in this model for spring-planted crops. These would require a third stage in each year of the model, in which the uncertainty about these events would be resolved. Solution of the model is sufficiently difficult with only two stages per year, so the addition of a third year remains for future work.

Other modifications are necessary to model prevented planting provisions. The following parameters, which are used to calculate a prevented planting payment, are added to the model: approved yield, MPCI coverage level, price election, PP coverage level, and the premium per acre paid (Appendix C). All parameters are chosen based on options available in year 2004, so that premiums are consistent with other costs. Yield and price elections are set to the levels that most closely match maximum yield and average historical price, as defined in the base case model. These assumptions could be altered, however, to conduct sensitivity analyses. Fall costs of insured crops are adjusted to include the premium paid for insurance coverage. Lastly, profit is redefined to reflect prevented planting payments received if insured crops are abandoned in a dry year. No payment is received if the crop is abandoned during a full allotment year (water must be insufficient to receive a payment), or if the insured crop is planted successfully. The structure of the base case model remains unchanged, so it is not presented again.

4.6 Model Validation

The model described above abstracts from some aspects of the complex decision environment in which producers operate. Such abstraction is needed in order to focus on water supply uncertainty. Isolation of this aspect of the decision environment enables the model to identify cropping and profit impacts that might otherwise be obscured. The cost of this abstraction, however, is that the model cannot be expected to reproduce outcomes observed on an actual farm. While the model results display similarities to certain responses observed in the area, such as types of cropping activities and adoption of specific irrigation technologies, quantitative validation of such a stylized model is difficult and not particularly relevant to the objectives of the study. It is important, however, in the absence of quantitative validation, to express clearly the limitations and appropriate interpretation of the model's results.

Recognition of aspects of the producer's decision environment that are simplified or excluded from the model is critical. These include, but are not limited to the following: 1) the assumption of a risk-neutral producer, or exclusion of risk-aversion, 2) the exclusion of many sources of uncertainty, 3) the discrete treatment of water supply, 4) the over-simplification of complex capital management issues (e.g. it is assumed that the producer can acquire and dispose of machinery and equipment each year without transactions costs, and hire and dismiss labor as needed), and 5) the exclusion of the farm household's consumption decision. The first point of departure is sufficient to cause discrepancies in the model's solution versus observed cropping activities in the study area.

These assumptions and simplifications should, however, generally lead to conservative estimates of drought's true impact. Inclusion of other sources of uncertainty, for example, would likely reduce the emphasis on drought preparedness and thus generate crop plans that leave the producer more vulnerable to drought. Continuous representation of the state of nature would include drought events more severe than the discrete categories defined in this model, and hence increase drought's profit impact. More accurate representation of short-term capital constraints would reduce the producer's flexibility, and thus also increase drought's profit impact. Accounting for the consumption-smoothing tendencies of many farm households (Kwon, Orazem, and Otto 2006; Langemeier and Patrick 1990), rather than excluding consumption from the model entirely, would decrease farm profit further in every scenario. It is unclear, however, whether the profit impact of drought would be larger or smaller for a risk-averse producer. A risk-averse producer would choose a plan that generates lower expected profit, but less variable profit. The difference in profit between a drought scenario and a drought-free scenario would therefore be less. Whether the current model over- or under-estimates drought's impact for a risk-averse producer would therefore depend on how one defined "profit impact of drought."

The implication of the above abstractions is that the model used here is only one step towards a complete understanding of drought management. The optimal preparedness and response plans presented in chapter 5 are not prescriptions to be applied directly in the study area. They do, however, help elucidate the tradeoffs that water supply uncertainty creates in a dynamic farm system, and in doing so help clarify for producers and extension educators an overwhelmingly complex decision problem. It will also help policymakers and others concerned with agricultural drought management think more critically about the meaning of optimal drought preparedness and response.

Despite its abstractions, the model is based very closely on characteristics of farms in the study area. Specifically, conversations with producers and other experts in the study area provided information that was used to construct the model. Examples include the timing of decisions versus water supply information, common agronomic practices and the underlying reasons for them, common drought management tools, and insights about the aspects of drought they find most challenging. These and other details inspired the model's two-stage framework and intra- and inter-year dynamics. In addition to producer input, enterprise budgets constructed for the county in which the study area is located were the primary source of data for model calibration. In summary, the model, as with all models, is an abstraction from reality, but it captures several fundamental and important aspects of an actual farm system under drought conditions.

5 Results and Discussion I: The Base Case Solution

Results and discussion are divided into chapters 5 and 6 for ease of exposition. Chapter 5 describes and compares the solutions of a binary versus continuous variables version of the base case model. Continuous variables are commonly used to approximate a binary variables problem because large stochastic integer programming models are often difficult to solve. The implication for the solution of using continuous variables to approximate binary variables is rarely explored. In this study, both a binary and continuous version of the base case model can be solved, which presents an opportunity to determine how closely the solutions resemble one another. Section 5.1 reports and examines the solution to the binary version of the model. The importance of alternative drought preparedness and response tools is considered first, followed by a discussion of the magnitude and variability of drought's profit impact. Section 5.2 reports the solution to the continuous variables version of the base case model, and compares it to that of the binary model. Readers are reminded that "optimal" refers simply, in this dissertation, to activities that are included in the mathematical programming model's solution; it does not indicate that the activities are Pareto optimal or socially efficient.

5.1 The Base Case Solution (Binary Variables Model)

The base case model is representative of recent conditions in the study area. It is constructed as a six-year stochastic integer programming model, with two decision stages (fall and spring) in each year. Water supply is known only probabilistically at the time of fall decisions, and is revealed prior to spring decisions in each year of the planning horizon. To avoid the influence of a subjective crop history, the farm's ten fields (35 acres per field) are assumed to have no constraining crop history. Sensitivity of the solution to crop history is reported in section 5.5. Table 5.1 reports the assumed values for several parameters in the base case; tables of other parameter values used in the base case are reported in Appendix A. Sensitivity of the solution to select parameters is discussed in chapter 6.

Table 5.1. Parameter values assumed for the base case.

Parameter	Value	Parameter	Value
Interest rate	7%	Water supply during drought	24 acre-inches per acre
Discount rate	5%	Full Allotment	40 acre-inches per acre
Crop History	None	Expected onion price	$6.00 per cwt
Pr(Drought) in any given year	40%	Price Stochastic	No
Pr(Full Allotment) in any given year	60%	Difference between the optimal and reported solution	< 3.00%

The final entry in table 5.1, i.e. "Difference between…," indicates that the commercial solution algorithm used to solve the model (CPLEX) generally reports a solution that only approximates the true optimal solution. This is often the case for large and complex models, such as the stochastic integer programming model developed here. The user can define the percentage difference allowed between the reported solution and the true optimal, including a 0% difference; however, obtaining a smaller difference often adds hours to the solve time. The approximate optimal solution, which is within 3% of the true optimal solution for most cases, is referred to henceforth as the optimal solution, unless otherwise indicated.

The base case solution includes the optimal portfolio of crops, irrigation technologies, and deficit irrigation levels, as well as discounted profit for 64 water supply scenarios, and the expected stream of discounted profit. The cropping activities and profit components of the solution are discussed next.

5.1.1 Optimal Cropping Activities

The crop plan that maximizes the expected stream of discounted profit, given a 40% chance of drought, includes the following activities in the fall of year 1 (figure 5.1): prepare seven fields for onions under drip irrigation, prepare one field for sugar beets under furrow irrigation, plant one field to winter wheat under furrow, and plant one field to winter wheat under reuse-furrow. Spring activities

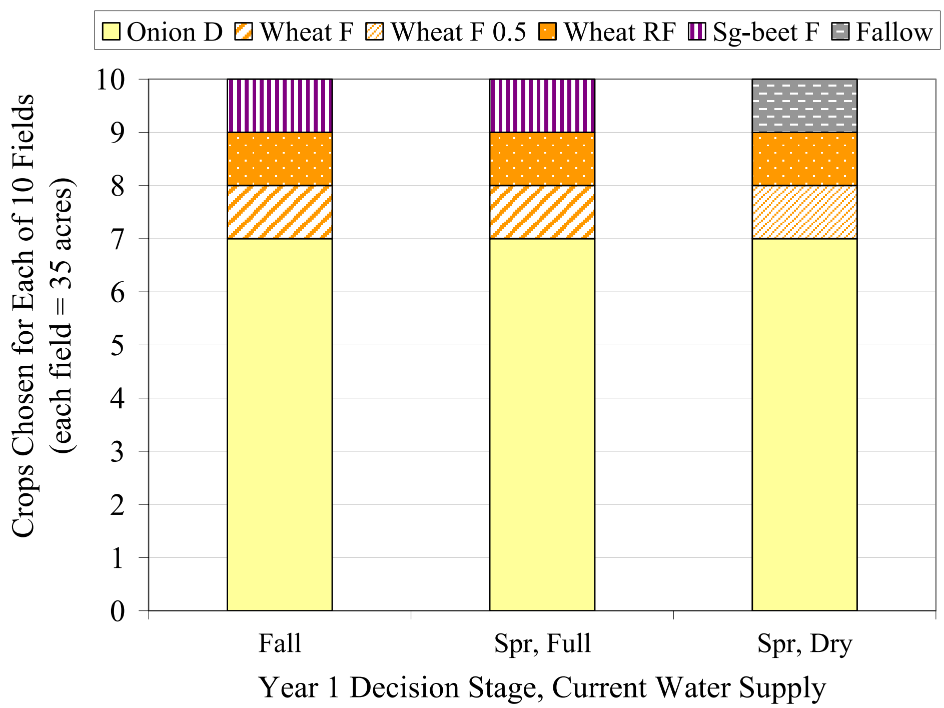


Figure 5.1. Optimal fall and spring activities in year 1 of the base case. Note that spring activities differ for alternative water supply outcomes (full or dry). Crop Key: F = furrow, RF = reuse furrow, D = drip, 0.5 = 50% of crop's irrigation requirement is provided.

depend on whether the water supply outcome (allotment) is full (40 acre-inches per acre) or dry (24 acre-inches per acre). Activities for a full allotment include planting and fully irrigating onions and sugar beets in the fields prepared for them, and fully irrigating wheat. Activities for a dry spring include planting and fully irrigating onions in the fields prepared for them, fallowing the field prepared for sugar beets, and deficit irrigating the furrow-irrigated wheat (meeting 50% of its crop water requirement).

Activities prescribed for year 2 are summarized in figure 5.2. The set of three bars on the left indicates optimal year 2 activities given a full water allotment in year 1, including individual recommendations for a full versus dry year 2. The set on the right indicates optimal year 2 activities given a dry year 1, again including individual recommendations for a full versus dry year 2. Activities prescribed for year 3 are presented in the same manner in figure 5.3. Graphical presentation of optimal activities for years 4 through 6 quickly becomes unmanageable (e.g. year 6 results would require 32 sets of bars), so results for these years are provided in an Excel file located on the attached floppy disk.

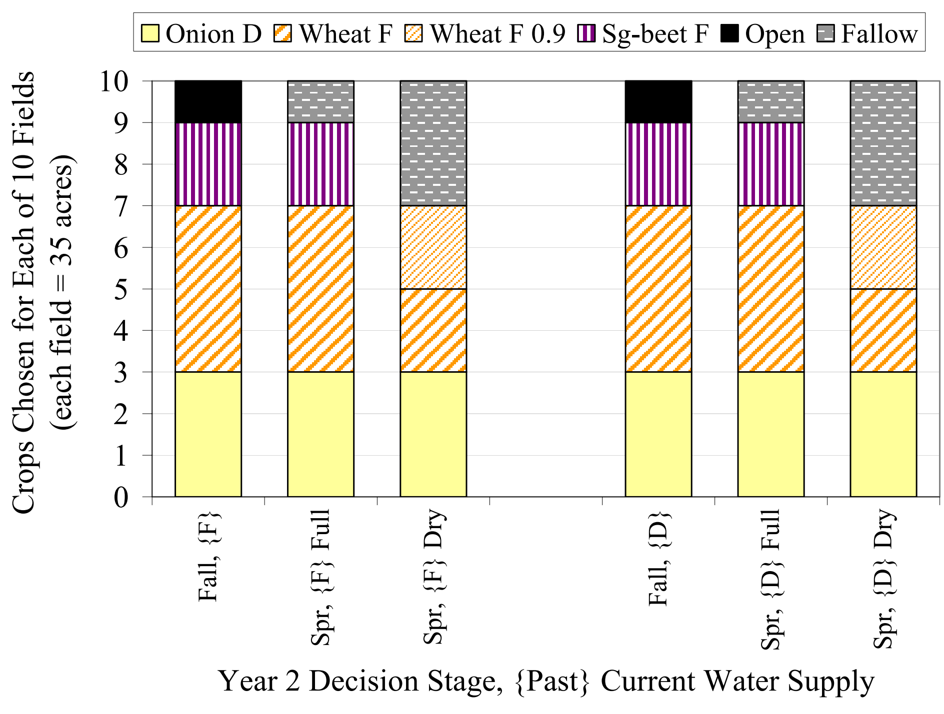


Figure 5.2. Optimal fall and spring activities in year 2 of the base case. Crop Key: F = furrow, D = drip, 0.9 = 90% of crop's irrigation requirement is provided.

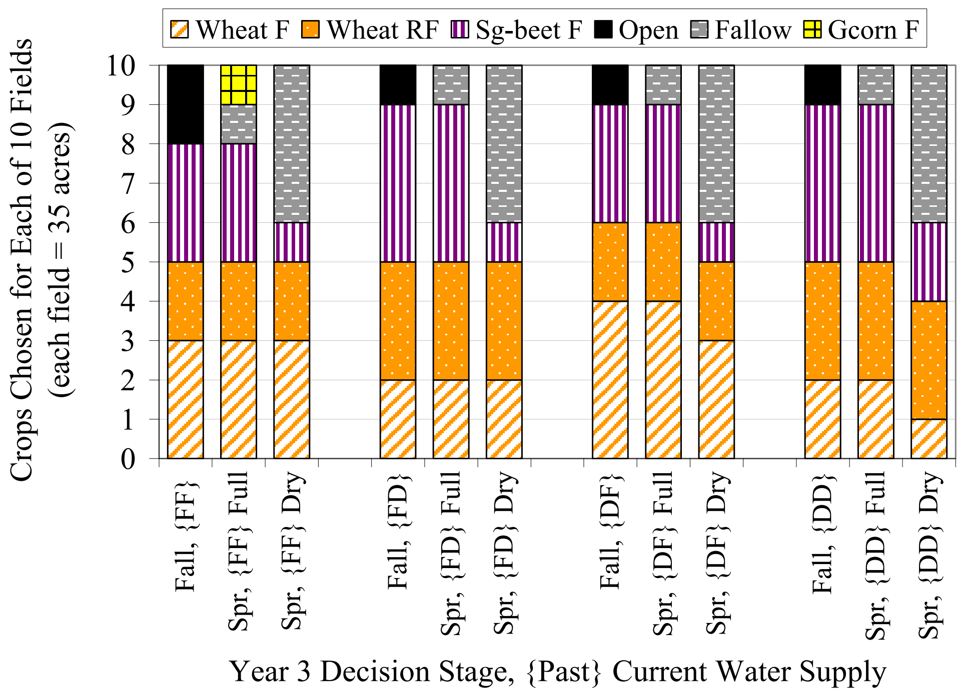


Figure 5.3. Optimal fall and spring activities in year 3 of the base case.
Crop Key: F = furrow, RF = reuse furrow.

Note that the activities prescribed for years 2 through 6 are only an approximation of the optimum. A producer would technically re-solve the six-year planning problem each year, taking into consideration the outcomes of the previous years, as well as the effects of the current decision on the next six years. To mimic this behavior, the model would have to be re-solved for every possible past water supply outcome. For example, the model would be re-solved twice to determine optimal year 2 activities for a dry versus full year 1. Re-solving the model to determine optimal activities for years 3 through 6 is cumbersome because the number of past water-supply scenarios increases exponentially. The model would have to be re-solved sixty-four times to generate the conditional set of optimal activities for year 6. The approximate solution obtained for years 2 through 6 is sufficient for the purposes of this study.

The first objective of this research is to determine the role of drought preparedness versus response in an optimal farm plan. Recall that drought preparedness techniques are implemented in the fall, before the producer knows whether the upcoming spring will be full or dry. Drought preparedness reduces the potential for loss in the event of a drought, and is therefore a form of self-protection (Ehrlich and Becker 1992). Drought response techniques, in contrast, are implemented in the spring, after the producer knows that the spring will be dry. Drought response reduces the magnitude of loss during a drought, and is therefore a form of self-insurance (Ehrlich and Becker 1992). The following two drought preparedness techniques appear in the base case solution: using relatively efficient irrigation technologies on some crops, and leaving some fields open in the fall. The following two drought response techniques also appear in the base case solution: fallowing fields, and deficit irrigating crops. These techniques are not used exclusively in anticipation of, or in response to drought. For example, a producer who knows that the next six years' water allotments will be full does leave some fields open, fallow a field occasionally, and uses relatively efficient irrigation technologies (figure 5.4). However, these techniques are used more intensively when the possibility of drought exists (figure 5.4). Each technique is discussed next.

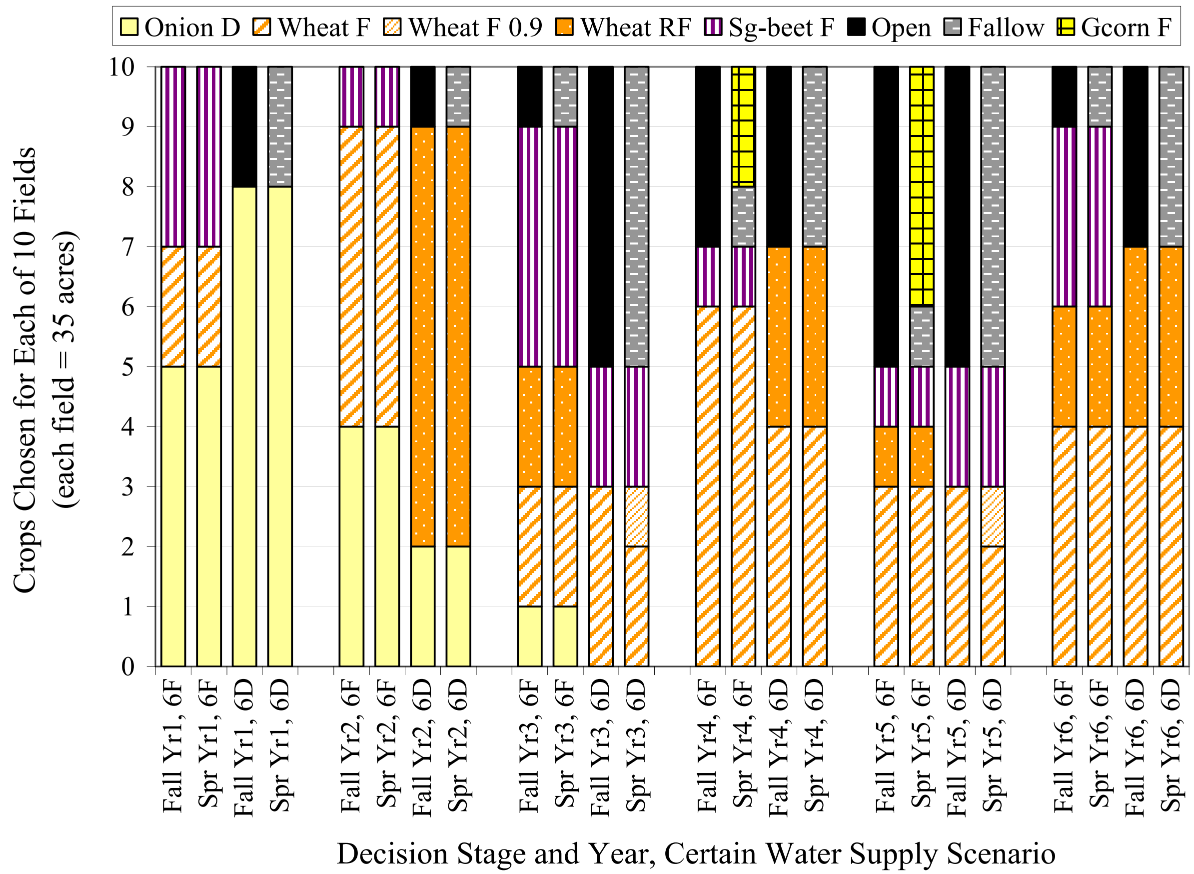


Figure 5.4. Optimal fall and spring activities when the producer knows that the next six years' water allotments will be full (6F) versus dry (6D). Crop Key: F = furrow, RF = reuse furrow, 0.6 = 60% of crop's irrigation requirement is provided, 0.5 = 50% provided.

5.1.1.3 IRRIGATION TECHNOLOGY EFFICIENCY

One form of drought preparedness that appears in the optimal solution is the use of relatively efficient irrigation technologies. Efficiency refers here to the proportion of delivered water that is available to the crop for use (i.e. that remains in the root zone) (table A.4). Irrigation technologies with relatively high efficiency typically cause less runoff, evaporation, and deep percolation, and therefore decrease the volume of water that must be delivered to meet crop water requirements. Irrigation technologies from which the model can choose include furrow, reuse furrow, wheel line sprinkler, solid set sprinkler, center pivot sprinkler, and subsurface drip. Readers are likely familiar with most technologies, with the exception of reuse furrow, which is a modified furrow irrigation system, in which runoff from the field is collected in a small pond, filtered, and pumped through pipelines to the top of the field or a nearby field for reuse (Hart et al. 1980). A producer can reduce a crop's irrigation requirement by using more efficient irrigation technology. This reduces the probability of a shortage during dry years, and increases the set of feasible crop combinations during full years. However, more efficient systems are also more expensive (table A.2). The expected benefit and cost of investing in more efficient irrigation systems to increase total crop production or to reduce the likelihood of a water shortage must therefore be weighed.

The optimal solution suggests growing onions under drip irrigation only. Drip irrigation is highly efficient (90%), which is beneficial during a water shortage; however, it also supplies water more uniformly, across time and space, to the root zone, which increases onion yields. Drip irrigation, therefore, is likely chosen for reasons other than its water-saving property. That the technology is also chosen when there is no possibility of drought confirms this (figure 5.4). Sensitivity analyses are conducted to test whether drip irrigation's water-saving property plays any role in its selection, as compared to its yield-enhancing property. Specifically, the yield and cost of onions under furrow and reuse furrow are set equal to drip irrigation's, such that the technologies differ only in their efficiency. The model is re-solved, and drip irrigation is still chosen over furrow or reuse furrow (this result holds whether drought is certain or uncertain), suggesting that higher efficiency is valuable.

To rule out multiple optima, the model is further modified by disallowing drip irrigated onions, and then re-solved. Onions under reuse furrow irrigation are selected over furrow irrigation, and profit (or expected profit in the case of uncertainty) is less than when drip irrigation is allowed. This confirms that the water-saving property of drip irrigation is valuable, not just its yield-enhancing property. Producers might use drip irrigation on onions largely to increase yield; however, the technology also enhances profit by reducing onion's irrigation requirement, thereby freeing up water for other crops in a full year, and potentially decreasing the need to deficit irrigate or abandon fields in a dry year. Note, however, that drip irrigation might also increase the number of fields abandoned or deficit irrigated in a dry year, particularly if the water savings are sufficient to support additional fall-prepared or planted crops in a full year (thus causing additional fields to be attempted), but insufficient in a dry year (thus causing those additional attempted fields to be abandoned).

It is interesting to note that although producers in the study area grow onions predominantly under furrow irrigation, drip irrigation is increasingly being adopted. Additionally, one producer recently updated their drip system such that the associated pumps, pipes and filters could be moved from year to year. The yield benefits of drip irrigation were the focus of this producer's comments, however, they did indicate that the drought in the early 1990s spurred them to first consider drip irrigation.

Reuse furrow technology, which is 80% efficient, is also suggested for a portion of the base case solution's wheat acreage. Although it is also used when there is no possibility of drought (figure 5.4), the technology is more prevalent when there is a positive probability of drought (figures 5.1 through 5.3). This suggests that reuse furrow serves, in part, as a drought preparedness tool. The ability of reuse technology to reduce water supply risk has been established for other farm systems (Ziari and McCarl 1995). The above result suggests the same for an irrigated row crop system. Producers also indicate a recent increase in the use of reuse furrow systems in the study area. It is unclear, however, to what degree this is attributable to the recent drought, versus cost-sharing programs aimed at improving water quality in local waterways.

A numerical example illustrates the water-savings that wheat under reuse furrow generates, as compared to wheat under furrow irrigation. Wheat under furrow irrigation requires 40.2 inches of water to meet its seasonal crop water requirement of 24.1 inches, assuming 50% efficiency and 4 inches of effective precipitation during the growing season. Wheat under reuse furrow, in contrast, requires only 25.1 inches to meet its seasonal requirement, because it is 80% efficient. The use of reuse furrow for an acre of wheat, rather than furrow irrigation, frees up 15.1 acre-inches for some other use. Alternatively, it decreases the need to deficit irrigate or abandon wheat during a dry year.

Note that the gains from adopting more efficient technology would be less if a portion of water "lost" during furrow irrigation actually supported other fields via subsurface irrigation or return flow (Green and Hamilton 2000). For simplicity, this is assumed not to occur. It is also assumed that the producer can replace any field's irrigation system with another, annually, without incurring a transaction cost. Specifically, a producer is presumed to be able to sell the old irrigation system for exactly the balance on the original investment. This assumption provides more flexibility than is available in reality, and therefore provides a lower bound on the impacts of drought. Improving the realism of this feature would require if-then relationships that track and assign costs when a field's irrigation technology is changed; however, this causes endogeneity in the existing modeling framework. One alternative for this assumption is to choose an irrigation system for each field in the first year, and then require this system to remain in place for the entire planning horizon. This more restrictive assumption would provide an upper bound on the impacts of drought. It would not, however, reflect the current use of reuse furrow and drip irrigation in the study area.

5.1.1.4 OPEN FIELDS IN THE FALL

A second form of drought preparedness that appears in the base case solution is to leave some fields open (i.e. neither prepared nor planted) in the fall (figures 5.2 and 5.3). Leaving fields open in the fall creates flexibility in the crop plan; specifically, the producer can accommodate a full or dry spring without incurring sunk costs, which are generated when a field is fall-prepared or fall-planted (table A.2). Fields left open in the fall can either be allocated to a spring-prepared and planted crop (e.g. barley, grain corn, or silage corn) if the spring water allotment is full (figures 5.3 and 5.4), or left fallow if the spring is dry (figures 5.2 through 5.4). Fields that are prepared or planted in the fall (i.e. not left open) can also be fallowed if the spring is dry; however, sunk costs generate no return if the field is fallowed.

The drought literature commonly eludes to the importance of production flexibility as a drought preparedness strategy (Clawson et al. 1980; Lomas 2000; Thompson et al. 1996); flexibility is an important concept in the broader uncertainty literature as well (e.g. Albers 1996). Few studies elaborate, however, on the specific means by which flexibility can be built into a farm system. A notable exception is Weisensel et al. (1991), who explicitly examines the value of flexibility in a dryland wheat-fallow system. The base case solution reveals, for an irrigated row crop system, that leaving fields open in the fall is an optimal means to achieve production flexibility. Observations of the study area reveal that producers frequently use this drought preparedness tool in their year-to-year operations.

5.1.1.5 FALLOWING

Fallowing is the first of two drought response tools considered in this study. Fallowing can take the following two forms: 1) abandoning a field that was prepared or planted in the previous fall, or 2) leaving an open field bare. Fallowing is recommended frequently in the base case solution, particularly when high-value crops are planned and a water shortage occurs. Fallowing reduces crop acreage and thus decreases the farm's total irrigation requirement; it also frees up water from one field for use in another. Fallowing is an important drought response tool because the per-acre water allotment during a dry year (24 acre-inches) does not meet the per-acre net irrigation requirement of several crops, including onions (28 acre-inches, assuming 90% efficiency of drip irrigation and 4" of effective precipitation, see table A.8). Model results indicate that producers should take advantage of this drought response tool; observations from the study area indicate that producers do. Several survey-based studies of producer decisions during drought also identify fallowing as a common drought response tool (Rich 1993; Schuck, Frasier, and Webb 2003; Zilberman et al. 2002).

Figures 5.1 through 5.3 show that, in the event of a drought, open fields are fallowed first, followed by sugar beet fields, and then wheat fields. Sugar beets are fallowed before wheat, even though beets are more profitable than wheat. The choice to abandon one crop rather than another therefore depends on parameters other than profitability, specifically, available water. The following example illustrates this point. Cropping activities in either of the "dry year 2" scenarios (figure 5.2) leave 137 acre-inches of excess water. Suppose that after a drought is revealed in year 2, a producer decides to modify the optimal solution. Instead of fallowing sugar beets and keeping wheat, they decide to keep one field of sugar beets under furrow irrigation, and fallow one field of wheat under furrow irrigation. The quantity of water saved by fallowing the wheat field satisfies only 70% of the beet's water requirement, and deficit irrigated sugar beets are less profitable than fully irrigated wheat. Suppose the producer instead keeps one field of sugar beets under reuse furrow. Sugar beets under reuse furrow are also less profitable than wheat under furrow or reuse furrow. The rational choice for the producer, given a water shortage of the magnitude modeled here, is to fallow sugar beets, rather than wheat.

Note that fallowing during a full year is limited in the model to one field or less. This constraint forces crops that generate small or negative profit directly, but that contribute to more profitable crops though soil-quality enhancement and nutrient management, into the plan. Production functions that quantify these and other crop inter-dependencies are not readily available, nor are data of sufficient detail or duration available to estimate functions for the study area. In addition, agronomic constraints included in this model do not capture completely the true production function. Constraints, such as limited fallowing during a full year, are therefore used in lieu of the true production function. These constraints primarily prevent unrealistic solutions, such as growing only potatoes and onions, and fallowing the land for years until it is again eligible for these crops.

5.1.1.6 DEFICIT IRRIGATION

Deficit irrigation is the deliberate and systematic under-irrigation of crops (English and Raja 1996). The goal of deficit irrigation is to expose plants to controlled levels of water stress in order to conserve water without causing significant yield reductions (Kirda 2002). Alternatively, deficit irrigation can be used to equilibrate the marginal value of water across crops. That is, profit might be increased by deficit irrigating a crop with low marginal value of water (even if it reduces yield significantly) to provide water to a crop with high marginal value of water (English and Nakamura 1989; Kirda 2002). Two types of deficit irrigation can be practiced: season-long deficit irrigation, in which the crop is deficit irrigated by the same proportion throughout the entire growing season, and strategic deficit irrigation, in which the crop is deficit irrigated only during its most drought-tolerant growth stages (Kirda, Kanber, and Tulucu 1999).

Strategic deficit irrigation generally results in smaller yield reductions than season-long deficit irrigation (Bazza 1999; Hargreaves and Samani 1984); therefore, producers are likely to use the strategic rather than season-long approach. However, a linear yield response function for strategic deficit irrigation is not readily available; in contrast, a function for season-long deficit irrigation exists and is well-established in the literature (Doorenbos and Kassam 1979). Season-long deficit irrigation is therefore used in this dissertation, and table A.6 reports the effect of alternative deficit irrigation levels on per-acre yield and profit. Deficit irrigation may be used more frequently, in practice, than the optimal solution indicates, if producers use strategic deficit irrigation rather than season-long deficit irrigation. Note, however, that Bazza (1999) indicates that a producer who is uncertain of the most critical growth stage in which to irrigate might do better to practice season-long deficit irrigation to achieve water conservation goals.

Deficit irrigation, the second drought response tool considered in this study, appears in the base case solution. Wheat, in particular, is the primary crop that is deficit irrigated. This is attributable to wheat's relative drought tolerance (its yield response coefficient (table A.5) is not greater than 1), its low cost of production (table A.2), and its relatively low market value (table A.1). Wheat, in summary, is one of the few crops that remain profitable under season-long deficit irrigation (table A6). Additionally, wheat has a relatively low total irrigation requirement (table A.3), which enables the producer to more frequently support deficit irrigated wheat during years in which the quantity of excess water is small, as compared to more water-demanding crops.

The above result is consistent with existing studies that show winter wheat to be well-suited for, and profitable under deficit irrigation in many cases (Bazza

1999; English 1990a; Musick and Dusek 1980). More generally, it supports the findings of Bernardo et al. (1987) and English (1990b), who report, respectively, that producers in Washington's Columbia River Basin (an area of similar climate and farming systems) should and do practice deficit irrigation during a water shortage. Producers in the study area also indicate that they deficit-irrigate less sensitive and less valuable crops to ensure water for more sensitive and more valuable crops, or to increase the proportion of fields planted. It is not known, however, how common the use of deficit irrigation is among producers in the study area. Zilberman et al. (2002) and Schuck et al. (2003) report, respectively, that only a small portion of California and Colorado producers used deficit irrigation during past droughts.

The literature also indicates minimal yield loss under deficit irrigation for sugar beet (Kirda, Kanber, and Tulucu 1999); however, sugar beet is rarely deficit irrigated in the base case solution. This corresponds with Bazza's finding (1999) that maximum profit from sugar beet is obtained when the crop's water requirement is fully met. Nonetheless, under the model's assumed parameters, sugar beet is profitable if 80% or more of their irrigation requirement is met. It is not clear then why sugar beet is not deficit irrigated in the optimal solution. One possible explanation is that sugar beet requires a relatively large quantity of water, particularly in comparison to wheat. Sugar beet might therefore have to be severely deficit irrigated to generate sufficient water savings during a drought. Severe deficit levels are associated, in the model, with unprofitable sugar beet yields. Another possible explanation is that results from the literature are largely based on strategic deficit irrigation, whereas the model's results are based on season-long deficits. The season-long representation used in the model likely overestimates yield losses associated with strategic deficit irrigation (Fujun et al. 1999), in which case deficit irrigation will be recommended less under season-long deficit irrigation than it would be under strategic deficit irrigation. Finally, one benefit of deficit irrigation that is highlighted throughout the literature is the ability to expand crop acreage using the conserved water (English 1990a). The producer in the model is unable to expand farm acreage beyond the 350 owned acres; the benefit of deficit irrigation to which the literature refers might therefore be larger than that captured in the model.

To summarize the above results regarding optimal cropping activities, the base case solution indicates a role for both drought preparedness tools (leaving fields open and using relatively efficient irrigation technologies) and drought response tools (fallowing and deficit irrigation). Observations of producers in the study area validate this result; many of the preparedness and response activities are currently used. Specifically, producers commonly leave fields open to provide production flexibility, deficit irrigate less sensitive crops, and fallow fields in response to drought. More efficient irrigation technologies are also becoming more common in the study area, in particular, reuse furrow and drip irrigation. The preparedness and response tools discussed above have been analyzed in previous studies. However, few studies have considered them simultaneously. The above results indicate that all of the tools are needed to optimally prepare for and respond to drought. The results also illustrate the degree to which a risk-neutral producer in an irrigated row crop system should use each tool.

5.1.2 Profit Outcomes

Profit outcomes associated with the base case solution are presented in table 5.2, figure 5.5, and table A.7. Recall from chapter 4 that "profit" refers, in this study, to returns to land and management. Table 5.2 and figure 5.5 describe the distribution of the stream of discounted profit for the six-year planning horizon. These will be compared in subsequent sections with profit outcomes from alternative versions of the model. The profit impact of drought, particularly as it varies with the duration of drought, is the focus of this section. The profit impact of drought is defined as the difference in discounted profit between a scenario that includes drought and a scenario that does not (e.g. [Dry Full Full Full Full Full] versus [Full Full Full Full Full Full] for a single-year drought of interest, or [Dry Dry Full Full Full Full] versus [Full Full Full Full Full Full] for a multi-year drought of interest).

Table 5.2. Summary statistics of the base case solution's profit outcome.

Statistic	**Value ($)**
Expected Stream of Discounted Profit	531,853
Standard Deviation of Expected Stream	36,076
Maximum Discounted Profit	590,100
Discounted Profit of Scenario [Full Full Full Full Full Full]*	582,703
Minimum Discounted Profit	408,273

*An explanation for the discrepancy between maximum discounted profit and discounted profit for this scenario is provided at the end of section 5.2.1.

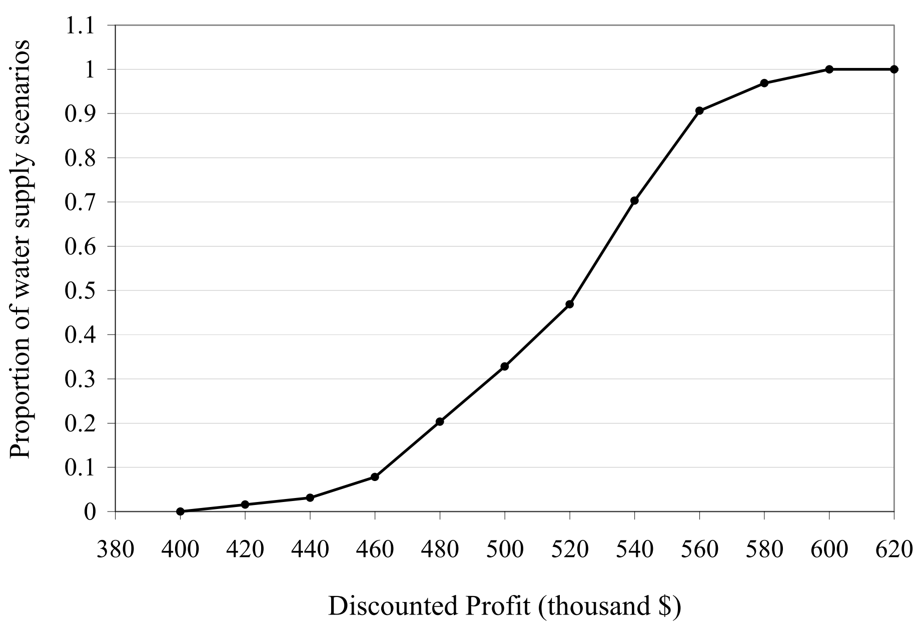


Figure 5.5. Cumulative distribution function of the stream of discounted profit for the base case solution. E.g. approximately 70% of water supply scenarios (n=64) generate less than $540 thousand in discounted profit.

The primary objective of this section is to determine whether the impacts of drought can be generalized in a useful manner for policymakers. For example, it is not clear whether a three-year drought can be presumed to generate a larger profit loss than a two-year drought. In reality, the characteristics of individual droughts are sufficiently unique to make comparison difficult. The model, in contrast, assumes a single level of severity for every drought (24 acre-inches per acre, rather than 40), such that the affect of duration on profit loss can be analyzed. Figure 5.6 reports the average loss of discounted profit for droughts of various duration (from one year to six years), as well as the minimum and maximum profit loss for each duration category. Average profit loss is reported because a drought of particular duration (e.g. a single-year drought) can occur at alternative points in the six-year planning horizon (e.g. [Dry Full Full Full Full Full] versus [Full Full Full Full Full Dry]). The profit impact of drought varies depending on the point in the crop plan at which it occurs (Appendix H), because crop plans vary across years. Drought that occurs during a year in which many fields are left open in the fall, for example, has less impact than one that occurs during a year in which all fields are fall-prepared.

Three features of figure 5.6 indicate that few generalizations can be made about the profit impact of drought by duration alone. First, average profit loss increases as the number of droughts during the planning horizon increases. However, the magnitude of profit loss increases at a decreasing rate. Two years of drought cause 183% larger losses than one year of drought. Three years of drought cause 68% larger losses than two years of drought; four years of drought cause 48% larger losses than three years; five years cause 38% larger losses than four years, and six years cause 33% larger losses than five years. The marginal impact of each additional drought is smaller. This result stems from the fact that the impacts of drought are larger for some scenarios than others. As the number of years of drought experienced increases, the probability increases that the worstimpacted scenarios have already been experienced. Hence, the marginal impact of an additional year of drought is likely to be small on average.

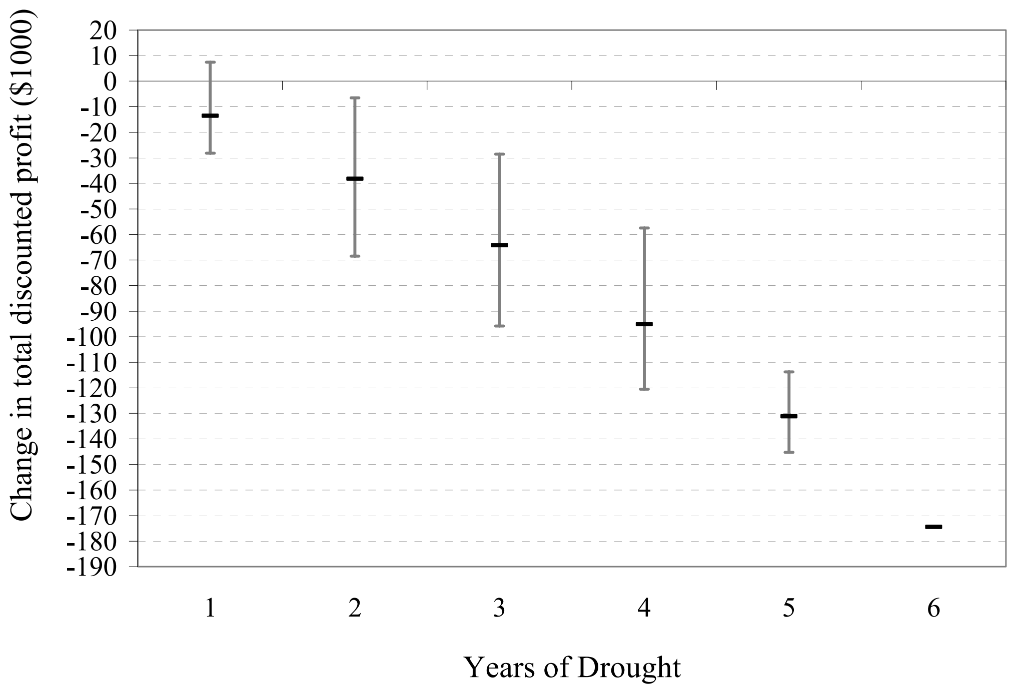


Figure 5.6. Average change in total discounted profit (black dashes) by years of drought experienced (as compared to 6 years of full water supply). Gray brackets indicate the maximum and minimum impact of drought. E.g. Three years of drought can cause a minimum loss of $29,000 in discounted profit, or a maximum loss of $96,000, depending on the years in which the droughts occur. Discounted profit loss, on average, is $64,000 when droughts occur in three years out of six.

Second, profit loss within each drought category varies widely, with the standard deviation of loss generally increasing as the number of droughts increases (table 5.3). An example illustrates the importance of this feature. The largest profit loss attributable to three years of drought is $96,000, which occurs in the scenario [Full Dry Dry Full Dry Full]. The smallest profit loss attributable to three years of drought is $29,000, which occurs in the scenario [Full Dry Full Full Dry

Dry]. A drought in year 3, rather than year 6, more than triples profit loss. The policy implication of this result is that the number of droughts alone cannot precisely predict the magnitude of profit losses. In fact, as the number of droughts increases, profit loss becomes more variable and harder to generalize. The timing of drought events within the planning horizon (i.e. within the crop plan) is a crucial determinant of profit losses. Unfortunately, crop plans are likely to vary widely across producers; even producers who implement the same six-year crop plan could be in different years of the plan when a drought occurs. Profit losses attributable to a particular drought event are therefore likely to vary widely across producers.

Table 5.3. Characteristics of change in total discounted profit ($) as the years of drought experienced (during the 6-year planning horizon) increases.

Years of Drought	**Avg. Change in Disc. π***	**Max. Change in Disc. π**	**Min. Change in Disc. π**	**Std. Dev. of Change**
1	-13,488	-28,106	7,397	13,502
2	-38,216	-68,491	-6,499	16,600
3	-64,198	-95,840	-28,543	18,484
4	-95,109	-120,484	-57,427	19,246
5	-131,145	-145,230	-113,777	12,082
6	-174,430	-174,430	-174,430	0

*Change in discounted profit is calculated as discounted profit of the drought scenario less the discounted profit of scenario [Full Full Full Full Full Full]. Negative numbers indicate profit loss.

The discount rate, interest rate, and differences in the crop plans of years 3 and 6 explain how the timing of drought influences the resulting profit loss. The discount rate implies that losses in year 3 are given more weight than losses in year 6. The interest rate implies that losses in year 3 will reduce earned interest (on savings) for more years than losses in year 6. Finally, fall crop plans in place prior to the year 3 drought versus the year 6 drought lead to larger losses in the year 3 drought. Specifically, one field is left open in the fall of year 3 (scenario [Full Dry]), while four fields are left open in the fall of year 6 (scenario [Full Dry Full Full Dry]). Drought in year 3 forces the producer to fallow four fields, including three fields prepared for sugar beets. Drought in year 6 also forces the producer to fallow four fields, but all were open, so no fall investments were lost.

A third feature of figure 5.6 that has important implications for generalizations about drought is that the maximum loss attributable to two years of drought can exceed the average loss attributable to three years of drought. The same holds for three years of drought, whose maximum loss can exceed the average loss of four years of drought. This feature highlights the difficulty of generalizing profit loss attributable to drought. Profit loss grows larger, on average, as the number of droughts increases, but in some cases, fewer years of ill-timed drought can cause greater losses than more years of favorably-timed drought.

In conclusion, few generalizations can be made about the profit impact of drought based on its duration alone. Specifically, policymakers should not view droughts within the same duration category equally, or necessarily base their expectations of loss for a drought on the impacts of similar past droughts. A producer could experience multiple identical droughts throughout their life, and be affected differently by each of them, depending on the crops in place when the droughts occur. Similarly, two producers that follow the same crop plan, but are in different stages of that plan, could experience the same drought and yet incur considerably different profit losses. This result highlights the difficulty that policymakers face when determining the need for, and appropriate extent of, assistance during or after a drought. The magnitude of impact might be highly variable across producers, even in a homogeneous agricultural area. Policymakers would also be ill-advised to assume that the profit impact of a relatively short-lived drought is less than that of a more prolonged drought. While this is true on average, there is considerable overlap of the ranges of profit loss for droughts of various durations.

The base case solution raises several questions that parametric or structural variations of the base case model can be used to address. These questions are raised and addressed in the remaining sections of chapter 5 and in chapter 6. Before proceeding, however, readers may have noted from tables 5.2 and A.7 that the scenario “six full years” does not generate the maximum discounted profit. This implies that a scenario containing drought generates more profit than the scenario with no drought. The reason for this initially counterintuitive result is explained here. Fallowing is limited in the model to one field or less during a full year; in contrast, fallowing is unlimited in a dry year. Several crop-irrigation combinations in the model generate negative returns to management and land under the assumed prices, yields, and costs (including a 7% opportunity cost of money). Grain corn under reuse furrow, for example, generates -$38.55 per acre. However, from a whole farm budget perspective, they contribute to the sustainability of long-term production of profitable crops, such as onions, by utilizing excess nutrients, reducing pests and disease, and maintaining soil quality. The model does not capture these benefits, however, and therefore underestimates the economically profitable level of such crops. To counter-balance the systematic under-estimation of these crops’ economic benefits, the model is required to plant most acres during a full year, regardless of whether the crops brought into solution are economically profitable on that field in that year.

Fallowing is not limited during dry years, however, because fallowing is needed to ensure water for high-value crops. Crops that generate small or negative profit are fallowed first. Fallowing crops that generate negative profit (e.g. grain corn under reuse furrow) causes profit in the drought scenario to be higher than that in the full scenario. The impact on most scenarios’ profits is relatively small, however, typically around $1000. A reader might infer that fields are fallowed during dry years for profit-purposes only, rather than water-management purposes. This does not appear to be the case. Excess water (i.e. the volume of allocated water less the volume required for a specific crop plan) is insufficient in all 63 drought scenarios to support an additional field of any crop. That is, it is almost always a physical necessity, not just profitable, to fallow rather than plant an unprofitable crop during a drought.

5.2 The Base Case Solution (Continuous Variables Model)

Many farm-level linear programming models define decision variables as continuous, rather than integer, to enhance problem solvability. The results reported in this dissertation are primarily from an integer (binary) model, which enables crop history for each field to be tracked through time, and hence agronomic constraints to be enforced at the field-level, rather than at the farm-level. The binary variables model is a more accurate representation of production in the study area; however, it requires a more powerful solution algorithm and more time to solve than a continuous variables model. The solution to a continuous variables version of the base case model is presented in this section, and the similarities and differences between the continuous and binary models' solutions are discussed.

Figures 5.7 through 5.9 report the optimal crop plan for years 1 through 3 of the continuous variables model. Similarities to the optimal crop plan for the binary variables model include the following: 1) most of the acres are planted to onions under drip irrigation in the first year, with the remaining eligible acres planted in year two; 2) reuse furrow irrigation is used on a portion of the wheat acreage, 3) some acres are left open in the fall, and 4) aside from open fields, sugar beets are the first crop fallowed during drought. The continuous model's optimal solution differs, however, in the following ways: 1) deficit irrigation is not included, 2) more onions are planted in the first year, and 3) more wheat is planted under reuse furrow and less under furrow irrigation. The profit outcomes for the continuous variables model (table 5.4 and figure 5.10) are similar, however, to the binary variables model. Differences in the optimal solutions do not lead to significantly different profit outcomes, in this case.

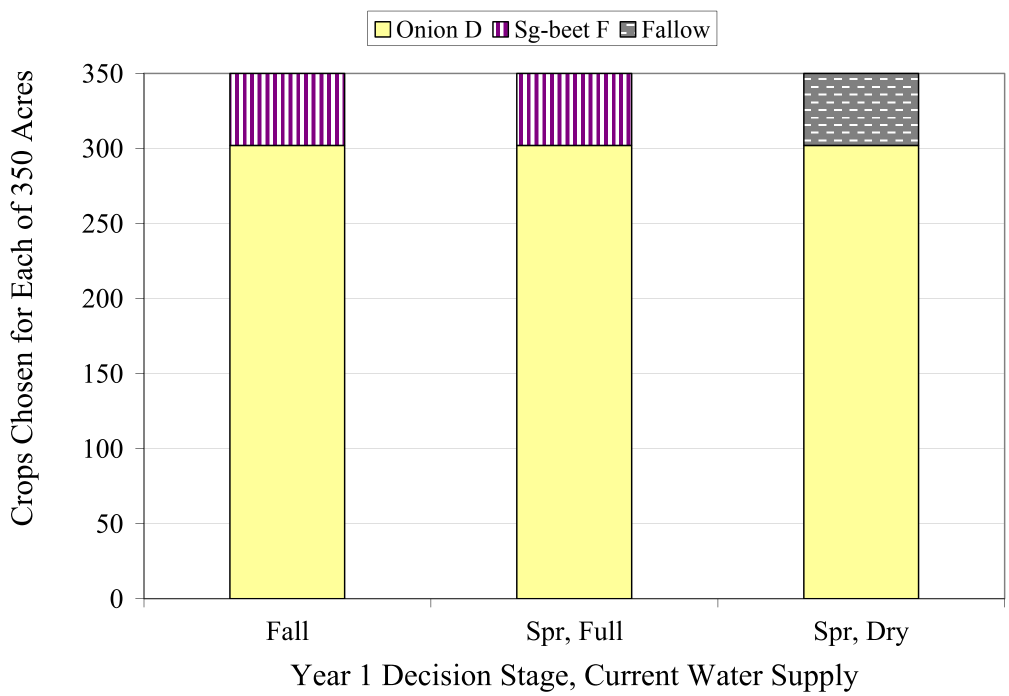


Figure 5.7. Optimal fall and spring activities in year 1 of the continuous variables model's base case solution. Note that spring activities differ for a full versus dry spring. Crop Key: F = furrow, D =drip.

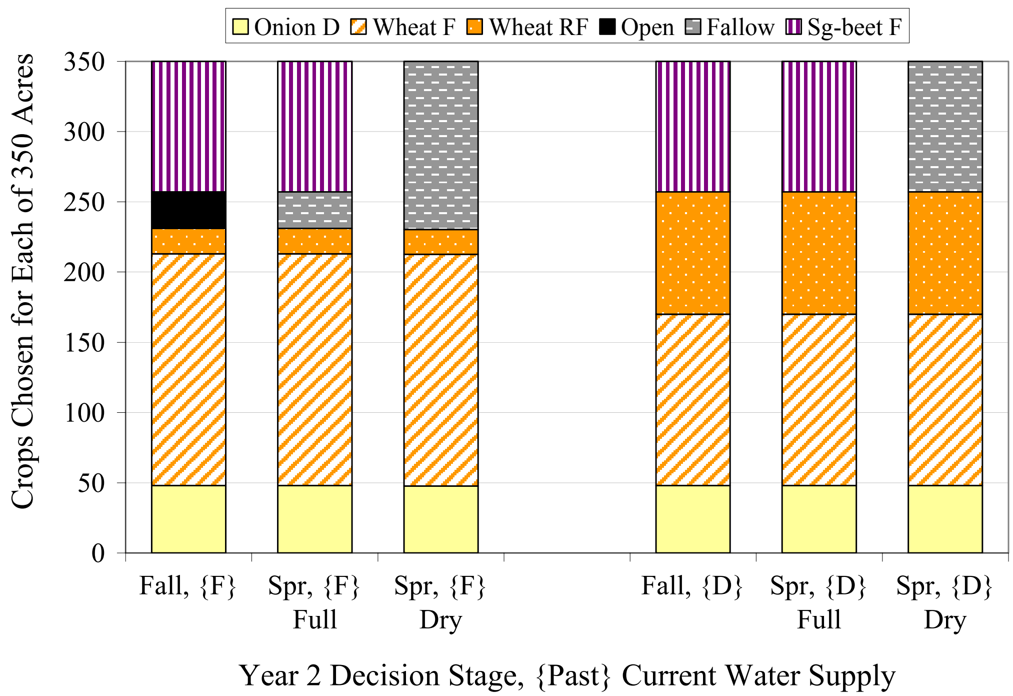


Figure 5.8. Optimal fall and spring activities in year 2 of the continuous variables model's base case solution. Crop Key: F = furrow, RF = reuse furrow, D =drip.

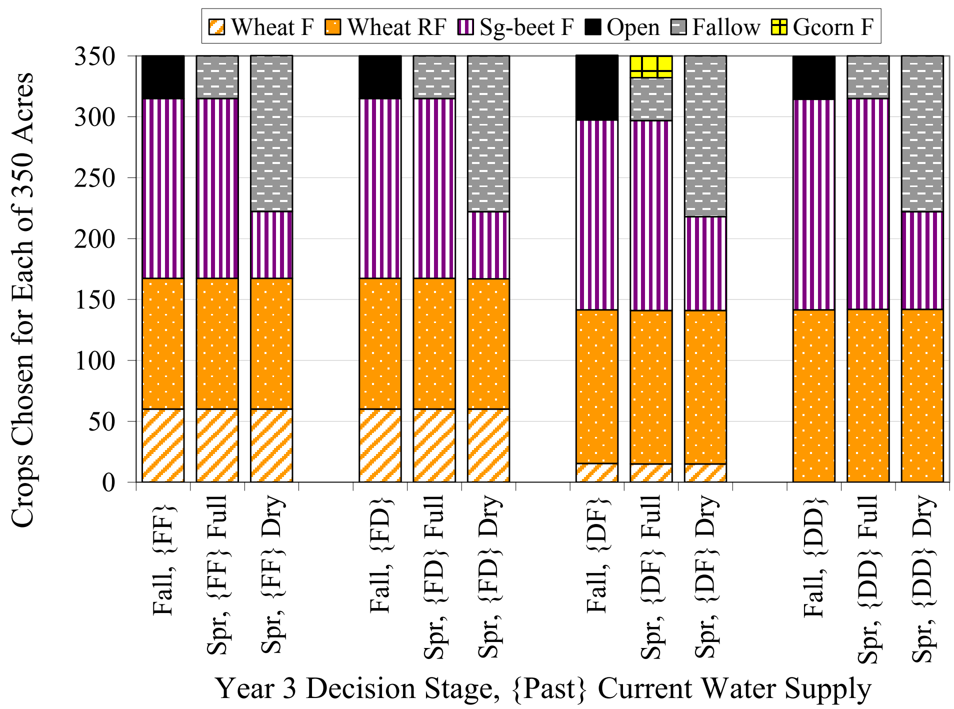


Figure 5.9. Optimal fall and spring activities in year 3 of the continuous variables model's base case solution. Crop Key: F = furrow, RF = reuse furrow.

Table 5.4. Summary statistics of the base case's profit outcome for the continuous variables model.

Statistic	Value ($)
Expected Stream of Discounted Profit	547,049
Standard Deviation of Expected Stream	36,436
Maximum Discounted Profit	597,958
Minimum Discounted Profit	416,793

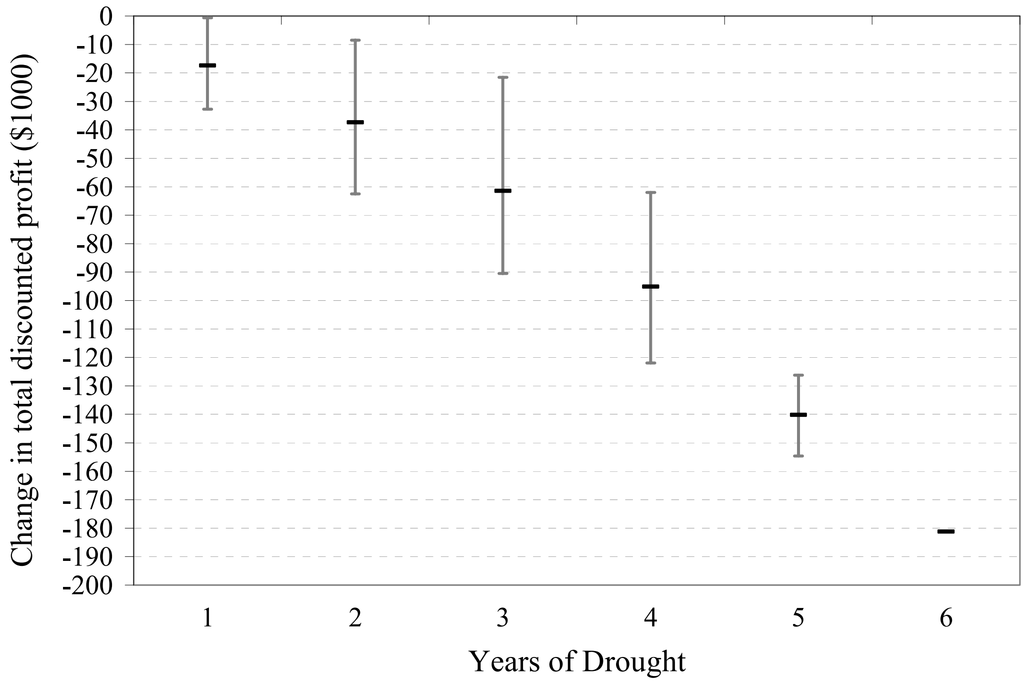


Figure 5.10. Average change in the continuous variables model's total discounted profit (black dashes) by years of drought experienced (as compared to 6 years of full water supply). Gray brackets indicate the maximum and minimum impact of drought.

The most noteworthy difference in the solutions is that deficit irrigation appears in the binary model's optimal solution, but not in the continuous model's. This is because the binary model constrains producers to make discrete decisions, specifically 35 acres at a time. The continuous model, in contrast, allows the producer to make continuous acreage decisions, which allows more flexible allocation of resources. A producer could choose in the continuous model, for example, to furrow irrigate 18.6 of their 350 acres. The equivalent choice in the binary model, in contrast, is to furrow irrigate 35 acres (1 field), or no acres. Suppose the producer chooses, in the binary model, to furrow irrigate 1 field. They might have to use deficit irrigation, in the event of drought, to compensate for the "extra" 16.4 acres of relatively inefficient furrow irrigation. The producer, in the continuous model, can apply a more efficient irrigation technology to the 16.4 acres, and possibly eliminate the need for deficit irrigation. Therefore, a modeler who uses a continuous variables model to represent a binary variables farm system might conclude erroneously that deficit irrigation is unnecessary.

The farm system being modeled should influence whether a binary or continuous variables model is used. Many farm landscapes are divided into discrete fields by windbreaks, streams, and roads. It is impractical, in some cases, to apply multiple crops or irrigation technologies to an individual field, or to change the size of a field, at least in the short-run. These producers are likely to choose one crop and irrigation technology per field. A binary variables model would best represent this decision environment. How closely a continuous variables model can approximate this is likely to decrease as field size increases (again, assuming the producer can choose only one crop and technology per field, regardless of field size).

For example, suppose a farmer has two 100-acre fields to which they can apply only one crop each. A binary variables model might suggest allocating one field to wheat, and the other to sugar beets. A continuous variables model might suggest allocating one-fifth of the acreage (0.4 fields) to corn, three-fifths (1.2 fields) to sugar beets, and one-fifth to wheat. While it would be clear from the continuous model's solution that the (more accurate) binary model would allocate at least one field to sugar beets, it would be less clear which crop it would allocate to the second field. The continuous model might also identify more than two irrigation technologies, making it unclear which technology a binary model would assign to each field. As a result of these tendencies, the continuous model might also misestimate profit outcomes. Smaller field sizes would likely reduce the difficulty of translating a continuous model's solution into a binary (field-by-field) solution.

In summary, it is unlikely that a continuous variables model will accurately represent the farm system being studied when taking scale characteristics such as field size into consideration. However, the availability of a solution algorithm that is capable of solving more complex binary models, as well as time limits, should also influence the choice of a continuous versus binary model.

6 Results and Discussion II: Applications of the Binary Model

Chapter 6 is the second of two chapters devoted to results and discussion. The binary variables version of the base case model is used in this chapter to explore several aspects of optimal drought preparedness and response given water supply uncertainty and inter-year dynamics. Readers are again reminded that "optimal" refers simply, in this dissertation, to activities that are included in the mathematical programming model's solution; it does not indicate that the activities are Pareto optimal or socially efficient. Section 6.1 explores the role of the interest and discount rates in the base case solution. Section 6.2 presents solutions to a certainty version of the model, which differentiates the impact of anticipated versus unanticipated drought. Section 6.3 discusses the importance of recognizing inter-year dynamics when estimating the impacts of drought on cropping activities and profit. Section 6.4 investigates the impact of previous crop history on the base case solution. Section 6.5 introduces price uncertainty into the model and explores its effects on optimal drought preparedness and response. Section 6.6 explores the usefulness of the multi-peril crop insurance program's prevented planting provision as a drought preparedness tool. Section 6.7 considers the impact of climate change on optimal drought preparedness and response, and the resulting profit impact. Specifically, the impacts of increases in the frequency of drought, severity of drought, and both frequency and severity of drought are considered.

6.1 The Role of Interest and Discount Rates

Agronomic constraints dictate that each field can be planted to onions only once in a six-year period to avoid disease; hence, a total of 10 fields can be planted to onions over the six-year planning horizon. The binary variables version of the base case solution prescribes planting seven of those ten fields to onions in the first year. This seems counter to the notion of diversification as a drought preparedness tool (Lomas 2000; Vlachos and James 1983; Yevjevich and Vlachos 1983) and to the approach taken by most onion producers in the study area. Onions are the primary source of profit in the study area; they require a $600 fall investment, and are among the most water-sensitive crops grown. A more intuitively appealing plan, from a drought preparedness perspective, would spread the ten fields of onions out over several years, and include drought-tolerant crops, such as wheat, in the suite of crops planted each year. This would reduce the likelihood of abandonment or deficit irrigation of onions during a water shortage. The objective of this section is to determine what drives the model's initially counterintuitive solution, or alternatively to determine what motivates producers in the study area to spread high-value crops throughout the planning horizon.

Positive interest and discount rates provide incentive to plant valuable crops first, primarily to generate as much profit as soon as possible. Interest on profit can thus be earned for a longer period, and the discounting of profit can be minimized. These incentives could be driving the specialization (as opposed to diversification) in year 1 of the base case solution. However, water supply uncertainty, and agronomic constraints that generate inter-year dynamics, also influence the solution. It is therefore not clear, based on intuition alone, whether specialization in year 1 of the base case solution is attributable to the discount and interest rates alone, or also to water supply uncertainty and inter-year dynamics. Sensitivity of the solution to alternative interest and discount rates is therefore tested.

The interest and discount rates are reduced from the base case values of 7 and 5%, respectively, to the extreme values of 0 and 0% to test their role in the base case solution. No onions are planted in the year 1 when the interest and discount rates are set equal to zero (figure 6.1). A few fields are planted to onions in years 2 and 3 (figures 6.2 and 6.3). Onions are planted, in fact, throughout the planning horizon in the absence of an interest or discount rate, in sharp contrast to the base case. Drought management does not appear to be the motivation for diversification in the absence of discount and interest rates, however. The motivation is the opportunity to shift crops through time to make use of a larger proportion of the total water allotment expected over six years, thereby increasing crop acreage and profit. Details of this opportunity are described next.

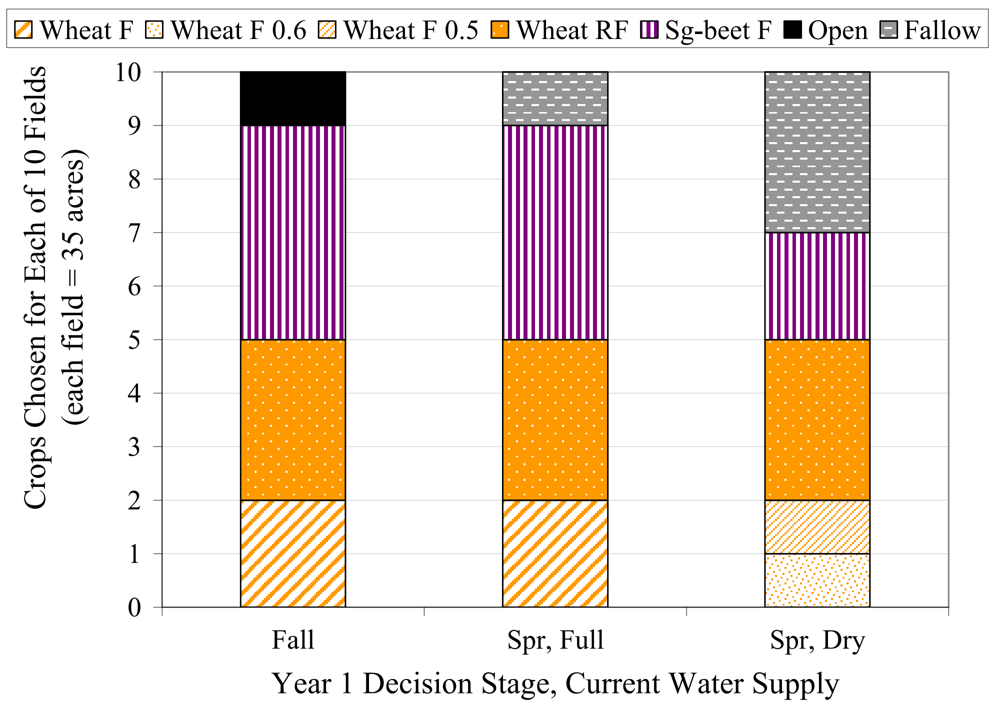


Figure 6.1. Optimal fall and spring activities in year 1 of the “zero interest and discount rates” case. Crop Key: F = furrow, RF = reuse furrow, 0.6 = 60% of crop’s irrigation requirement is provided, 0.5 = 50% provided.

Onions under drip irrigation require less water than many other crops. The base case crop plan, which allocates most fields to onions in year 1, leaves 2,800 acre-inches of the year 1 water allotment (in a full year) unused. This quantity of excess water is sufficient to supply 40 acre-inches to two additional fields. The producer in this model does not have access to additional fields, however, nor can they sell or store the excess water. The only means of using this water is to plant more water-intensive crops in year 1, and shift onion production into future years.

The benefit of increasing the proportion of the water allotment used is that more fields can be planted over the six-year planning horizon. The opportunity cost is the delay of onion profit. Cost exceeds benefit when discount and interest rates are positive, but not when discount and interest rates are zero. In the latter case, onion production is therefore shifted from year 1 to years 2 through 6, more water-intensive crops are shifted into year 1, and additional fields can be planted, in most scenarios, over the planning horizon.

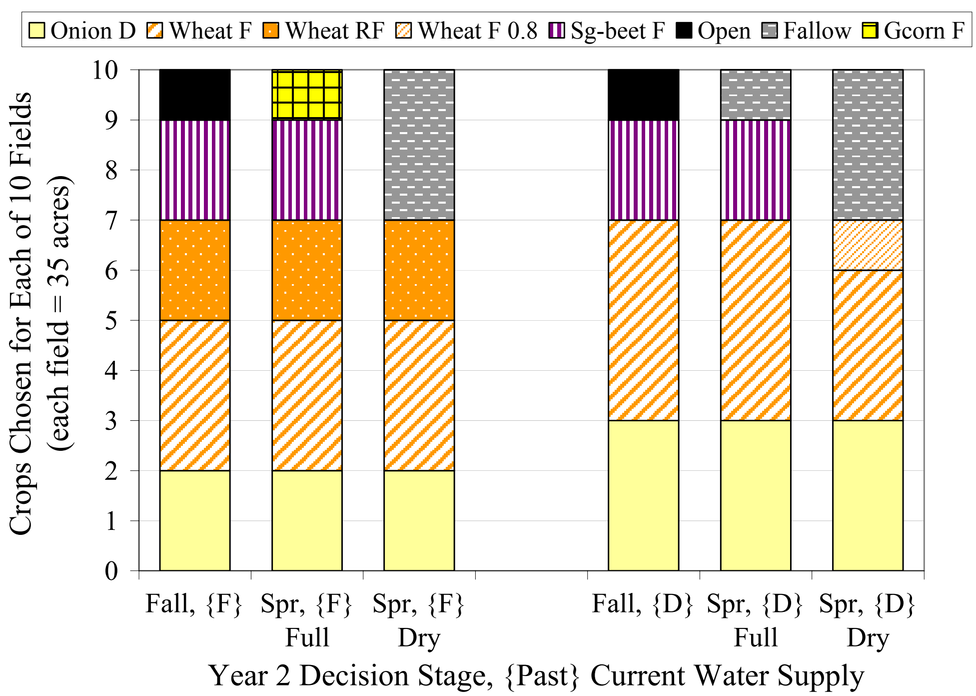


Figure 6.2. Optimal fall and spring activities in year 2 of the "zero interest and discount rates" case. Crop Key: F = furrow, RF = reuse furrow, D = drip, 0.8 = 80% of crop's irrigation requirement is provided.

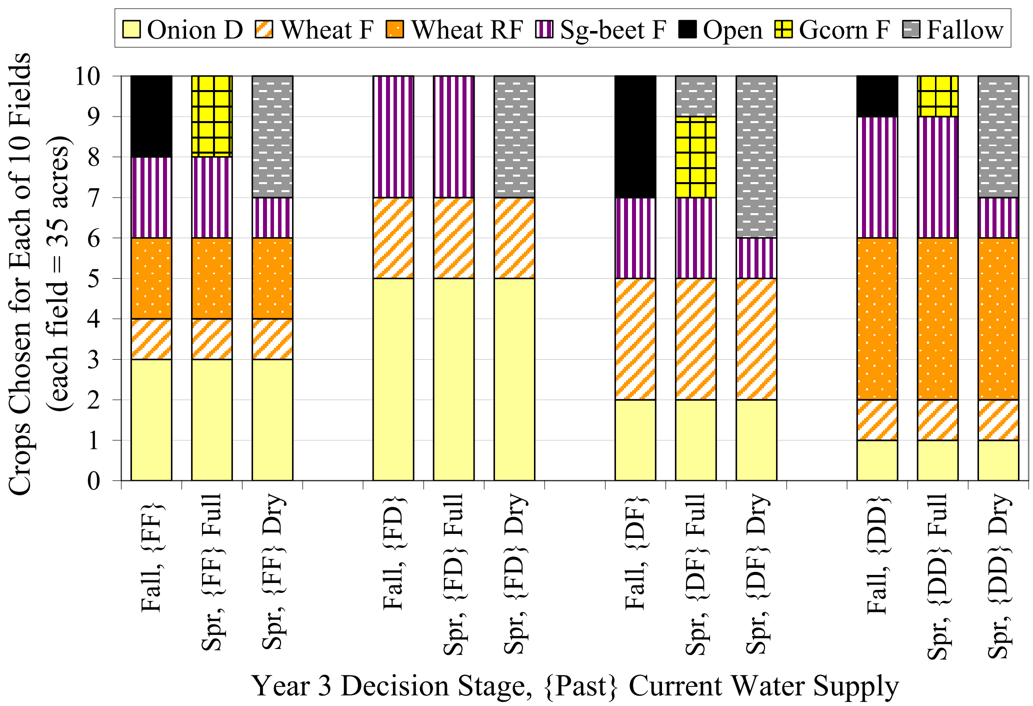


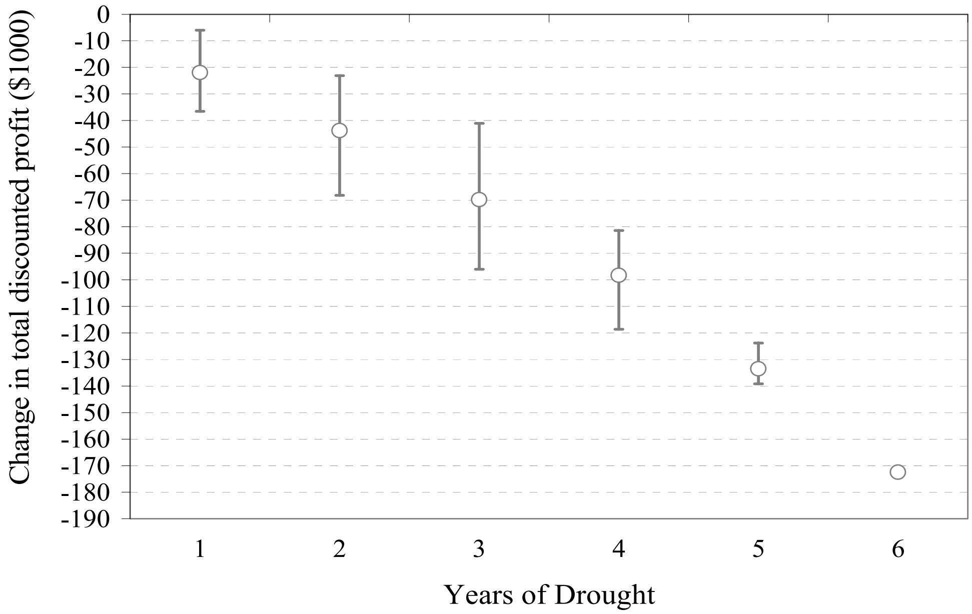
Figure 6.3. Optimal fall and spring activities in year 3 of the “zero interest and discount rates” case. Crop Key: F = furrow, RF = reuse furrow, D = drip.

A comparison of overall crop activities for the “zero rates” case versus the base case confirms that, in the absence of interest and discount rates, fall attempts of wheat and sugar beets increase. Additionally, for many water scenarios, more wheat and sugar beet fields are successful, i.e. fewer fall-planted fields are fallowed. The benefit of spreading onions over the planning horizon, in summary, is that more fields are planted, and more crops are successful. It appears, however, that the benefits of this strategy accrue mostly during full years. Shifting crops between years frees up additional water in all years. The model takes advantage by attempting more fall-prepared or planted crops. The additional water is sufficient in full years to allow for additional fields to be planted, but is insufficient in dry years. This leads to higher profits in full years, and higher expected net crop revenue overall, without an increase in profit variability.

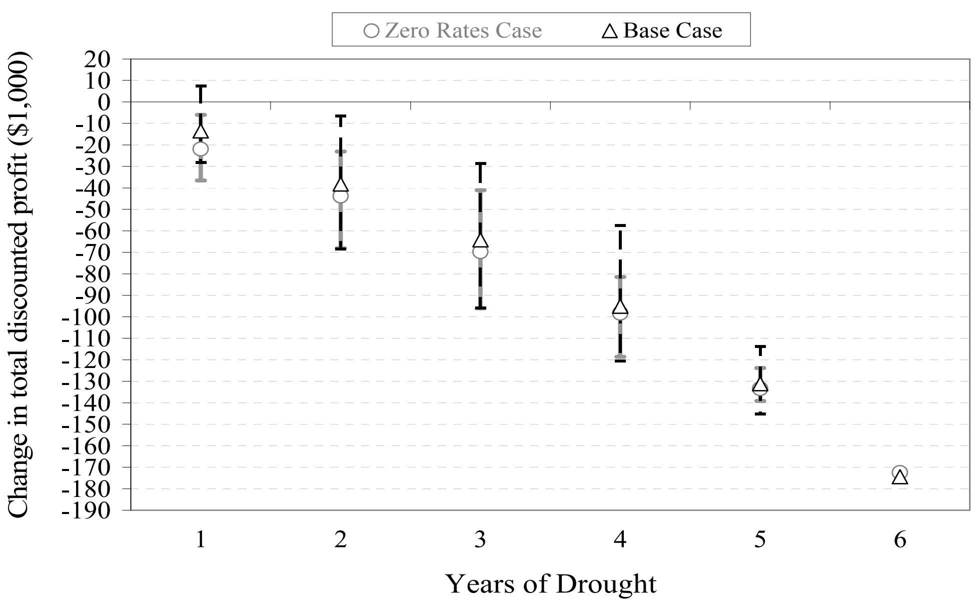
However, it also leads to reduced profits in some dry years (relative to the base case) because the additional prepared or planted fields have to be deficit irrigated or abandoned. Average profit losses associated with drought for the "zero rates" crop plan (figure 6.4a) are, therefore, slightly higher for some droughts than those for the base case crop plan (figure 6.4b).

The absence of interest and discount rates, in summary, decreases the benefit of specialization in the first year of the crop plan, or equivalently, decreases the cost of diversification (delayed profit). The benefit of diversification in year 1 is that more fields can be planted and grown successfully, particularly in full years, over a six-year period. Expected net crop revenue in the zero rates case is therefore higher (without an accompanying increase in profit variability) than the base case. Note, however, that diversification in the presence of positive discount and interest rates will not increase expected net crop revenue (otherwise the base case solution would recommend diversification). Surprisingly, diversification in year 1 does not lessen the average profit impact of drought, and actually increases it slightly for some droughts. Diversification is therefore not a form of drought preparedness for the conditions assumed in this model. The policy implication of this result is that extremely low interest and discount rates could induce producers to adopt crop plans that result in larger loss during some droughts.

These conclusions provide insight about some of the tradeoffs that producers under water supply uncertainty face when deciding whether to specialize or diversify within a production year. The tendency of producers in the study area to diversify, counter to the results found here, suggests the presence of equipment or labor constraints not captured in the model, or other sources of uncertainty (e.g. price) that make specialization too risky (the topic of section 6.5), other means to use excess water in year 1, more severe drought than what is defined here (the topic of section 6.7), or an erroneous compulsion to make full



(a)



(b)

Figure 6.4. (a) Average change in the "zero interest and discount rates" model's total discounted profit (gray circles) by years of drought experienced (as compared to 6 years of full water supply). Gray brackets indicate the maximum and minimum impact of drought. (b) A comparison of average change in total discounted profit for the "base case" (black triangles and brackets) versus "zero rates case" (gray circles and brackets).

use of their water allotment despite positive discount and interest rates. Risk aversion related to water supply uncertainty is not strongly implicated as the cause of producer's diversification behavior, since the standard deviation of discounted profit is nearly the same for the base case versus zero rates case solution ($36,100 versus $33,600).

As a final note, the above results highlight an interesting hypothetical link between instream flow issues and the effects of interest and discount rates on the crop plan. There is more excess-water during dry years than during full in the "zero rates" case, while this is rarely true in the base case. Again, this is attributable to the fact that the "zero rates" crop plan frees up additional water, which is then used in full years, but unused in dry years. Instream flows are often of critical concern during dry years. Extremely low or subsidized interest and discount rates could ease instream flow issues during dry years and increase them during full years. This result is highly sensitive, however, to increases in the interest rate. A 1% interest rate is sufficient to restore much of the base case solution, such that there is more excess water in full years than dry. Zero interest and discount rates are highly contrived, so this link likely has limited implications in practice. The notion that macroeconomic parameters can impact water use via crop rotation patterns is interesting, however, and perhaps worthy of additional research.

6.2 The Role of Uncertainty

Uncertainty about the timing and duration of drought exacerbates profit loss attributable to drought. A producer, who knows in advance when a drought will occur and how long it will persist, is able to prepare perfectly for the event. This does not imply that the drought will generate no loss. A water shortage, even when anticipated, is likely to reduce profit, because fewer crops can be grown. The cost of uncertainty for a particular scenario can be estimated by comparing profit in the stochastic model to that in the deterministic model (section 4.5.1).

The deterministic model assumes that the water supplies for all six years of the planning horizon are known in the fall of year 1. This is an extreme assumption, but provides insights about the impacts of uncertainty. A few scenarios are presented next to illustrate how optimal drought preparedness and response under certainty differs from that under uncertainty.

The first scenario analyzed is [Full Full Full Full Full Full]. The objective is to determine how certainty changes the crop plan and profit outcomes (compared to the base case crop plan under uncertainty). A producer who knows in the fall of year 1 that water allotments in the next six years will be full is able to change the crop plan, such that additional fields of more valuable fall-prepared or planted crops can be grown, rather than less-valuable spring-prepared and planted crops or fallowing. Specifically, two additional fields each of sugar beets and wheat are substituted for three fields of grain corn and one field of fallow (table 6.1). Discounted profit under certainty therefore exceeds that under uncertainty by $24,568 (a 4% increase).

The producer is able to increase the number of successful fields not only because a full water supply is guaranteed, but also because they shift the timing of crops across the planning horizon (figure 6.5) to more fully utilize the certain water supply each year. Table 6.2 shows that excess water is both smaller and less variable under certainty than under uncertainty. The primary shift in the timing of crops is that onions are spread over three years, rather than two, and additional sugar beets, which are more water-intensive, are planted in year 1. A tradeoff exists, however, between the benefit and cost of retiming crops. The benefit is an extra field of sugar beets or wheat, but the cost is the delay of profit from onions. The benefit outweighs the cost for this particular water supply scenario under certainty, but it may not for all scenarios, and it does not under uncertainty.

Table 6.1. Number of fields successfully planted to various crops in scenario [Full Full Full Full Full Full] under certainty and uncertainty.

			# Successful Fields	
Crop	**Irrig**	**Deficit**	**Cert**	**Uncert**
Onion	Drip	D1	10	10
Sugbeet	Furrow	D1	13	11
Wheat	Furrow	D1	22	19
Wheat	Reusefrw	D1	5	6
Gcorn	Furrow	D1	6	8
Gcorn	Reusefrw	D1	0	1
Fallow	Furrow	D7	4	5
			60	60

Table 6.2. Excess water (i.e. the quantity of water remaining after crop water requirements are met) by year for scenario [Full Full Full Full Full Full] under uncertainty and certainty.

	Excess Water (acre-inches)						
	Yr1	**Yr2**	**Yr3**	**Yr4**	**Yr5**	**Yr6**	**Total**
Uncertainty	2,801	1,241	54	54	302	451	4,903
Certainty	4	969	27	161	213	292	1,666

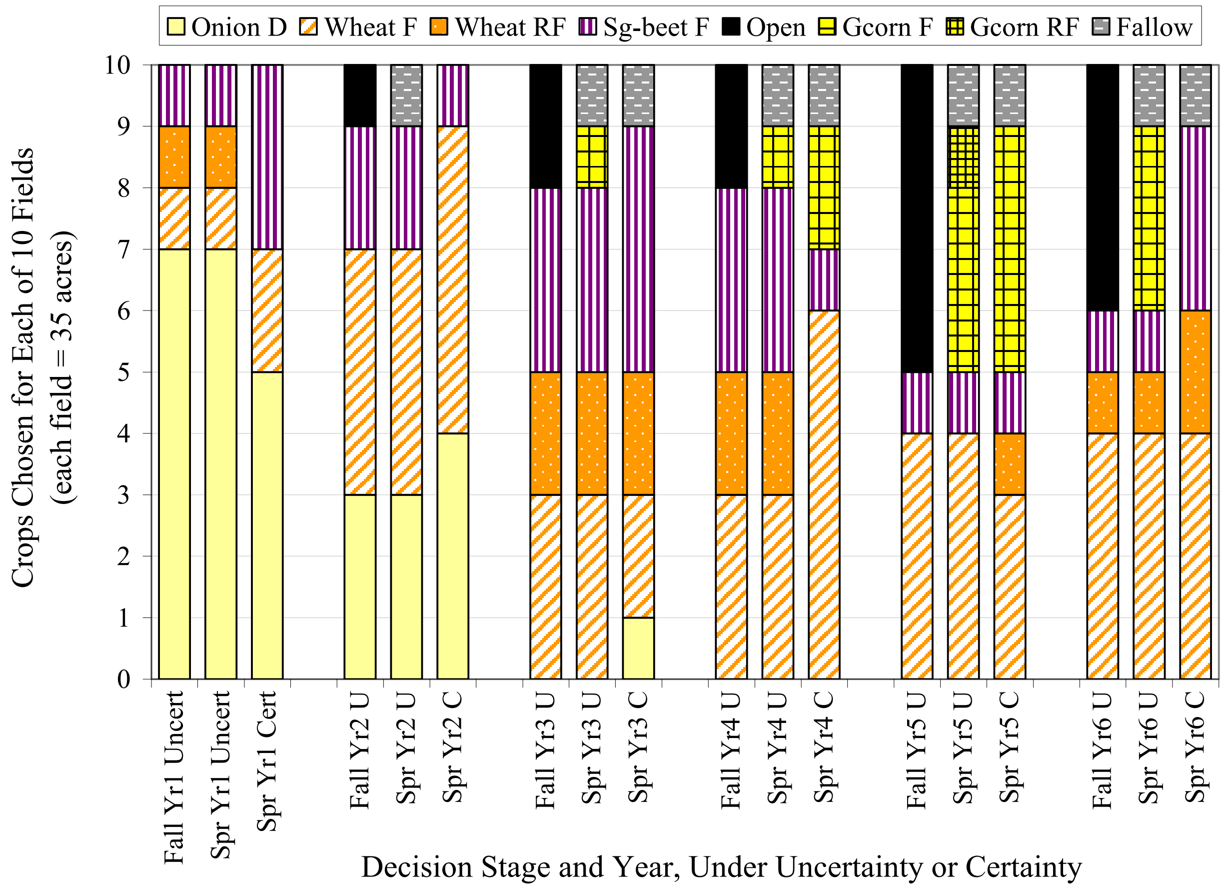


Figure 6.5. Cropping impacts of water supply certainty for scenario [Full Full Full Full Full Full]. A stage-by-stage comparison of activities under uncertainty and certainty. Crop Key: F = furrow, RF = reuse furrow, D = drip.

The next scenario analyzed is [Dry Dry Dry Dry Dry Dry]. A producer who knows in the fall of year 1 that the next six years will be dry is able to change the crop plan (from the base case crop plan under uncertainty), such that one additional field of wheat is fully irrigated, and two additional fields of wheat are substituted for one field each of sugar beet and fallow (table 6.3). Discounted profit for this scenario under certainty exceeds that under uncertainty by $109,824 (a 27% increase). However, six years of perfectly anticipated drought still reduces profit by $89,173 (15%), compared to six years of perfectly anticipated full water allotments. This is a drastic improvement, however, over the profit impact of six years of unanticipated drought, which reduces profit by $174,430 (30%).

Compared to the uncertainty case, additional fields are planted in this scenario under certainty. However, the large disparity in profit under certainty versus uncertainty is largely attributable to the number of attempted versus successful fields under certainty versus uncertainty (table 6.3). Under uncertainty, only five of seventeen attempted sugar beet fields are successful, and twenty-five of twenty-six wheat fields are successful, with one field severely deficit irrigated (table 6.3). In contrast, under certainty, all four attempted sugar beet fields are successful, and all twenty-seven attempted wheat fields are successful with less severe deficit irrigation. No fields are abandoned under certainty. The producer knows in the fall that the upcoming growing season will be dry, and therefore attempts exactly the quantity that can be supported.

The retiming of crops does not play a role in the adjusted crop plan for six dry years, as it did for six full years. All fields in the former scenario are planted to onions within the first two years of the planning horizon (figure 6.6), even though the producer knows in advance that six years of drought will occur. This provides additional evidence that diversification within a year is not an optimal drought preparedness strategy. The lack of diversification in scenario [Dry Dry Dry Dry Dry Dry] is because the annual water allotment is sufficiently small that

Table 6.3. Number of fields attempted and successfully planted to various crops in scenario [Dry Dry Dry Dry Dry Dry] under certainty and uncertainty.

			# Fields Attempted	
Crop	**Irrig**	**Deficit**	**Cert**	**Uncert**
Onion	Drip	D1	10	10
Sugbeet	Furrow	D1	4	17
Wheat	Furrow	D1	12	15
Wheat	Furrow	D2	2	0
Wheat	Reusefrw	D1	13	11
			41	53
			# Successful Fields	
Crop	**Irrig**	**Deficit**	**Cert**	**Uncert**
Onion	Drip	D1	10	10
Sugbeet	Furrow	D1	4	5
Wheat	Furrow	D1	12	11
Wheat	Furrow	D2	2	2
Wheat	Furrow	D6	0	1
Wheat	Reusefrw	D1	13	11
Fallow	Furrow	D7	19	20
			60	60

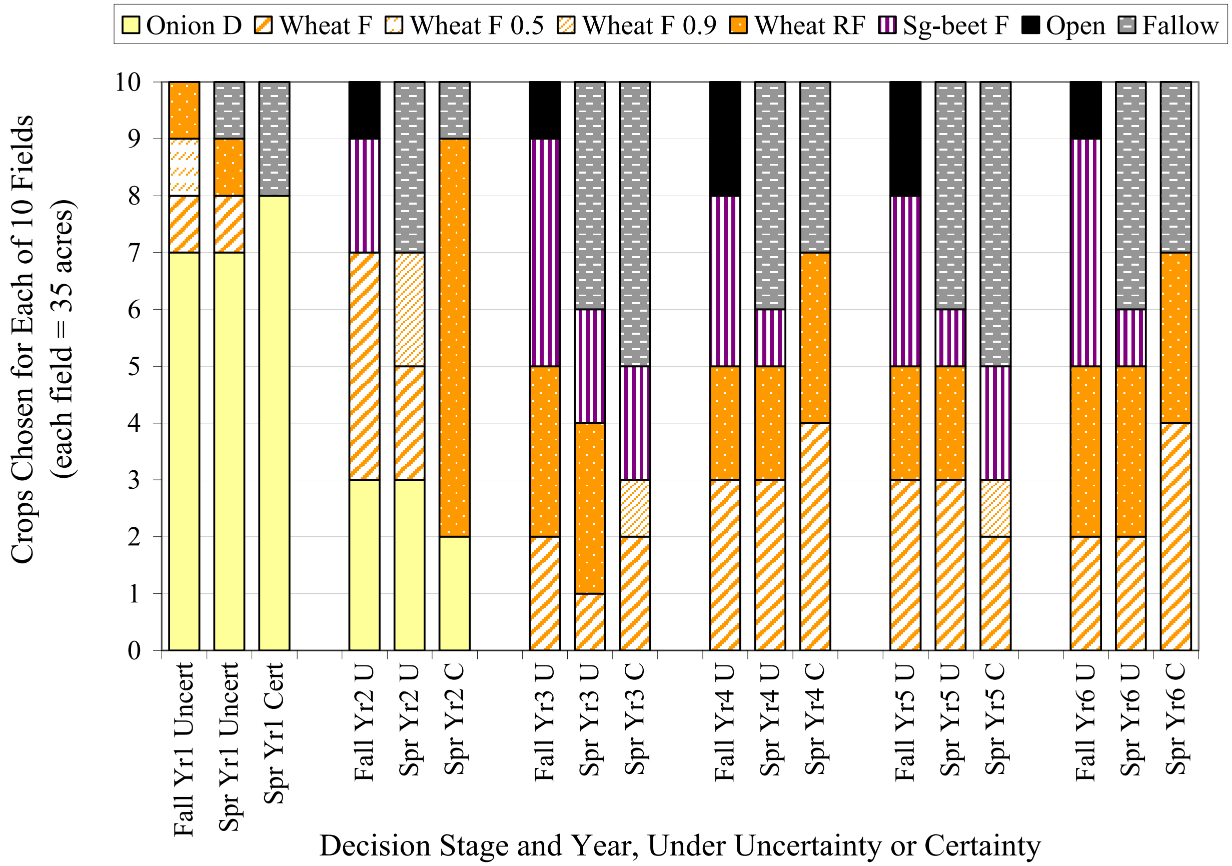


Figure 6.6. Cropping impacts of water supply certainty for scenario [Dry Dry Dry Dry Dry Dry]. A stage-by-stage comparison of activities under uncertainty and certainty. Crop Key: F = furrow, RF = reuse furrow, D = drip, 0.5 = 50% of crop's irrigation requirement is provided, 0.9 = 90% provided.

water conserved by the retiming of onions would be insufficient to support additional fields (table 6.4). The benefit of spreading onions across the planning horizon is therefore smaller than the opportunity cost. In summary, the primary effect of unanticipated versus anticipated drought is that more fall-prepared fields are abandoned; particularly, those prepared for water-intensive sugar beets. This result is relevant to the discussion of the impact of climate change in section 6.5, and to the discussion of participation in the multi-peril crop insurance program in section 6.6.

Table 6.4. Excess water (i.e. the quantity of water remaining after crop water requirements are met) by year for scenario [Dry Dry Dry Dry Dry Dry] under uncertainty and certainty.

	Excess Water (acre-inches)						
	Yr1	**Yr2**	**Yr3**	**Yr4**	**Yr5**	**Yr6**	***Total***
Uncertainty	12	137	141	313	313	841	*1,757*
Certainty	622	300	106	134	106	134	*1,401*

One final observation regarding drought under certainty versus uncertainty is that the expected value of a perfect six-year water supply forecast can be calculated by solving the deterministic model for all sixty-four water supply scenarios, taking the difference between profit under certainty and uncertainty, and weighting those differences by the probability of each scenario. There is no anticipated ability to predict water supplies that far in advance, so this exercise was not undertaken. The value of a perfect fall forecast for only the upcoming spring's water supply is more useful, but also more difficult to estimate. The model would have to be modified to allow for perfect information for the current year, but only probabilistic information for the remaining years of the planning horizon. Due to time constraints, this was not pursued. However, there is no shortage of literature providing estimates of the value of water supply forecasts (Adams et al. 1995; Adams et al. 2003; Johnson and Holt 1997; Mjelde and

Cochran 1988; Mjelde, Hill, and Griffiths 1998; Mjelde et al. 1988; Solow et al. 1998; Wyse 2004).

6.3 The Role of Inter-year Dynamics

Inter-year dynamics are an important characteristic of many farm systems, including row crop farms in the study area; yet, they receive limited attention in the economics literature (Antle 1983). The effects of inter-year dynamics on drought preparedness and response and the profit impacts of drought are relatively unexplored. Equations 14 through 21, and 27 through 29 of the binary variables model (section 4.3) represent agronomic constraints that connect current cropping decisions to those in past years. Producers indicate that such inter-year dynamics sometimes result in the persistence of drought's effects, well after the drought subsides. The base case solution is therefore examined for evidence of this persistence.

The set of inter-year agronomic constraints influence the optimal solution in two ways. They necessitate careful sequencing of crops across space and time, to maximize profit, which is partly a function of the number of fields of crops that can be grown over the planning horizon. If crops are not carefully sequenced, fallow has to be used to break up infeasible crop sequences (e.g. wheat-fallow-wheat), and profit opportunities are lost. Inter-year dynamics also require careful sequencing of crops to manage total water requirements in each year. Suppose that the sequence of crops that maximizes the number of profitable fields has total crop water requirements that can only be met with the use of highly efficient (and thus more costly) irrigation technologies. It might be more profitable to reduce the total number of fields planted over the planning horizon, such that the total crop water requirement is reduced and less costly irrigation technologies can be used. Inter-year crop dynamics, in summary, require the producer to consider the impact of current decisions on future opportunities.

In the presence of inter-year crop dynamics, drought and the producer's drought response can generate impacts not only in the years in which the drought occurs, but in subsequent years as well. Clawson et al. (1980) expressed the following:

> Much of the discussion about the economics of drought management seems to be concerned, often implicitly, with what to do when drought strikes and when it continues. It seems sometimes to be assumed, when the rains finally come, that the drought has ended and that all is well. The need for help may still exist, even when the drought is over in an agricultural sense. Moreover, the form of the recovery from one drought may greatly affect the flexibility of the persons to deal with the inevitable next drought.

If this is true, then studies that ignore inter-year dynamics, or limit the timeframe of their analyses to the years in which drought occurs are likely to misunderstand drought's full impact, or worse, to recommend drought preparedness and response plans that fail to consider what the producer will do after the drought is over. The base case solution provides an opportunity to ask whether drought and drought response, in the presence of inter-year dynamics, generates effects in subsequent years.

6.3.1 Single-Year Drought

The following water supply scenarios are compared first to determine whether a year 2 drought affects cropping activities and profit after the drought subsides: (a) [Full Dry Full Full Full Full] and (b) [Full Full Full Full Full Full]. Response to a year 2 drought includes fallowing two fields that were prepared in the fall for sugar beets, and deficit irrigating two wheat fields (figure 6.7). Net revenue in year 2 is $25,641 less than if no drought occurs (table 6.5). Changes in both total revenue and total cost occur. Total revenue decreases because sugar beets that are not planted cannot be sold, and because yield in the deficit irrigated wheat fields is less than if fully irrigated. Total cost decreases because spring planting costs for sugar beets are not incurred. The impact of drought in the year in which it occurs is straightforward. Considered next is whether inter-year crop dynamics generate impacts in years subsequent to the drought.

Differences in the two scenarios' profit and cropping activities subsequent to the drought would indicate that the impacts of drought are not isolated to the year in which it occurs. The two scenarios' profits in years subsequent to the drought are, in fact, not equal (table 6.5). One might expect profit following the drought to be lower in scenario (a) than in scenario (b) because less profit in year 2 implies less earned interest in subsequent years. Scenario (a)'s profit is indeed lower in year 6, and the subsequent six years, which capture terminal values. Profit in years 3 through 5, however, is higher for scenario (a). This is because drought affects profit in subsequent years not just through reductions in earned interest, but also through changes in cropping activities.

The two scenarios' cropping activities differ in years subsequent to the drought (figures 6.7 and 6.8). Drought's role in these differences is clear for years 3 and 4. The producer, having abandoned two sugar beet fields during the year 2 drought, reattempts those fields in subsequent years. Specifically, sugar beet production is increased from three to four fields in both years 3 and 4 (note: scenario (b)'s activities serve as the reference point). This requires them, however, to adjust other cropping activities as well, because water is insufficient, ceteris paribus, to support an extra field of sugar beets. Adjustments include removing grain corn from the crop plan in years 3 and 4 to accommodate sugar beets, and using reuse furrow on one additional field of wheat. The above adjustments to the crop plan in response to drought result in higher profit in years 3 and 4 than in scenario (b) (table 6.5). Profit lost in year 2 is therefore partially recaptured in years 3 and 4. An economic analysis that focuses on activities during the year of drought alone will fail to capture this post-drought rebound.

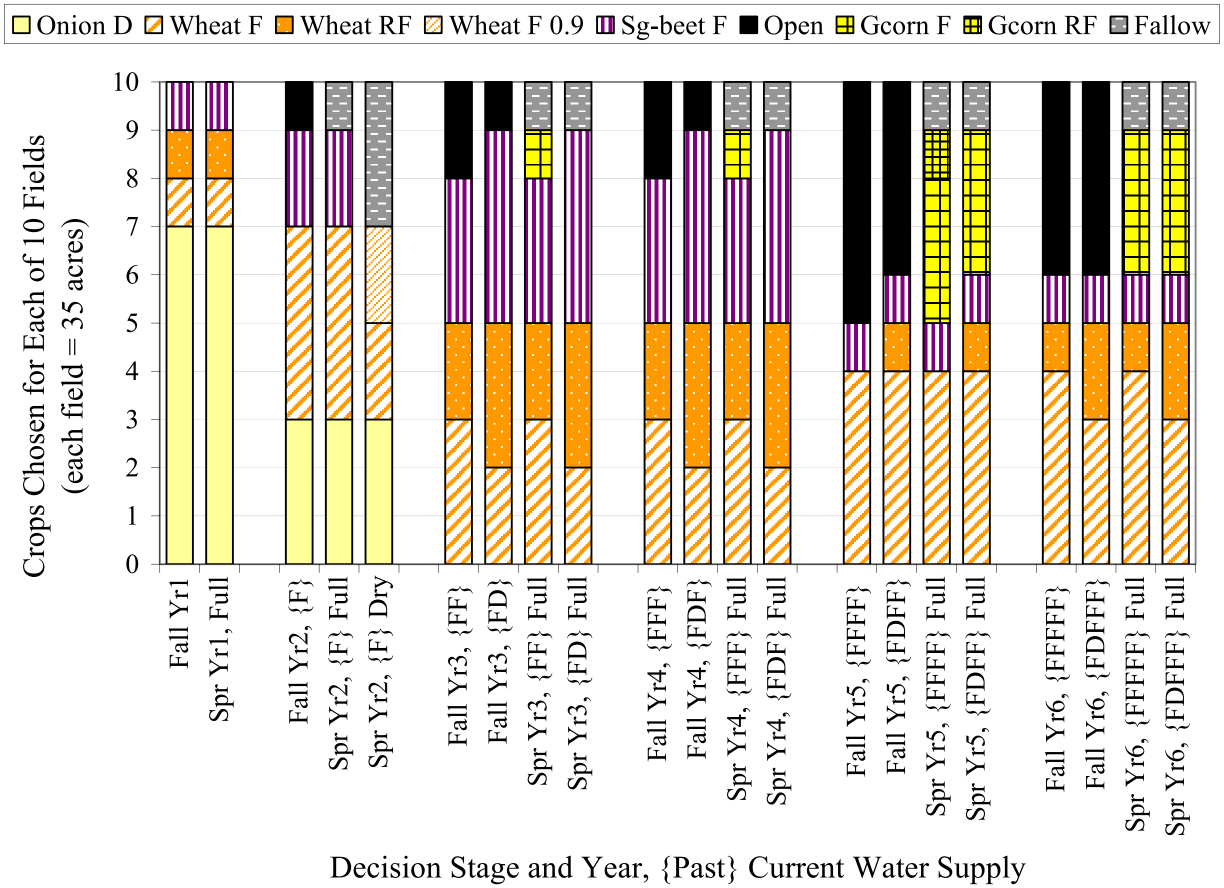


Figure 6.7. Cropping impacts of a year 2 drought. A stage-by-stage comparison of optimal cropping activities for scenarios [Full Full Full Full Full Full] and [Full Dry Full Full Full Full] of the base case. Crop Key: F = furrow, RF = reuse furrow, D = drip, 0.9 = 90% of crop's irrigation requirement is provided.

Table 6.5. Impact of a year 2 drought on undiscounted profit. A year-by-year comparison of undiscounted profit for scenarios (a) [Full Dry Full Full Full Full] and (b) [Full Full Full Full Full Full] of the base case optimal solution.

	Undiscounted Profit ($)												
	6-Year Period of Active Production						6-Year Period of Terminal Values						
Scenario	**Yr1**	**Yr2**	**Yr3**	**Yr4**	**Yr5**	**Yr6**	**Yr7**	**Yr8**	**Yr9**	**Yr10**	**Yr11**	**Yr12**	***Total***
(a)	74,121	26,257	32,727	35,018	22,946	23,054	160,052	108,683	69,362	74,217	79,413	84,972	*790,823*
(b)	74,121	51,898	30,180	32,293	19,885	25,764	161,453	110,183	70,966	75,934	81,249	86,937	*820,863*
(a)-(b)	0	-25,641	2,547	2,725	3,061	-2,710	-1,401	-1,499	-1,604	-1,717	-1,837	-1,965	*-30,040*

Table 6.6. Impact of a year 3 drought on undiscounted profit. A year-by-year comparison of undiscounted profit for scenarios (b) [Full Full Full Full Full Full] and (c) [Full Full Dry Full Full Full] of the base case optimal solution.

	Undiscounted Profit ($)												
	6-Year Period of Active Production						6-Year Period of Terminal Values						
Scenario	**Yr1**	**Yr2**	**Yr3**	**Yr4**	**Yr5**	**Yr6**	**Yr7**	**Yr8**	**Yr9**	**Yr10**	**Yr11**	**Yr12**	***Total***
(c)	74,121	51,898	6,820	25,102	32,415	28,844	160,407	109,064	69,769	74,653	79,878	85,470	*798,439*
(b)	74,121	51,898	30,180	32,293	19,885	25,764	161,453	110,183	70,966	75,934	81,249	86,937	*820,863*
(c)-(b)	0	0	-23,361	-7,191	12,530	3,080	-1,046	-1,119	-1,198	-1,281	-1,371	-1,467	*-22,424*

(i)

Year 1 [Full]				
O	O	SB	F	W
O	W	O	O	O

Year 2 [Full]				
F	W	O	SB	O
W	O	SB	W	W

Year 3 [Full]				
W	GC	W	W	W
SB	W	F	SB	SB

Year 4 [Full]				
SB	W	GC	F	SB
W	SB	W	W	W

Year 5 [Full]				
W	SB	W	W	GC
F	W	GC	GC	GC

Year 6 [Full]				
GC	W	SB	F	W
W	GC	W	GC	W

(ii)

Year 1 [Full]				
O	O	SB	F	W
O	W	O	O	O

Year 2 [Dry]				
F	W	O	**F**	O
W	O	**F**	W	W

Year 3 [Full]				
W	**SB**	W	W	**SB**
SB	W	**W**	**F**	SB

Year 4 [Full]				
SB	W	**F**	**SB**	**W**
W	SB	**SB**	W	W

Year 5 [Full]				
W	**F**	W	W	GC
GC	W	**W**	**SB**	GC

Year 6 [Full]				
GC	W	SB	**GC**	W
W	GC	**F**	**W**	W

Figure 6.8. Crops assigned to each field (first row of each box reads from left to right, F1 to F5; second row reads from left to right, F6 to F10) in each year of the six-year planning horizon. Boxes on the left (column (i)) are for scenario (b) [Full Full Full Full Full Full]; boxes on the right (column (ii)) are for scenario (a) [Full Dry Full Full Full Full]. Key: O=onion, SB=sugar beet, W=wheat, GC=grain corn, F=fallow. Bold letters in column (ii) indicate fields whose crops differ from those in column (i).

The producer's ability to rebound from drought by re-planting an abandoned crop is possible because of the agronomic constraints, which prevent producers from continuously growing an individual crop. Suppose instead that the producer could continuously plant an individual crop without risk of pest, disease, or depleted soil quality. If the producer was forced to abandon the crop in year t, they could not replant in subsequent years without displacing the current year's crop. The producer in the base case model, in contrast, can replant an abandoned field of sugar beets, for example, without displacing next year's sugar beet crop because the field is eligible for sugar beets only once every five years. Future sugar beet crops in that field are delayed; however, the farm's total sugar beet acreage over the six-year crop plan is not reduced.

Although some profit is recovered after the drought by replanting crops in later years, the portion that is not recovered causes reductions in earned interest, and these reductions compound through time. Eleven years after the drought, losses attributable to drought total $30,040, a 17% increase from their initial value of $25,641. This contrasts to losses just five years after the drought, which total $20,018, a 22% decrease from profit loss during the drought. Reductions in earned interest more than offset the preliminary recovery of losses via replanting. This result changes, however, when discounting is considered. The total loss of discounted profit eleven years after the drought is $24,700, which is very close to the initial loss of $25,641. Nonetheless, studies that only examine drought's immediate crop and profit impacts might misestimate total impacts and misinterpret subsequent crop choices.

There are additional differences in the crop plans of scenario (a) and (b). However, not all differences are caused by the year 2 drought. Specifically, crops in fields F5, F8 and F9 of year 3 are different in the two scenarios (figure 6.8), but not because of drought. The crops allocated to these fields in column (ii) allow the producer to grow an additional successful field of wheat in year 5. However, the same crop plan for these three fields could also be followed in scenario (b). The approximate optimal solution simply did not detect the opportunity to increase undiscounted profit by $4,500. This implies that undiscounted profit in year 5 should be similar for the two scenarios (table 6.5), and total profit loss attributable to drought is actually higher than $30,040.

It is more difficult to determine whether the drought in year 2 causes the differences in cropping activities for years 5 and 6. Close inspection of figure 6.8 reveals, however, that some of the differences in year 5 activities can be traced back to the drought. In year 5, sugar beets are planted in field F9 in column (ii), rather than in F2 as in column (i). This has no effect on profit in year 5, but illustrates that drought can generate impacts several years after it subsides. Sugar beets' location on the farm is altered in year 5 because F9 is the only field that remains eligible. Field F2, which was the planned location prior to the drought, was planted to sugar beets in year 3, in an effort to recover one of the fields of beets abandoned in year 2. The remaining crop differences in year 5 and 6, however, including the extra field of wheat in year 5 of column (ii), are attributable to the approximate nature of the optimal solution, as discussed above. Sufficient evidence exists to conclude that drought in year 2, or more precisely, the producer's response to the drought, generates impacts not only during the year in which drought occurs, but also in subsequent years.

6.3.2 Multi-Year Drought

The inter-year dynamics of the model also enable the study of multi-year or prolonged drought, a topic that has received relatively little attention in the literature (Iglesias, Garrido, and Gomez-Ramos 2003; Tapp et al. 1998; Thompson et al. 1996; Toft and O'Hanlon 1979; Ward et al. 2001). The potential for the impacts of one year of drought to modify the impacts of a subsequent year of drought is of particular interest (Clawson et al. 1980). Consecutive years of drought have the potential, because of inter-year crop dynamics, to generate complex impacts on cropping activities and profit. A comparison of the following four scenarios is made to understand the potential impacts of a two-year drought occurring in years 2 and 3: (a) [Full Dry Full Full Full Full], (b) [Full Full Full Full Full Full], (c) [Full Full Dry Full Full Full], and (d) [Full Dry Dry Full Full Full].

A year 2 drought generates a loss of $30,040 in undiscounted profit (table 6.5). A year 3 drought generates a loss of $22,424 (table 6.6). If the impacts of these droughts were isolated within the year in which they occurred, two outcomes would be expected: 1) the profit impact of a two-year drought that occurs in years 2 and 3 should be approximately equal to the sum of the individual droughts' impacts ($52,464), and 2) the losses attributable to a year 3 drought should be the same regardless of whether it preceded by a dry or full year. The result, however, is that a two year drought generates a loss of $85,737 (table 6.7), which is much larger than the hypothesized loss of $52,464. Also, the impact of a year 3 drought is $55,697 when preceded by a year 2 drought (table 6.8), and only $22,424 when not preceded by drought (table 6.6). These two results indicate that the impact of a year 3 drought depends on whether it was preceded by drought, or equivalently, that the impact of a year 2 drought depends on whether a drought is revealed in year 3. The results suggest, more generally, that the impact of a multi-year drought is more complex than the sum of its parts. This result also reinforces the previous subsection's conclusion, i.e. that the impact of drought in a farm system that has inter-year dynamics can continue after the drought subsides.

The impact of a year 3 drought is larger when preceded by a year 2 drought than when not because of the response to the year 2 drought. Specifically, the producer attempts to recover from the year 2 drought by preparing four fields for sugar beets in the fall of year 3, rather than three fields (figure 6.7). When drought is revealed in the spring of year 3, the producer has to abandon three fields, rather than two (figure 6.9). Investments in fall field preparation are sunk, so the producer receives no return on a fall-prepared field that is later abandoned.

Table 6.7. Impact of a two-year drought (years 2 and 3) on undiscounted profit. A year-by-year comparison of undiscounted profit for scenarios (b) [Full Full Full Full Full Full] and (d) [Full Dry Dry Full Full Full] of the base case optimal solution.

	Undiscounted Profit ($)												
	Period of Active Production						Period to Capture Terminal Values						
Scenario	**Yr1**	**Yr2**	**Yr3**	**Yr4**	**Yr5**	**Yr6**	**Yr7**	**Yr8**	**Yr9**	**Yr10**	**Yr11**	**Yr12**	***Total***
(d)	74,121	26,257	-2,091	26,596	30,101	22,026	157,454	105,904	66,388	71,035	76,007	81,328	*735,126*
(b)	74,121	51,898	30,180	32,293	19,885	25,764	161,453	110,183	70,966	75,934	81,249	86,937	*820,863*
(d)-(b)	0	-25,641	-32,271	-5,697	10,216	-3,738	-3,999	-4,279	-4,579	-4,899	-5,242	-5,609	*-85,737*

Table 6.8. Impact on undiscounted profit of a year 3 drought when preceded by a year 2 drought. A year-by-year comparison of undiscounted profit for scenarios (a) [Full Dry Full Full Full Full] and (d) [Full Dry Dry Full Full Full] of the base case optimal solution.

	Undiscounted Profit ($)												
	Period of Active Production						Period to Capture Terminal Values						
Scenario	**Yr1**	**Yr2**	**Yr3**	**Yr4**	**Yr5**	**Yr6**	**Yr7**	**Yr8**	**Yr9**	**Yr10**	**Yr11**	**Yr12**	***Total***
(d)	74,121	26,257	-2,091	26,596	30,101	22,026	157,454	105,904	66,388	71,035	76,007	81,328	*735,126*
(a)	74,121	26,257	32,727	35,018	22,946	23,054	160,052	108,683	69,362	74,217	79,413	84,972	*790,823*
(d)-(a)	0	0	-34,818	-8,422	7,155	-1,028	-2,598	-2,780	-2,974	-3,183	-3,405	-3,644	*-55,697*

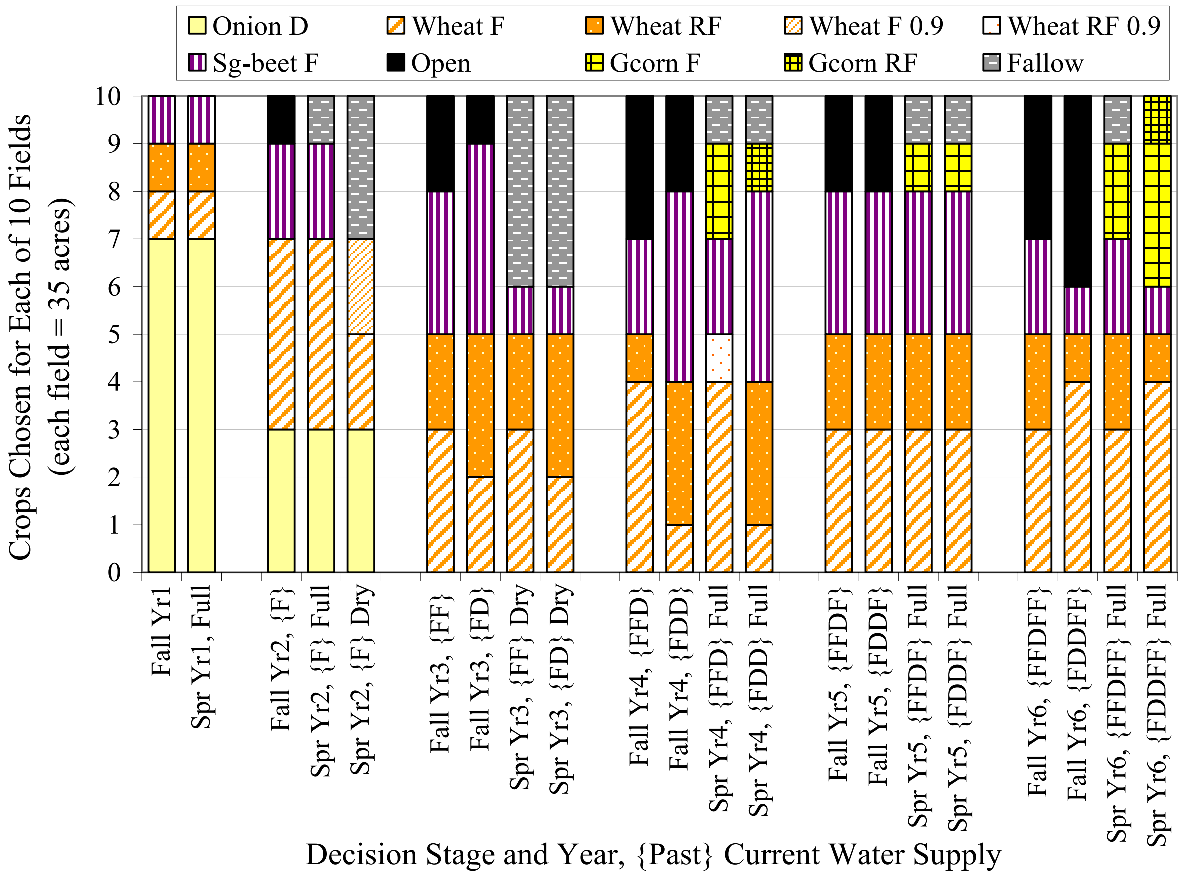


Figure 6.9. Cropping impacts of a year 3 drought when preceded by a full versus dry year 2. A stage-by-stage comparison of activities for scenarios [Full Full Dry Full Full Full] and [Full Dry Dry Full Full Full] of the base case. Crop Key: F = furrow, RF = reuse furrow, D = drip, 0.9 = 90% of crop's irrigation requirement is provided.

Fifteen sugar beet fields are attempted in scenario (d), but only ten are successful. This contrasts to eleven attempts and successes in scenario (b). Similarly, only five fields are planted to grain corn in scenario (d) versus nine in scenario (b).

Following the second year of drought, the producer's approach to recovery is the same. They attempt four sugar beet fields in year 4, and thus face the same risk of abandoning more fields of sugar beets in the event of a dry spring. The producer, in scenario [Full Dry Dry Dry Full Full], would attempt sugar beets in eighteen fields, with only nine successes. In scenario [Full Dry Dry Dry Dry Dry], sugar beets would be attempted in eighteen fields, with only seven successes. Only one field of grain corn is grown in each of these scenarios, in contrast to nine in scenario (b). The cropping and profit impacts of an unanticipated multi-yeardrought are complex; specifically, they are more than just a scaled version of a single-year drought's impacts.

The above results have important implications for government assistance in the event of drought. Suppose a government official asks a producer, after enduring one year of drought, to report profit impacts of the drought. A producer in the study area should answer, "I don't know yet." The total impact of a drought will depend on water supplies in subsequent years. The producer will initially recover some of their loss if they receive a full allotment next year. In contrast, their loss will be larger if next year is also dry.

6.4 The Role of Crop History

The base case solution for the binary variables model assumes no crop history prior to the first year of production. Fields are assumed to have had no crops on them in the previous six years that would limit the producer's planting options in the next six years. The producer can therefore consider any crop plan as long as it meets the agronomic constraints defined for years 1 through 6. Producers, in reality, have a crop history, one that potentially limits their ability to follow the base case optimal solution. It is therefore useful to consider the degree to which the optimal drought preparedness and response tools identified in section 5.1 can be transferred to farms that have crop history. An infinite number of crop histories are possible in reality; this section illustrates the impact of only one example crop history on the producer's optimal drought preparedness and response plan. This example is hereafter referred to as the "history" model.

The crop history used in this example (table 6.9) approximates the crop history of a row crop producer in the study area during the period 1997 to 2002. Crops that do not appear in the base case optimal solution appear in the crop history, including potatoes, alfalfa and silage corn. The producer, after whom the history was modeled, has a livestock enterprise in addition to the crop enterprise. Some of the crops are used as an input to the livestock enterprise, which might justify their appearance in the crop history, but not in the base case solution. Potatoes are not an input to livestock in this case, but a favorable contract with the local processor could have caused them to enter the producer's plan.

Table 6.9. Crop history used in the "history" model. Year 1 of the historic period occurred six years prior to the current planning period. Year 6 of the historic period occurred one year prior to the current planning period.

	Year in the Historic Period					
	1	**2**	**3**	**4**	**5**	**6**
Crop	*(# of fields)*					
Onion	1	2	2	2	1	2
Winter Wheat	3	2	2	2	2	1
Russet Potato	1	1	1	1	1	1
Sugar Beet	2	2	1	1	2	3
Alfalfa-1 yr old	1			1	1	
Alfalfa-2 yrs old	1	1			1	1
Alfalfa-3 yrs old		1	1			1
Alfalfa-4 yrs old			1	1		
Grain Corn	1	1	1	1	1	1
Silage Corn			1	1	1	
Total	10	10	10	10	10	10

The resulting optimal crop plan (figures 6.10 through 6.12) is similar to that of the base case. Specifically, fields are left open in the fall; reuse furrow is used in some fields; open fields and sugar beets are fallowed in dry years; wheat is deficit irrigated in dry years, and grain corn is planted in some full years, if water is available. Crop history alters the optimal crop plan, however, in several important ways. First, alfalfa appears in years 1 and 2, while it does not appear in the base case solution. This is because young alfalfa stands appear in year 6 of the crop history, and the producer is required to keep alfalfa, once planted, in place for four years. This constraint enforces the use of alfalfa in the study area for long-term maintenance of soil quality. The model is unable to systematically capture the agronomic benefits of alfalfa in soil quality maintenance, which combined with its high water requirements, prevents alfalfa from entering the base case solution.

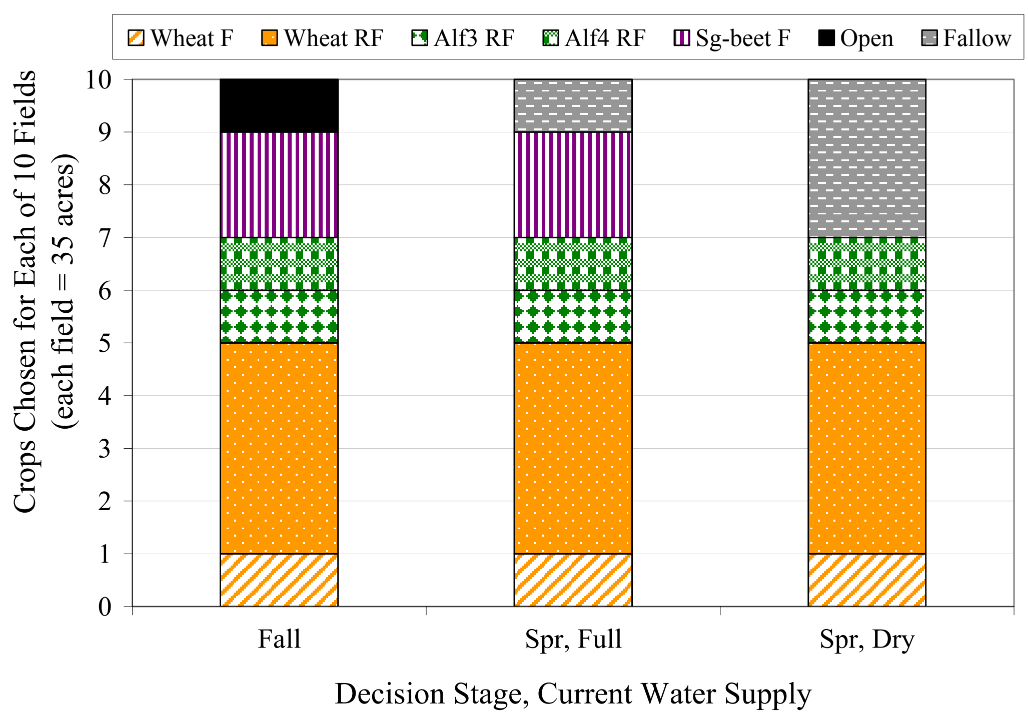


Figure 6.10. Optimal fall and spring activities in year 1 of the "history" case. Crop Key: F = furrow, RF = reuse furrow.

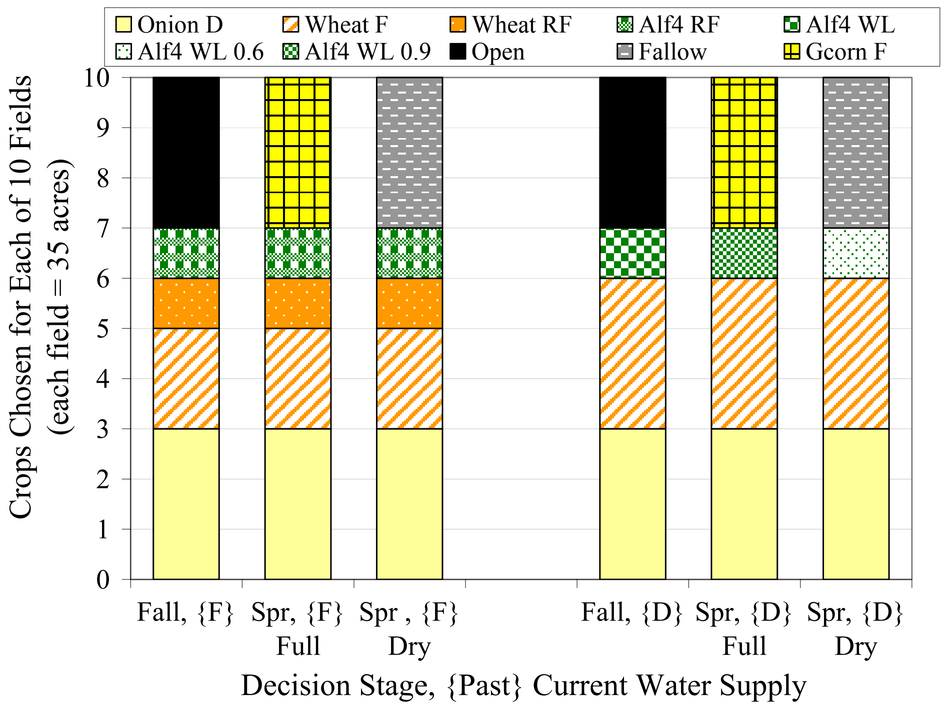


Figure 6.11. Optimal fall and spring activities in year 2 of the "history" case. Crop Key: F = furrow, WL = wheel line, RF = reuse furrow, D = drip, 0.9 = 90% of crop's irrigation requirement is provided, 0.6 = 60% provided.

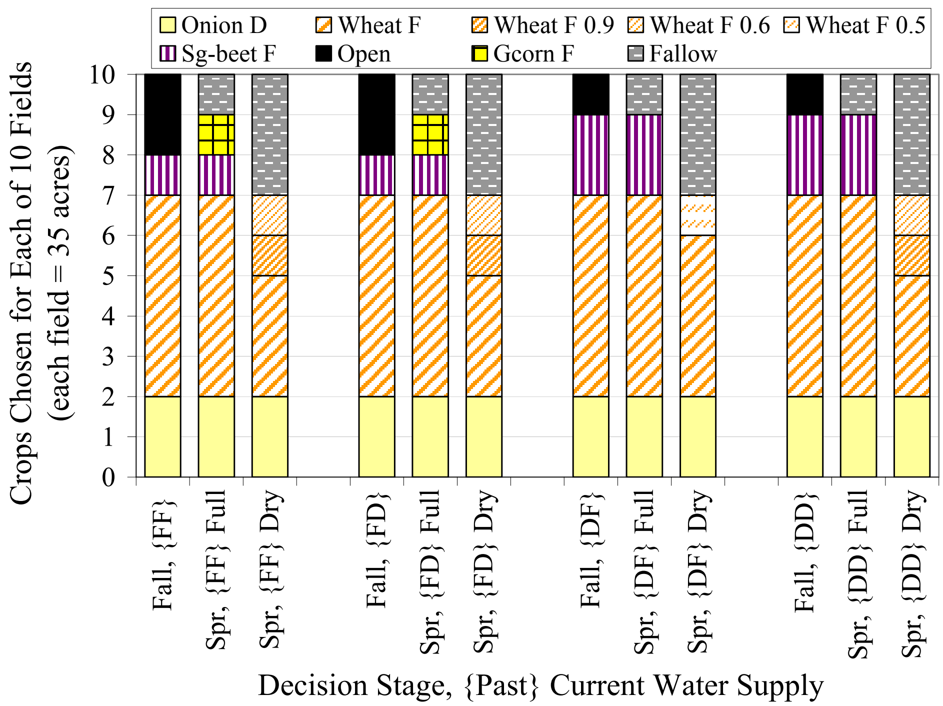


Figure 6.12. Optimal fall and spring activities in year 3 of the "history" case. Crop Key: F = furrow, D = drip, 0.5 = 50% of crop's irrigation requirement is provided, 0.6 = 60% provided, 0.9 = 90% provided.

Alfalfa is also deficit irrigated in year 2, rather than wheat, for the same reasons that sugar beets are deficit irrigated, rather than wheat, in the base case. A related difference is that fewer fields of sugar beets are planted overall in the history model, because alfalfa displaces sugar beets in years 1 and 2. A third difference is that onions are planted throughout years 2 through 6, rather than in years 1 and 2, as in the base case solution. Onions are planted in the history model as soon as fields become eligible, but the crop history delays this for most fields. The cost of this delay is foregone earned interest on savings, and higher discounting of profit because it is delayed. Crop history clearly limits the producer's feasible set of crop plans. However, it does not change the applicability of most drought preparedness and response tools.

Crop history limits the feasible set of activities, and should therefore reduce expected profit, and increase the average impact of drought. Expected profit in the history case is $55,000 (table 6.10), or 11% less than in the base case (table 5.2). Maximum profit is $50,000 (9%) less, and minimum profit is $40,000 (10%) less. The average profit impact of drought is $10,000 more in the history case (figure 6.13 versus 5.6) for all drought categories, except six years, which is $13,000 less. That is, the effect of drought in the crop history case is 88% worse for a one-year drought, 32% worse for two years of drought; 26% worse for three years of drought, 13% worse for four years of drought, 6% worse for five years of drought, and 7% better for six years of drought. In conclusion, crop history, in this example, necessitates an alternative solution, one that is less profitable in expectation and less successful during all but the most extreme drought. Future modeling efforts should attempt to expand the model's time horizon, such that one could test whether a producer with any starting crop history will eventually transition to the base case solution's crop plan.

Table 6.10. Summary statistics of the "history" case's profit outcome.

Statistic	Value ($)
Expected Stream of Discounted Profit	475,036
Standard Deviation of Expected Stream	37,431
Maximum Discounted Profit	538,573
Minimum Discounted Profit	368,101

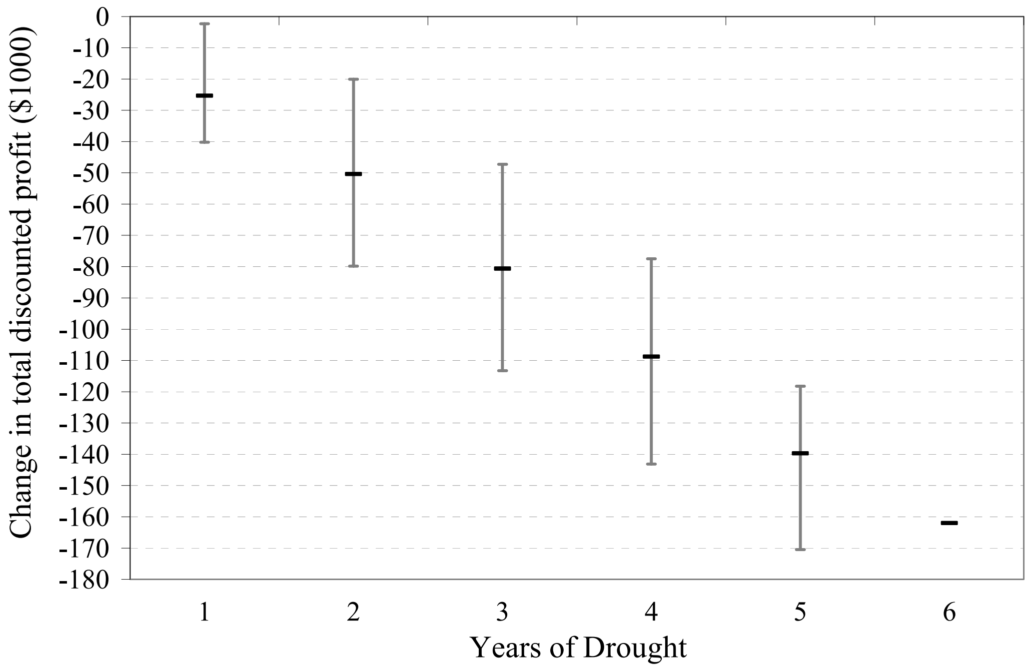


Figure 6.13. Average change in the "history" model's total discounted profit (black dashes) by years of drought experienced (as compared to 6 years of full water supply). Gray brackets indicate the maximum and minimum impact of drought.

6.5 Price Uncertainty

The economics literature has increasingly emphasized the joint effect of multiple sources of uncertainty on farm decisions (Isik 2002; Pannell, Malcolm, and Kingwell 2000; Thompson and Powell 1998). Producers in the study area face both water supply and output price uncertainty. Onions, which generate much of the profit in the model, have an especially volatile output price (table 6.11). The purpose of this section is to determine whether onion price uncertainty changes the optimal drought preparedness and response plan. Specialization in onions in the first year of the base case solution is of specific interest, since producers in the study area tend to diversify instead for reasons that are not yet clear.

Table 6.11. Prices received (2004$) by growers for yellow onions over the period 1995-2004 (Malheur County Extension Service 2004a).

Year	Price Received[*] ($/cwt)
1995	4.09
1996	6.57
1997	8.50
1998	8.03
1999	2.37
2000	13.01
2001	4.85
2002	5.12
2003	5.51
2004	2.79
Mean	6.08
Std Dev	3.15

[*]Prices do not include packing and shipping premiums.

The base case model is modified to accommodate onion price uncertainty (section 4.5.2). Price uncertainty is represented by three price categories [Hi = $12.25, Med = $6.00, Lo = $2.50], derived from price data for the study area (Appendix B.3). Note that the price of onions in category "Med" is the same as the price in the certainty model. Price uncertainty is assumed to be resolved only after both fall and spring decisions are made. The producer therefore has no recourse after the price is revealed. The model's planning horizon has to be shortened from six years to three to enable the programming software to accommodate a third stage decision stage. This modification causes some discrepancies in the base case solutions of the six versus three-year models. It would therefore be inconsistent to compare the three-year price uncertainty model's solution to that of the six-year base case model. A three-year version of the base case model is constructed to facilitate comparison. The solution to this truncated model is used as the reference solution, against which the price uncertainty model's solution is compared.

The three-year base case solution is largely similar to the six-year base case solution for years 1 through 3 (figure 6.14). The three-year solution recommends more sugar beets than the six-year solution, specifically in year 3, because it has fewer years in which to plant them. The three-year model also plants one additional field of onions in year 1 instead of year 2, which enables it to accommodate an additional sugar beet field in year 3. With a three-year base case solution established, the effects of introducing onion price uncertainty can be determined.

Optimal cropping activities for scenarios [Full Full Full] (price certainty) and [Full Med Full Med Full] (price uncertainty) are compared first. Overall, price uncertainty has little effect on the optimal crop plan (figure 6.15). The timing of onions remains unchanged, despite a 25% chance of receiving only $2.50 per hundredweight (cwt), which would result in a net loss of $2000 per acre for fully irrigated onions under drip irrigation. There is also, however, a 50% chance of receiving $6.00 per cwt, and a 25% chance of receiving $12.25 per cwt, which would generate net revenue of $320 and $4400 per acre, respectively. Expected net revenue under price uncertainty for fully irrigated onions under drip irrigation is therefore $760 per acre. Under price certainty, the producer receives $6.00 per cwt, for a per acre net revenue of $320. The price uncertainty model is also solved for the following price categories: Hi = $9.55, Med = $6.00, Lo = $2.44. These prices are such that the expected net revenue per acre for onions equals the net revenue per acre for onions in the price certainty model. The timing of onions, again, remains unchanged.

The optimal crop plan remains essentially unchanged when price uncertainty is added because the producer cannot influence the expected outcome of price uncertainty by manipulating their crop plan. That is, the expectation operator does not act over the decision variables. A simple example best illustrates this point. Suppose a producer can grow ten fields of onions (and no

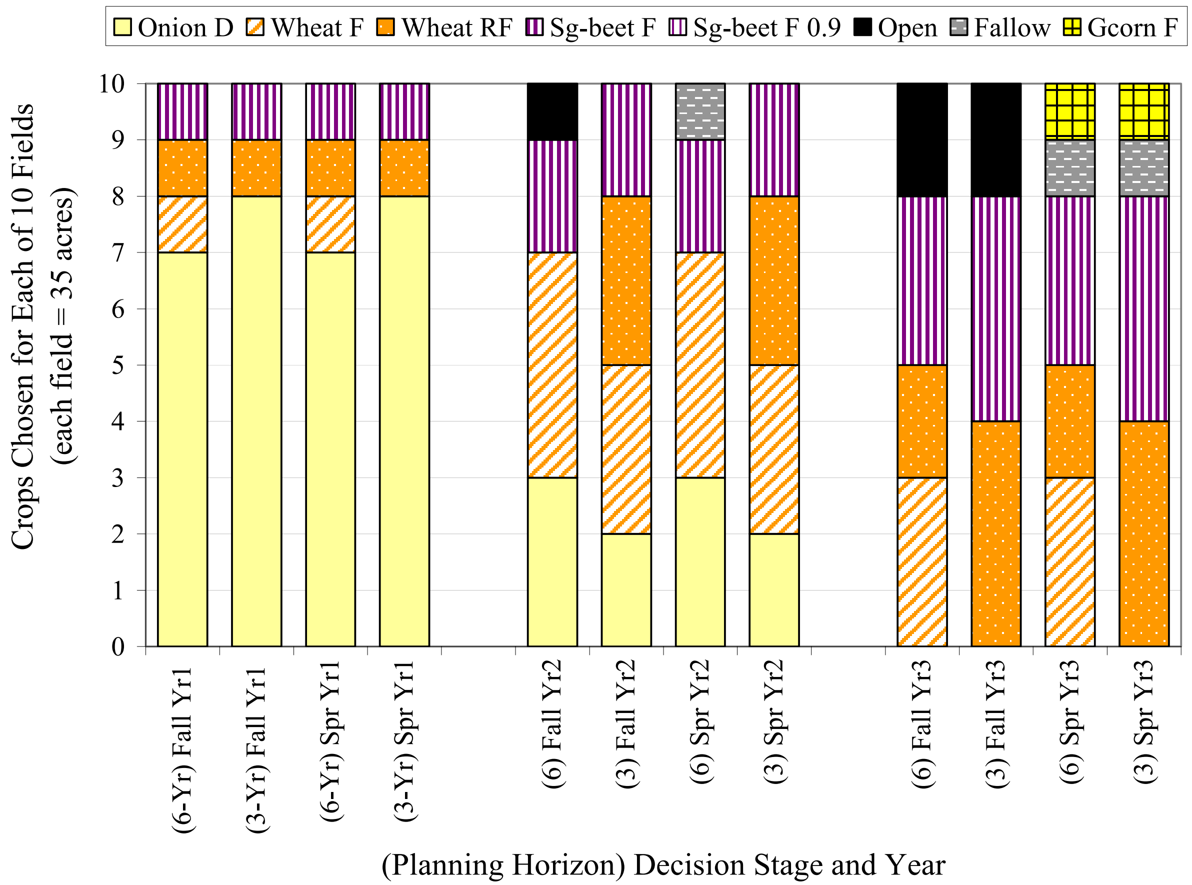


Figure 6.14. Optimal cropping activities for years 1 through 3 of scenario [Full Full Full], as generated by a six-year versus three-year version of the base case model. Crop Key: F = furrow, RF = reuse furrow, D = drip, 0.9 = 90% of crop's irrigation requirement is provided.

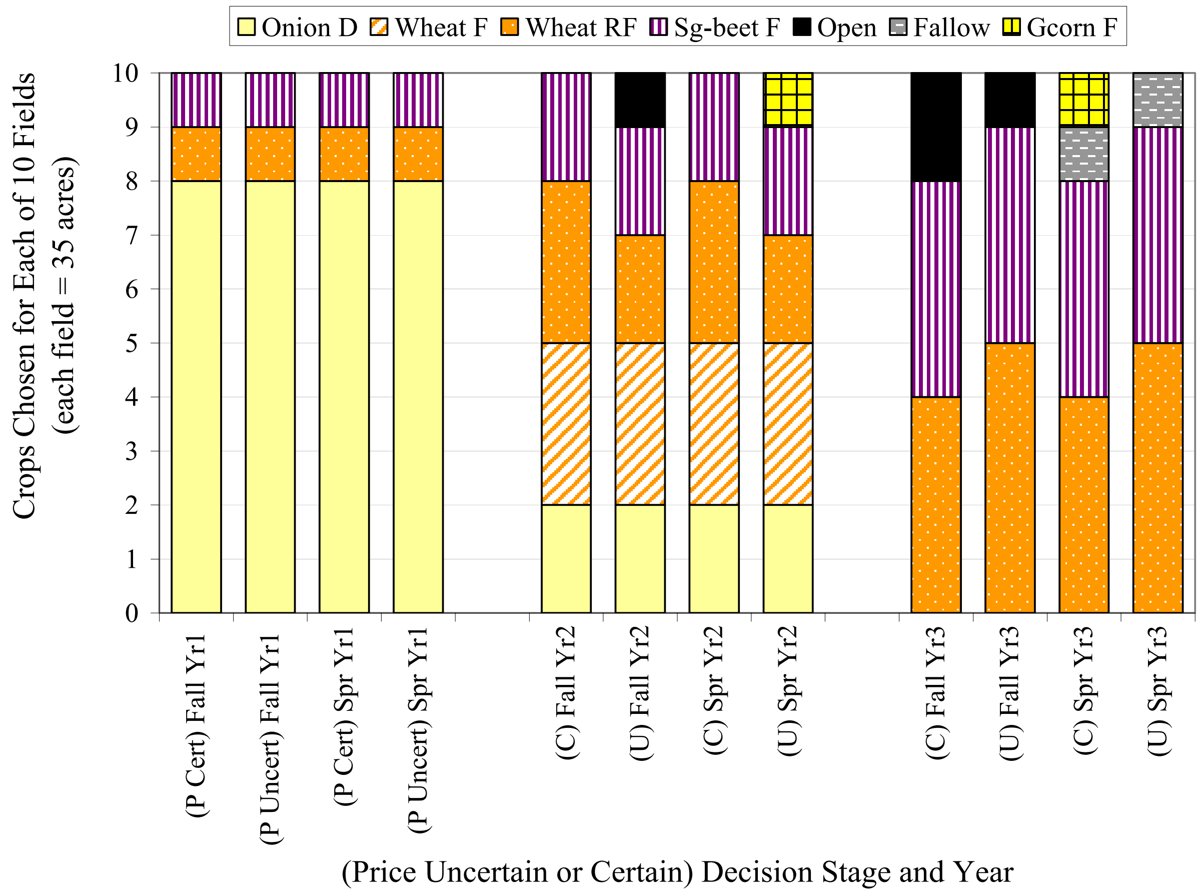


Figure 6.15. Optimal cropping activities for years 1 through 3 of scenarios [Full Full Full] (price certainty) and [Full Med Full Med Full] (price uncertainty), as generated by a three-year version of the base case model. Crop Key: F = furrow, RF = reuse furrow, D = drip

other crops) over a two-year period (assuming a zero discount rate), and that each field generates one unit of output. Assume the producer faces price uncertainty only, and that two prices are possible, *h* and *l*, with probabilities *pr(h)* and *pr(l)*, respectively. Prices are assumed independent between years. The producer considers two options: a) plant all ten fields in year 1, and risk receiving a low price for all ten fields, or b) plant five fields in each of years 1 and 2, and hope that a high price will occur in at least one year. The expected profit of option a) is:

$$\begin{aligned}&[pr(h)\cdot h\cdot 10 \;+\; pr(l)\cdot l\cdot 10]+[pr(h)\cdot h\cdot 0 \;+\; pr(l)\cdot l\cdot 0]\\ &\quad = E(price)\cdot 10+E(price)\cdot 0\\ &\quad = E(price)\cdot 10.\end{aligned}$$

The expected profit of option b) is:

$$\begin{aligned}&[pr(h)\cdot h\cdot 5 \;+\; pr(l)\cdot l\cdot 5]+[pr(h)\cdot h\cdot 5 \;+\; pr(l)\cdot l\cdot 5]\\ &\quad = E(price)\cdot 5+E(price)\cdot 5\\ &\quad = E(price)\cdot 10.\end{aligned}$$

Regardless of how the producer allocates the ten onion fields across time, expected net revenue is the same. Returning to the more complex model, it is clear why the optimal solution under water supply uncertainty remains unchanged when price uncertainty is introduced. Retiming of onions does not change the expected outcome of price uncertainty.

A parallel example for water supply uncertainty reinforces this point. Suppose the same producer faces water supply uncertainty only, and that two water supplies are possible, *f* and *d*, with probabilities *pr(f)* and *pr(d)*, respectively. The producer again considers the following two options: a) plant all ten fields in year 1 (and if the spring is dry they will have to abandon two fields), or b) plant five fields in each of years 1 and 2 (and if the spring is dry they will not have to abandon any fields). The expected profit of option a) is:

$$[pr(f)\cdot 10 \ + \ pr(d)\cdot 8] + [pr(f)\cdot 0 \ + \ pr(d)\cdot 0]$$
$$= [pr(f)\cdot 10 \ + \ pr(d)\cdot 8].$$

The expected profit of option b) is:

$$[pr(f)\cdot 5 \ + \ pr(d)\cdot 5] + [pr(f)\cdot 5 \ + \ pr(d)\cdot 5]$$
$$= [5 + 5] = 10.$$

In contrast to the price uncertainty example, the expected outcome of these two options is not equal (unless the water supply is certain, i.e. *pr(f)* equals one). In conclusion, the hypothetical producer who maximizes expected profit can do nothing to mitigate the effects of price uncertainty on expected profit, but can mitigate the effects of water supply uncertainty.

The structure of the price uncertainty problem, as modeled in this study, is different than that of the water supply uncertainty problem. The expectations operator in the price uncertainty problem acts on price independent of the producer's decisions. The expectations operator in the water supply uncertainty problem, in contrast, acts on the random variable through total yield, which is a function of the producer's decisions. This distinction is illustrated below.

$$\begin{aligned}\textbf{Price Uncertain:}\ E(\text{Net Revenue}) &= E(price \cdot totyield(decisions)) \\ &= E(price) \cdot totyield(decisions)\end{aligned}$$

$$\begin{aligned}\textbf{Water Supply Uncertain:}\ E(\text{Net Revenue}) &= E(price \cdot totyield(decisions, water)) \\ &= price \cdot E(totyield(decisions, water)) \\ &\neq price \cdot totyield(decisions, E(water))\end{aligned}$$

Although price uncertainty has no effect on a risk-neutral producer's optimal preparedness and response plan, it does affect the profit outcome. The addition of price uncertainty increases expected profit by nearly 50% (from

$473,000 to $700,000), due to a 25% chance of receiving $12.25 per cwt for onions rather than $6.00. Price uncertainty also drastically increases profit variability (from a standard deviation of $26,000 to $980,000), and creates the potential for large profit losses (table 6.12). A risk-neutral producer would be unconcerned by this, but a risk-averse producer would seek an alternative crop plan that reduces profit variability. Crop diversification within each year, specifically spreading onions over the planning horizon, reduces the standard deviation of profit from $980,000 to $650,000. This result suggests that producers in the study area might spread onions through the planning horizon as a risk-averse response to price uncertainty.

Table 6.12. Summary statistics of the profit outcome ($) for the following three-year models: (i) water supply uncertainty and onion price certainty, and (ii) water supply and onion price uncertainty.

Statistic	(i)	(ii)
Expected Stream of Discounted Profit	472,974	701,280
Standard Deviation of Expected Stream	26,179	981,272
Maximum Discounted Profit	507,876	2,597,705
Minimum Discounted Profit	416,048	-755,400

One final observation about the effect of price uncertainty on the base case solution is that a low onion price is clearly more devastating than a drought (table D1). A risk-averse producer would therefore likely focus their efforts on managing price uncertainty (e.g. planting onions throughout the planning horizon, or contracting onions in advance), rather than water supply uncertainty. Thompson and Powell (1998) also conclude that price risk is greater than yield risk for many, but not all Australian farm systems.

6.6 Prevented Planting Provision of the Multi-peril Crop Insurance Program

The multi-peril crop insurance program includes a prevented planting (PP) provision for irrigated crops. A PP payment is made when an insured producer provides evidence that as of the final planting date they have no reasonable expectation of receiving sufficient water to follow good irrigation practices, due to an insurable cause of loss, such as drought (Risk Management Agency 2003). This contrasts to a traditional MPCI claim, where a crop was planted, but later failed due to unanticipated drought. Producers in the study area indicate that the PP provision is a useful drought preparedness tool, and an insurance agent for producers in the study area attributes participation in MPCI largely to the PP provision (Agricultural Producers in the Vale Oregon Irrigation District 2003; Haight 2004). However, to the author's knowledge, no economic studies have examined the prevented planting provision in this role. Existing studies have focused instead on the provision's susceptibility to adverse selection and fraudulent claims (Rejesus, Escalante, and Lovell 2005; Rejesus et al. 2003). The prevented planting provision's effectiveness at the farm-level as a drought preparedness tool is therefore analyzed in this section. No attempt is made, however, to determine the social efficiency of the prevented planting provision.

The producer in the model has the option to purchase alternative coverage levels of multi-peril crop insurance (each with a fixed level of PP coverage) for individual fields of the following fall-planted crops: onions, potatoes, sugar beets, and wheat. The MPCI coverage level, in the context of PP claims, is the percent of historical crop yield that the insurance company will reimburse in the event of a loss. The PP coverage level is the percent of the MPCI indemnity that the producer will receive in the event of a successful PP claim. Crop insurance policies are purchased in the fall, before the upcoming growing season's water supply is known. If the water supply is revealed dry, the producer then chooses whether to abandon the crop and receive a prevented planting payment, or to plant the crop. No payment is received if the crop is abandoned during a year in which a full water allotment is received, or if the insured crop is planted successfully.

Claims for post-planting disasters, such as hail, pests, freeze, or abnormally high temperatures are not modeled. Crop insurance is also not offered in the model for spring-planted crops. These would both require a decision third stage in each year of the model. Solution of the prevented planting model is sufficiently difficult with only two stages per year. The exclusion of spring sources of crop loss implies that the producer pays the entire multi-peril crop insurance premium, but receives prevented planting coverage only. The portion of the premium attributed to prevented planting coverage is unknown, however, so a conservative approach is taken. The model, as a result, likely underestimates the adoption of multi-peril crop insurance with prevented planting provisions.

In the base case solution, the producer frequently abandons sugar beets in response to drought. The producer might therefore purchase multi-peril crop insurance with prevented planting provisions for at least some portion of their sugar beet fields. Theoretically, the producer should fully insure a crop (i.e. purchase insurance coverage equal to the potential loss) if the premium is actuarially fair. A premium is actuarially fair if it equals the expected insurance indemnity (i.e. the expected payment to the producer). An actuarially unfair premium should cause the producer to underinsure. An actuarially favorable premium should cause the producer to over-insure, if the insurance company allows it.

Unsubsidized and subsidized premiums (table 6.13) are estimated using the Risk Management Agency's online premium calculator for the year 2004 (the year to which all other cost and price data are calibrated) (2006). Expected insurance indemnities are estimated assuming alternative values for the expected probability of crop abandonment in any given year due to drought (i.e. the probability of an indemnity occurring) (table 6.13). The true abandonment probabilities are likely unique to each crop; for example, the base case solution indicates that 68% of attempted sugar beet is abandoned on average during drought, while only 5% of attempted wheat is abandoned during drought, and 0% of onions are abandoned. The expected probability of abandonment of sugar beets, wheat, and onions in any given year, assuming no abandonment during a full year and a 40% chance of drought, is 27%, 3%, and 0%, respectively. However, the base case solution also illustrates that the proportion of attempted fields abandoned during drought varies with the suite of accompanying crops. The proportion of abandoned sugar beets varies from 33 to 100%; the proportion of abandoned wheat varies from 0 to 20%.

Table 6.13. Unsubsidized and subsidized premiums, prevented planting payment, and expected indemnity ($ per acre) for alternative combinations of crop and MPCI coverage level. Parameter assumptions used to estimate PP payments appear in tables C.1, C.2, C.4, and A.2.

Insured Crop	**MPCI Cover-age Level**	**Unsub Prem-ium**	**Sub Prem-ium**	**Prevented Planting Payment***	**Expected Indemnity by Probability of Abandonment**			
					40%	*25%*	*5%*	*1%*
Onion	50	72	19	402	161	101	20	4
	65	128	42	523	209	131	26	5
	75	195	71	603	241	151	30	6
Potato	75	97	35	260	104	65	13	3
Sug Beet	50	20	5	272	109	68	14	3
	65	37	12	354	142	89	18	4
	75	65	24	408	163	102	20	4
	85	118	59	462	185	116	23	5
Wheat	55	6	2	138	55	35	7	1
	65	10	3	163	65	41	8	2
	75	15	6	188	75	47	9	2
	85	28	14	213	85	53	11	2

Table 6.13 reports expected indemnity for alternative probability of abandonment, specifically 40%, 25%, 5% and 1%. A probability of

abandonment equal to 40% assumes that the crop is always abandoned when drought is revealed; therefore, a 40% probability of drought implies a 40% probability of abandonment. It is clear from previous models' solutions that drought does not imply abandonment for all crops, because other drought responses are available (e.g. deficit irrigation, or abandon one crop to provide water for another). The middle and right columns assume, more conservatively, that a 40% probability of drought implies a 25, 5, and 1% probability of abandonment, respectively.

Pair-wise comparisons of premium and expected indemnity (table 6.13) indicate whether premiums are actuarially fair, favorable, or unfair at these assumed abandonment probabilities. Table 6.14 reports whether premiums are fair, favorable, or unfair for alternative probabilities of crop abandonment. All premiums (subsidized or unsubsidized) are actuarially favorable if the true probability of abandonment is 40%. All subsidized premiums are also actuarially favorable if the true probability is 25%. Recall that the expected probability of sugar beet abandonment indicated by the base case solution is approximately 25%. All premiums are unfair if the true probability of abandonment is 1%, which is the case for onions. Lastly, the base case solution indicates that the expected probability of wheat abandonment, when rounded up, is approximately 5%. Subsidized premiums for wheat are favorable, except for the highest coverage level; unsubsidized premiums for wheat are unfair, except for the lowest coverage level. (table 6.14). These results suggest that under subsidized premiums, sugar beets should be over-insured, onions under-insured, and wheat over-insured, but not to the maximum degree possible.

It is not immediately clear in the case of prevented planting coverage how a producer can over or under-insure, since the level of prevented planting coverage is fixed for each crop (in this model) (table C.4). A producer who anticipates $600 losses for an acre of abandoned onions, for example, cannot over-insure by simply

Table 6.14. Actuarial fairness of unsubsidized and subsidized multi-peril crop insurance (MPCI) premiums, in 2004, for alternative crops and coverage levels. Key: fair (+), favorable (++), unfair (-).

Insured Crop	**MPCI Cover -age Level**	**Fairness of Unsubsidized Premiums by Probability of Abandonment***				**Fairness of Subsidized Premiums by Probability of Abandonment***			
		40%	*25%*	*5%*	*1%*	*40%*	*25%*	*5%*	*1%*
Onion	50	++	++	-	-	++	++	-	-
	65	++	-	-	-	++	++	-	-
	75	++	-	-	-	++	++	-	-
Potato	75	++	-	-	-	++	++	-	-
Sug Beet	50	++	++	-	-	++	++	++	-
	65	++	++	-	-	++	++	++	-
	75	++	++	-	-	++	++	-	-
	85	++	-	-	-	++	++	-	-
Wheat	55	++	++	++	-	++	++	++	-
	65	++	++	-	-	++	++	++	-
	75	++	++	-	-	++	++	++	-
	85	++	++	-	-	++	++	-	-

* Fairness is reported for alternative probabilities of crop abandonment (40, 25, 5, and 1%). Premiums are actuarially fair if premium = expected indemnity; favorable if premium > expected indemnity; unfair if premium < expected indemnity. Premiums and expected indemnities are reported in table 6.13.

purchasing \$700 of prevented planting coverage. A producer can over-insure only by purchasing a higher MPCI coverage level. Specifically, if they wish to insure for \$700, they solve the following algebraic problem for X: [$550 \cdot X \cdot 0.45 \cdot \$3.25 = \$700$]. The equation's right hand side is the desired payment in the event of a prevented planting claim. The left-hand side is the equation used to determine the PP payment; specifically, it is the product of approved yield, MPCI coverage level, PP coverage level, and the elected price. The producer, in order to receive a \$700 payment in the event of onion abandonment, should elect for a MPCI coverage level of 87%. The producer could, in reality, achieve the same effect by selecting a higher price election for a particular MPCI coverage level, or purchasing additional PP coverage, which is not allowed for all crops. These two options are not considered here because the model becomes too large to be solved.

The equation illustrated above is used in combination with the parameters in tables C.1, C.3 and C.4, and the fall cost of each crop (table A.3) to provide rough estimates of the MPCI coverage levels necessary to fully insure a producer's abandonment losses (table 6.15). To fully insure sugar beets, for example, a producer solves the following equation for X: [31 · X · 0.45 · $39.00 = $150]. Fall preparation costs of $150 per acre represent the loss if an acre of sugar beets is abandoned. The producer should adopt an MPCI coverage level of 28% to fully insure sugar beets, assuming approved yield of 31 ton, prevented planting coverage of 45%, and a price election of $39.00 per ton. The producer over-insures (under-insures) if they choose MPCI coverage levels greater (less) than those reported in table 6.15.

Table 6.15. MPCI coverage levels required to fully insure a producer's losses from drought-induced abandonment. Parameter values in tables A.3, C1, C3, and C4 are assumed.

Insured Crop	MPCI Coverage Level (%)
Onion	75
Potato	29
Sugar Beet	28
Wheat	64

The prevented planting model's solution indicates that the producer enrolls all sugar beet acreage, in all scenarios, at the 75% coverage level. The producer, as expected, over-insures sugar beets. The number of wheat fields enrolled varies from 0 to 3 fields depending on the water supply scenario; however, on average, only one field of wheat is enrolled (out of 5 attempted fields on average), and at the unexpectedly high level of 85%. That the producer insures very little of their wheat compared to sugar beets reflects that wheat is abandoned relatively infrequently. The producer over-insures wheat, as expected, but to an unexpected degree. Recall that the subsidized premium for 85% MPCI coverage is unfair at the 5% abandonment probability. The producer's enrollment at this unfair level suggests that the probability of abandonment for wheat is actually higher than 5%, or that the model's approximate solution has not identified the optimal coverage level. Lastly, one onion field is enrolled at the 50% level in a small number of scenarios. Onions are never abandoned in the optimal solution, so it is unclear why a producer would enroll any onion field. The enrollment of an occasional field might be attributable, however, to the approximate nature of the optimal solution.

The availability of subsidized PP coverage affects both cropping activities and profit outcomes. Cropping activities change in the following ways. More fields of sugar beets are attempted; this is because PP coverage reduces the cost of abandonment in the event of a dry year. The following two adjustments make it possible to attempt more sugar beets: 1) shifting onions from year 1 to years 2 and 3 to make more complete use of water supplies, and 2) decreasing the number of open fields, which subsequently reduces the number of grain corn fields. Although more fields of sugar beets are attempted, fewer fields are successful in most scenarios. Fewer successful fields is not necessarily undesirable for the producer, however, particularly if the prevented planting payment for sugar beets exceeds actual losses. The producer in this model is allowed to and does over-insure, which implies that the payment exceeds actual losses.

The perverse incentive to plant additional sugar beet acreage is partially offset, however, by the fact that the producer cannot receive a prevented planting payment in the event of a full water allotment year. The pursuit of prevented planting payments must therefore be balanced against the consequences of getting trapped in a full year with too many beet fields. The latter could be problematic due to crop water requirements (e.g. only 6 sugar beet fields can be fully irrigated given a full allotment; all other fields would have to be abandoned), and agronomic constraints (e.g. eligibility of fields for sugar beets is quickly exhausted, so less profitable grain corn has to be rotated with wheat to avoid exhausting eligibility for wheat). Sugar beets are limited in most years and scenarios to three or four fields. Five or six fields do appear in some years; however, a portion of these fields are typically under reuse furrow, which reduces crop water requirements.

The profit impacts of subsidized prevented planting coverage are substantial (figure 6.16). Expected profit is increased by 16% ($85,000); minimum profit is increased by 41% ($150,000); maximum profit is increased by 15% ($88,000), and standard deviation is decreased by 38%. The PP provision therefore achieves the goal of most farm programs, to stabilize farm income (Lewandrowski and Brazee 1992). In addition, scenarios dominated by drought become more profitable than those that are not (figure 6.17). Six years of drought, for example, is 17% more profitable than six years of full water allotments (table C.5). Prevented planting coverage effectively eliminates profit losses attributable to drought. The actual effects of this program on profit in the study area have not been quantified. However, producers in the study area are generally positive about the usefulness of the PP provision as a drought management tool. This analysis suggests that PP coverage, for sugar beets in particular, is a very effective drought preparedness tool at the farm-level. Note again, however, that this study makes no attempt to determine whether the PP provision improves social welfare.

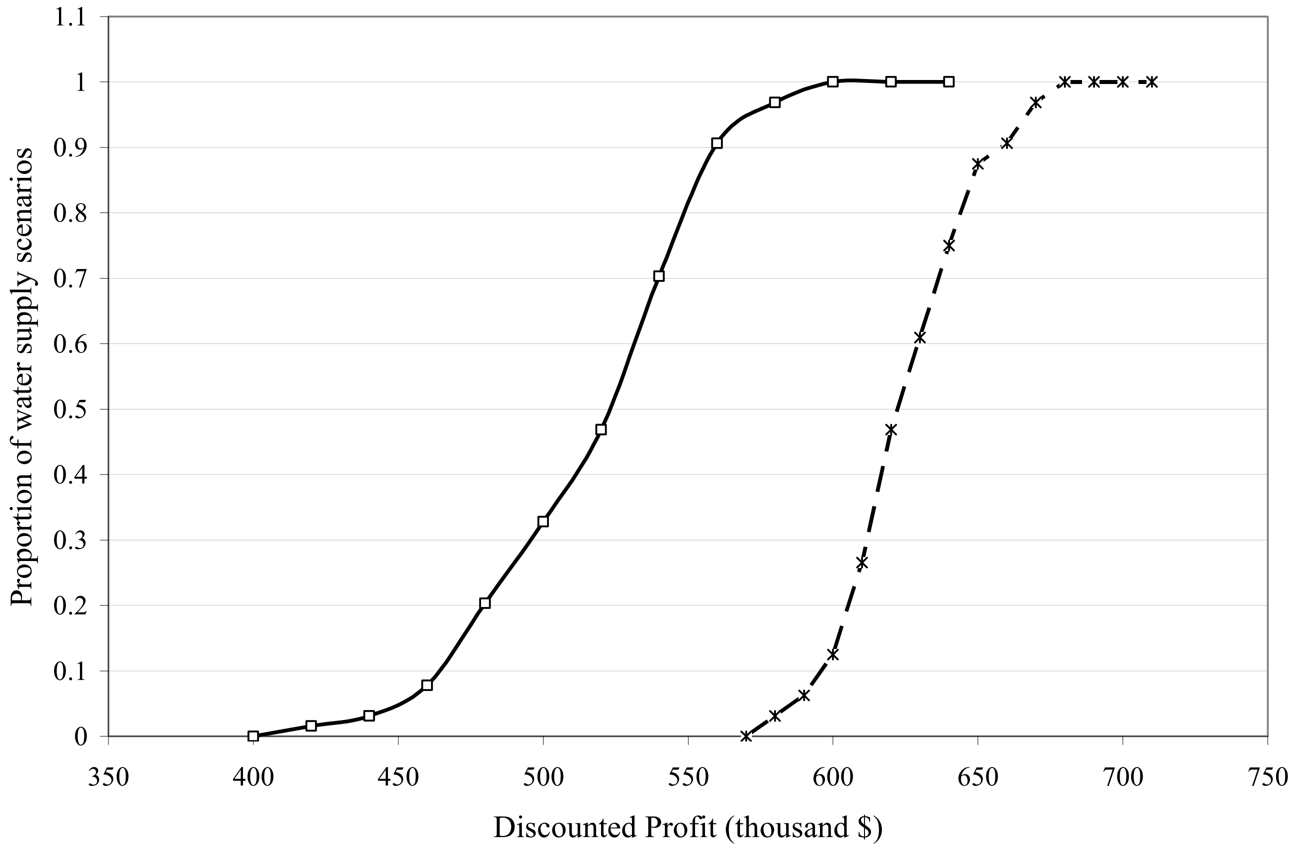


Figure 6.16. Cumulative distribution function of discounted profit without prevented planting coverage (solid line) and with subsidized PP coverage (dashed line).

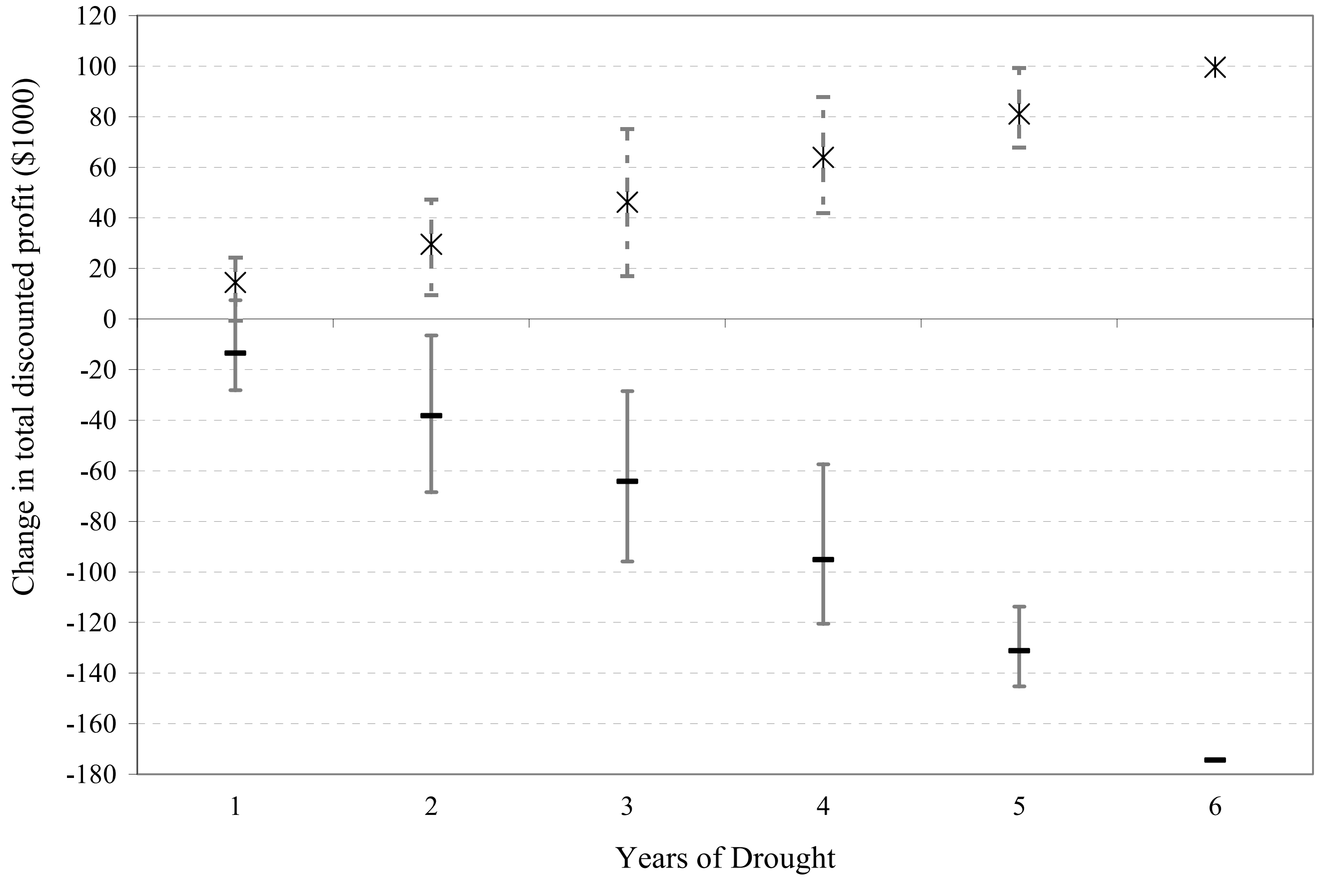


Figure 6.17. Average change in total discounted profit by years of drought experienced (as compared to 6 years of full water supply). Black dashes represent average change without prevented planting coverage. Black asterisks represent average change with subsidized PP coverage. Gray brackets indicate the maximum and minimum impact of drought with PP coverage (dashed gray) and without (solid gray).

The potential role of an unsubsidized PP provision as a drought management tool is investigated next. The solution to the unsubsidized coverage model indicates that the producer enrolls most, but not all sugar beet acreage at the 65% coverage level. This contrasts to the subsidized model, in which the producer enrolled sugar beets at the 75% coverage level. Enrollment of wheat ranges across scenarios from 0 to 3 fields, and at various coverage levels, including 55, 75, and 85%. Lastly, no onion fields are enrolled in prevented planting coverage. Despite the absence of subsidies, the producer still over-insures sugar beets, and wheat, in most cases. However, the number of insured fields of sugar beets decreases slightly, and the degree of over-insuring declines. The effects of unsubsidized prevented planting coverage on cropping activities are nearly identical to those of subsidized coverage. More fields of sugar beets are attempted, with fewer fields successful in most scenarios. Onions are shifted from year 1 to years 2 and 3. The number of open fields decreases, and thus so does the number of grain corn fields.

The profit impacts of unsubsidized prevented planting coverage remain positive, from the perspective of reducing drought impacts, but are less extreme. Expected profit is increased by 11% (versus 16% with subsidized coverage); minimum profit is still increased by 41%; maximum profit is only increased by 5% (versus 15%), and standard deviation is decreased by 72% (versus 38%). The additional decrease in the standard deviation of profit is attributable to a reduction in the right-tail levels of profit (figure 6.18) Scenarios dominated by drought are still more profitable than those that are not, but to a lesser degree (figure 6.19). Six years of drought, for example, is only 5% (versus 17%) more profitable than six years of full allotment (table C.6). Unsubsidized prevented planting coverage effectively eliminates profit losses attributable to drought, but does so while creating less extreme profit improvements (figure 6.18). The prevented planting provisions, in conclusion, would remain an effective component in producers' drought management toolbox even if premiums were not subsidized.

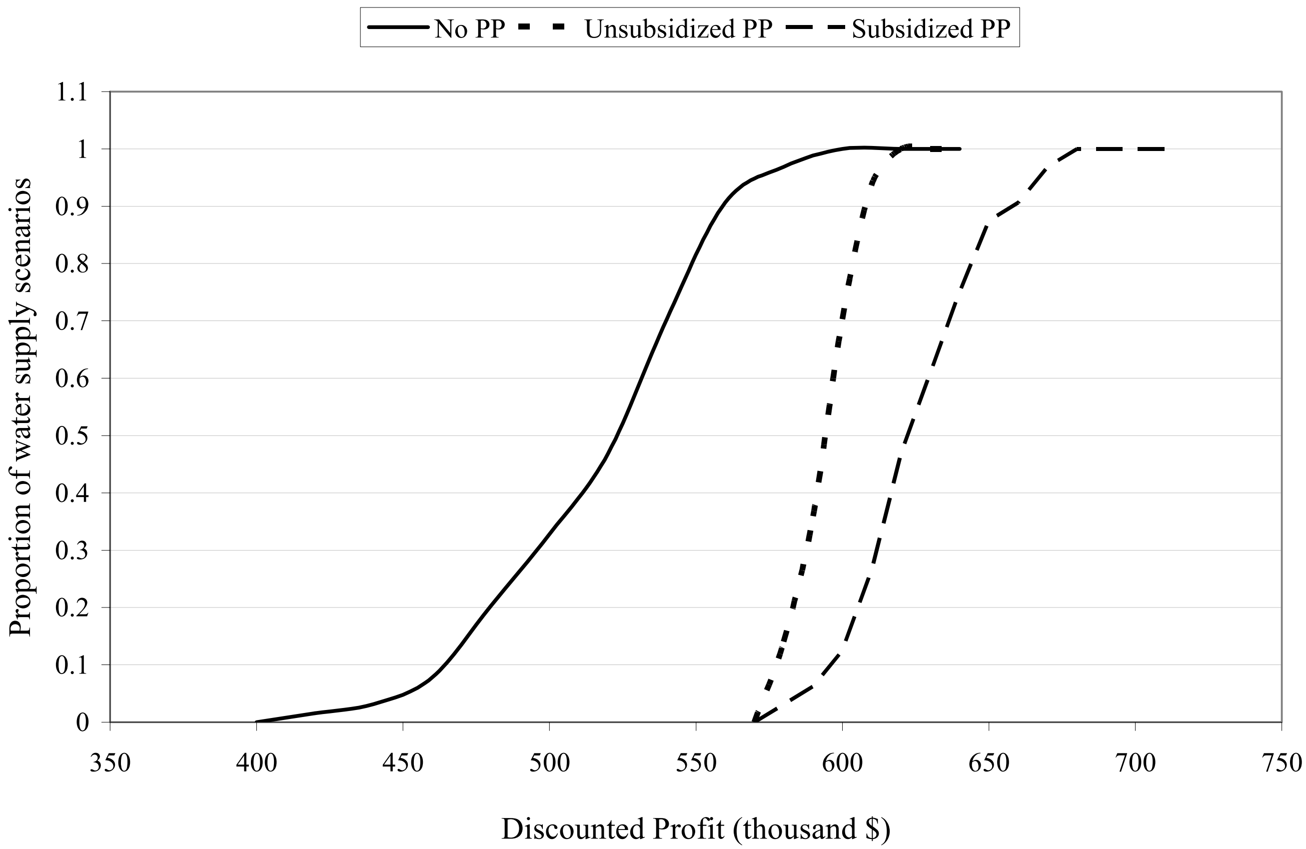


Figure 6.18. Cumulative distribution function of discounted profit without prevented planting coverage, with unsubsidized PP coverage, and with subsidized PP coverage.

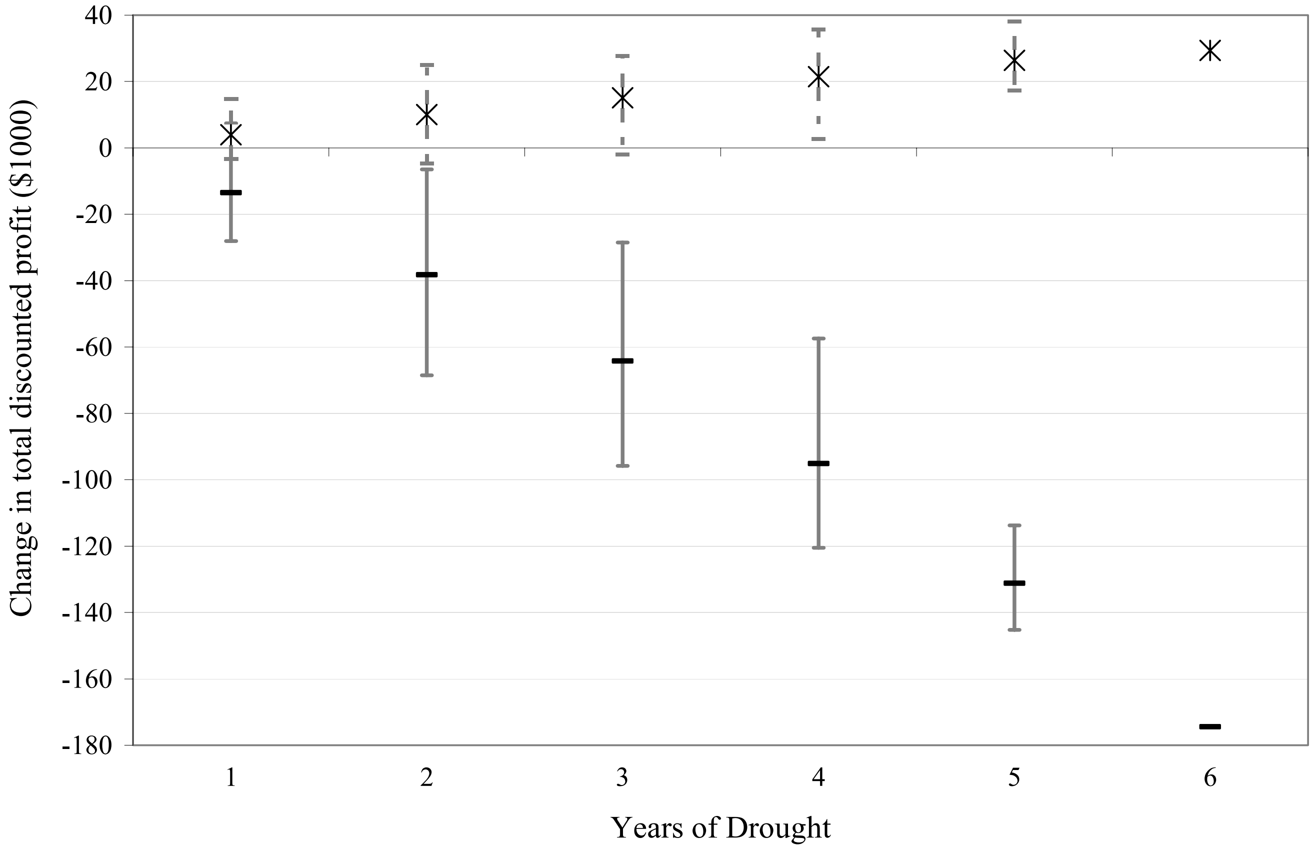


Figure 6.19. Average change in total discounted profit by years of drought experienced (as compared to 6 years of full water supply). Black dashes represent average change without prevented planting coverage. Black asterisks represent average change with unsubsidized PP coverage. Gray brackets indicate the maximum and minimum impact of drought with PP coverage (dashed gray) and without (solid gray).

6.7 Climate Change

One anticipated effect of climate change in the west is that mountain precipitation will be received increasingly as rain, rather than snow (Frederick and Gleick 1999; Intergovernmental Panel on Climate Change 2001a; Knowles, Dettinger, and Cayan 2006). Snow pack levels are also expected to form much later in the winter, to accumulate in much smaller quantities, and to melt earlier in the season (Intergovernmental Panel on Climate Change 2001a; Stewart, Cayan, and Dettinger 2004). Observation of the runoff process and resulting reservoir levels in the study area by the regional water master and water district manager indicate the potential for climate change to decrease runoff to reservoirs, and therefore increase the frequency of water shortage (Jacobs 2004; Ward 2004). The effects of increased drought frequency and severity on drought preparedness and response, and on the profit impact of drought, are examined in this section.

No estimate has been made yet of the expected increase in the frequency or severity of dry years in the study area. The following three climate-change scenarios, which are the focus of this section's analysis, are therefore hypothetical in nature: 1) a 25% increase in the probability (frequency) of drought from 40 to 50%, 2) a 25% increase in drought severity from 24 to 18 acre-inches per acre, and 3) a 25% increase in both drought frequency and severity. The three climate change scenarios' relative impact on cropping patterns and expected farm profit, as compared to the base case solution, is discussed next.

Producers adapt to increased drought frequency (case 1) by reducing the number of fields prepared for sugar beets, a water-intensive crop, and increasing those prepared for wheat, a less water-intensive crop. Although wheat, like sugar beet, is subject to the risk of abandonment, it is less prone to abandonment because it requires less water. Wheat is also more profitable under deficit irrigation than beets, which creates a viable alternative to abandonment in the event of a drought. Shifting the crop mix is considered one of the least-costly means of adjusting to climate change (Lewandrowski and Brazee 1992; Mjelde et al. 1997). More efficient irrigation technologies are also used on a larger number of fields; specifically, wheat is grown primarily under reuse furrow rather than furrow irrigation (figure 6.20). If the producer continued to implement the base case solution under increased drought frequency, more deficit irrigation and abandonment of fall-prepared sugar beet fields would be necessary. The case 1 solution indicates that it is instead more profitable to shift the crop mix by increasing the proportion of fields prepared for less water-intensive crops, and using more efficient irrigation technology.

Note that an increase in the probability of drought does not affect the timing of onions. A sensitivity analysis indicates that the timing of onions across years is not affected even by very extreme increases in the probability of drought (e.g. from 40 to 80%). It has already been determined, however, that the water supply during drought, defined as 24 acre-inches per acre, allows up to seven fields of drip-irrigated onions to be fully irrigated. Recall that the benefit of retiming onions is that it provides opportunities to support additional fields over the planning horizon by balancing total crop water requirements through time. This benefit is largest when water supplies are full. As the probability of a full allotment declines, due to climate change, the expected benefit of retiming onions declines.

Producers adapt to increased drought severity (case 2) by shifting one field of onions from year 1 to 2. Water is insufficient during a more severe drought to fully support seven fields, and the fall preparation cost of onions is too high to risk abandoning them. Producers also shift some wheat production from furrow to reuse furrow irrigation, which reduces wheat's net irrigation requirement, and subsidizes other crops' water needs, such as sugar beets (figure 6.21). The number of fields prepared for sugar beets increases under increased drought severity. This contrasts with the response to increased drought frequency. An increase in

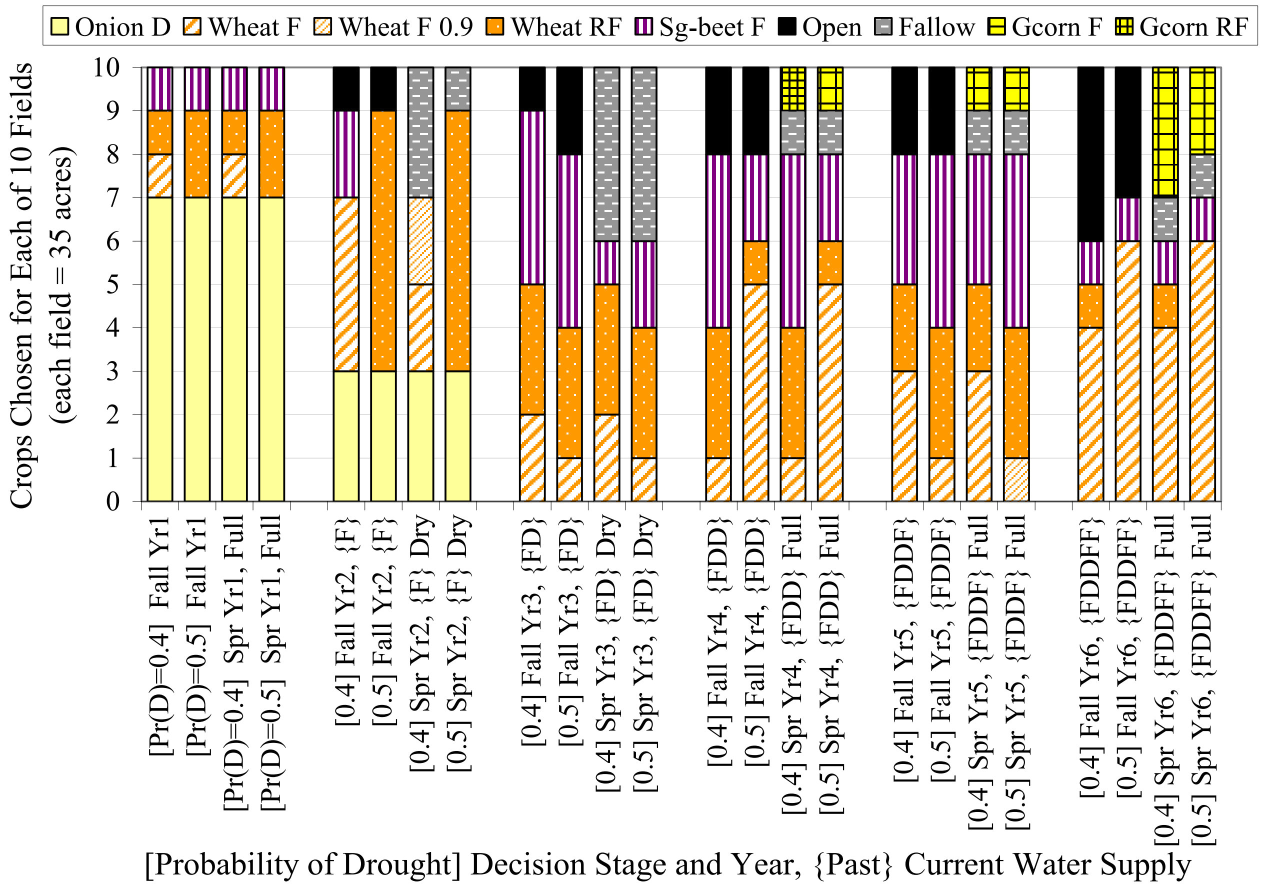


Figure 6.20. Cropping impacts of increased drought frequency (from 40 to 50%) on scenario [Full Dry Dry Full Full Full]. A stage-by-stage comparison of activities under a probability of drought of 0.4 versus 0.5. Crop Key: F =furrow, RF = reuse furrow, D = drip, 0.9 = 90% of crop’s irrigation requirement is provided.

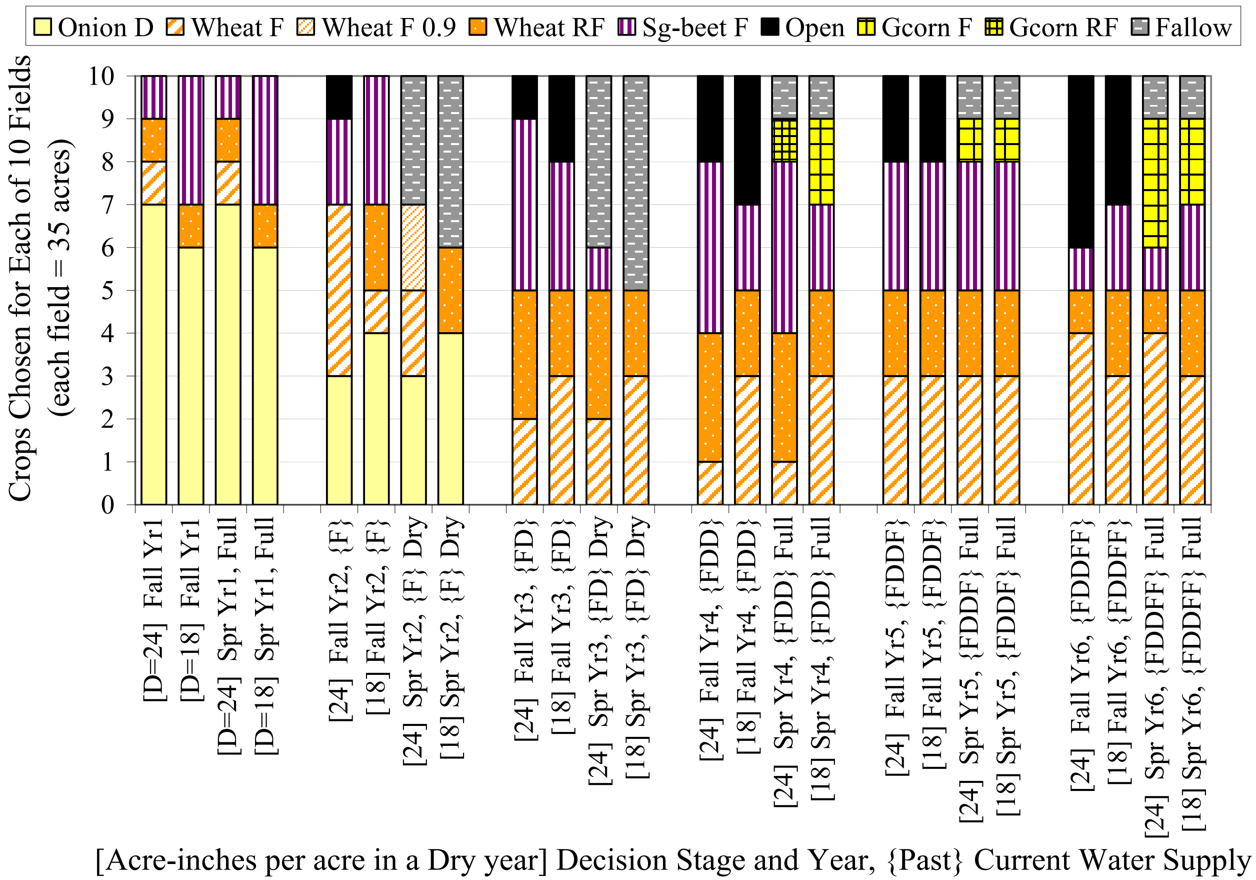


Figure 6.21. Cropping impacts of increased drought severity (from 24 to 18 acre-inches/acre) on scenario [Full Dry Dry Full Full Full]. A stage-by-stage comparison of activities under the base case versus more severe drought. Crop Key: F = furrow, RF = reuse furrow, D = drip, 0.9 = 90% of crop's irrigation requirement is provided.

drought severity will require more fields to be abandoned and fallowed. Failed sugar beet fields are typically reattempted in later years; increased failure therefore implies increased attempts over the planning horizon.

It is not immediately clear why wheat is not substituted for sugar beets in the case of increased drought severity, as it is for the case of increased drought frequency. Substitution of wheat for sugar beets reduces the abandonment of fields in the case of increased drought frequency, and so would seem beneficial in the case of more severe drought as well. It is not, however, because water is sufficiently short during the more severe drought to require even some wheat fields to be abandoned. Wheat requires larger fall investments than sugar beets, and is thus more costly to abandon. Wheat is substituted for sugar beets for its ability to avoid abandonment, but its ability to do so depends on the severity of the drought. Additionally, sugar beets, in the event of a full year and full irrigation, are more profitable than wheat. Again, if drought leads inevitably to field abandonment, a producer should prepare fields for the crop with a lower fall cost and higher profit in the event of a full year. Sensitivity analysis confirms the role of fall costs in the substitution, or lack thereof, of wheat for sugar beets. A reduction in the fall cost of wheat causes wheat to be substituted for sugar beets in case 2, just as in case 1.

As the severity of drought worsens, onions are increasingly spread across multiple years to avoid abandonment of onion fields. If drought is defined as 12 acre-inches per acre, for example, the producer plants four fields to onions in each of years 1 and 2, followed by two fields in year 3. More modest increases in drought severity, from 24 to 22 or 20 acre-inches per acre for example, do not affect the timing of onions, but do prompt a shift from furrow to reuse furrow irrigation of wheat. The shift of onions across an increasing number of fields as drought severity increases indicates some drought-preparedness role for the timing of onions. The tendency of producers in the study area to spread onions through time could reflect, in part, a positive probability of sufficiently severe drought. This would justify planting only one or two fields of onions per year, which may be all that can be supported during these severe droughts.

The results above indicate that the response to climate change depends on which climate characteristics change. The only similarity in response to a change in drought frequency versus severity is a shift from furrow to reuse furrow irrigation for wheat production. Reuse furrow irrigation, coincidentally, is becoming increasingly prominent in the study area. The technology was originally introduced there to reduce agricultural runoff and improve water quality. Producers who have adopted this technology are likely, however, to experience additional benefits from it if the predicted impacts of climate change materialize.

Producers adapt to an increase in both the frequency and severity of drought (case 3) in much the same manner as they adapt to case 2. Adaptations to case 3 include the following: a) shifting one field of onions from year 1 to 2, b) continuing to attempt sugar beets, rather than shifting to wheat, despite more frequent abandonment, which results in more fallowing in dry years, and c) replacing furrow irrigation with reuse furrow on many wheat fields. There is also a unique adaptation to case 3. The number of wheat fields attempted is reduced, and the number of open fields is increased. This adaptation, in an environment of more frequent and severe drought, reduces the cost of fallowing in dry years and increases grain corn production in full years. The producer, in summary, alters several features of their crop plan to mitigate the impacts of more frequent and severe drought. The impact of each climate change case on profit is discussed next.

The impact of increased drought severity (case 2) on expected profit, when responded to optimally, is nearly three times that of increased drought frequency (case 1) (table 6.16). Increased drought severity also significantly reduces minimum profit, which is opposite of increased drought frequency, which actually increases minimum profit. Lastly, the variability of profit increases by more than half in case 2, whereas variability decreases in case 1. The hypothetical producer is better able to mitigate for more frequent moderate drought than for less frequent but more severe drought. Suppose that both characteristics change simultaneously. The impact of an increase in both drought frequency and severity on expected profit is 50% larger than that of severity alone. Additionally, profit variability increases and minimum profit is reduced, as in case 2. Maximum profit also declines by more in case 3.

Table 6.16. Profit impacts ($1,000) of three climate change cases as compared to the base case: 1) increase in the frequency of drought from 40 to 50%, 2) increase in drought severity from a 24 acre-inch/acre water allotment to an 18 acre-inch water allotment, and 3) an increase in drought frequency and severity. Numbers in brackets indicate percent change from the base case.

Case	**Frequency** (% years)	**Severity** (ac-inches/ac)	**E(π)**	**Std Dev**	**Min π**	**Max π**
Base	40	24	532	36	408	590
1	50	24	515 [-3]	28 [-21]	429 [+5]	572 [-3]
2	40	18	476 [-11]	59 [+65]	272 [-33]	572 [-3]
3	50	18	448 [-16]	55 [+51]	302 [-26]	552 [-7]

The profit-maximizing producer is clearly worse off, in terms of expected profit, in each of the climate change scenarios examined. An increase in drought severity, or both severity and frequency leave the producer significantly worse off. The average profit impact of drought, however, is not necessarily worse for all climate change scenarios (table 6.17). An increase in the frequency of drought (case 1) actually decreases the percent profit impact of drought. As the probability of drought increases, the crop plan is increasingly tailored to drought, rather than the less common full year; therefore, the difference between expected profit and profit during drought is less than in the base case solution.

An increase in drought severity (case 2), in contrast, nearly doubles the percent profit impact of all drought categories. That is, the producer's expected profit declines, and the average impact of drought worsens. This again reflects the producer's difficulty in effectively mitigating more severe water shortages, in contrast to more frequent but moderate shortages. Lastly, an increase in both drought frequency and severity (case 3) also causes larger percent profit losses attributable to drought. The percent losses are slightly less than those experienced in case 2, but more than those in case 1. Again, more frequent drought provides the producer with incentives to prepare a crop plan in which drought is no longer the unexpected outcome. These adjustments (e.g. leaving more fields open) allow the producer to respond to more severe water shortages at less cost (e.g. fallowing open fields, rather than fall-prepared fields).

Table 6.17. Average percent change in total discounted profit, by years of drought experienced, for the base case and climate change cases 1 through 3.

	Average % change in π			
Years of Drought	Base Case*	Case 1	Case 2	Case 3
1	-2	-1	-6	-6
2	-7	-3	-13	-11
3	-11	-7	-20	-18
4	-16	-11	-29	-26
5	-23	-16	-40	-35
6	-30	-23	-52	-45

*Base case defined as Pr(D)=0.4, Dry = 24 ac-in/ac. Case 1 defined as Pr(D)=0.5, Dry = 24 ac-in/ac. Case 2 defined as Pr(D)=0.4, Dry = 18 ac-in/ac. Case 3 defined as Pr(D)=0.5, Dry = 18 ac-in/ac.

The above results suggest that climate change has the potential to alter agricultural producers' need for government assistance in response to drought, but in dramatically different ways, depending upon the characteristics of climate that are affected. This result can help guide the evolution of farm support programs in a changing climate. Specifically, producers will not be affected significantly by an increase in drought frequency alone. In contrast, producers will be affected significantly by an increase in drought severity or both severity and frequency. Even after producers adjust cropping plans in response to these changes, they will be much worse off during drought events than they are currently.

7 Summary of Results and Policy Implications

Chapter 7 summarizes the dissertation's motivation, objective, method, and major results. Chapter 7 also draws the large set of results together by discussing their broader implications for the administration of drought-related farm programs, in contrast to the farm-level implications presented in chapters 5 and 6. Readers should note, again, that the term "optimal," as used in this dissertation, refers simply to activities that are included in the mathematical programming model's solution; it does not indicate that the activities are Pareto optimal or socially efficient.

A transition from drought as 'disaster' to drought as 'managed risk' is underway. The impact of recent severe droughts throughout the United States, the potential for climate change to intensify the frequency and severity of drought, and discussion about the future of government assistance in agriculture have all increased the need to make this transition a reality. However, guidance for agricultural producers about how to optimally manage for the risk of drought remains insufficient.

Managing for the risk of drought involves two planning components, drought preparedness and drought response. Optimal drought preparedness and response is a challenging decision problem because few producers know *a priori* whether drought will occur in the near future, when or how frequently it will occur in the more distant future, how severe drought will be, or for how long any one drought will persist. Producers whose farm systems are characterized by intra- and inter-year dynamics face additional complexity in their decision environment. They must consider not only how the outcomes of their decisions will vary across states of nature, but also how their decisions today will affect opportunities and outcomes in future periods. The future consequences of their current decisions will also depend on the states of nature revealed through time. Given the considerable complexity of this decision environment, it is not clear what optimal drought preparedness and response, in practice, should look like.

A mathematical programming model that captures the stochastic and dynamic nature of a representative irrigated mixed crop farm in eastern Oregon is developed and used to explore the characteristics of optimal drought preparedness and response. Insights are gained about the role of alternative preparedness and response tools, the profit impact of droughts that vary in length, the tradeoff between maximizing the use of scarce water resources and minimizing the effects of discounting and interest costs, the role of crop history, the importance of inter-year dynamics, the potential effects of climate change, the effectiveness of the multi-peril crop insurance program's prevented planting provision for reducing drought's impact on producer profit, and the influence of price uncertainty on the management of water supply uncertainty. These insights, which are presented in detail in chapters 5 and 6, are summarized below in the context of a broader discussion of their potential implications for drought-related farm programs.

The magnitude of profit loss attributable to drought under optimal preparedness and response increases as the number of years of drought increase. It is difficult to generalize the impact of drought beyond this, however, because profit loss exhibits large variation depending upon the year in which drought occurs, or more specifically, the crops planted at the time the drought occurs. This presents a challenge to the administration of drought-related farm programs. Disaster declaration, for example, is based on the severity of loss at the county level; that is, some threshold of loss must be reached at the county-level to qualify for disaster assistance. This study illustrates that drought could impact identical farms very differently if they are in a different stage of the crop plan when the drought occurs. A farm community's collective losses might therefore be insufficient to receive disaster assistance, particularly if producers do not synchronize their crop plans. Note, however, that the community's economy is likely sheltered from risk when producers do not synchronize their crop plans. There are distributional implications of such a threshold-based policy; severely impacted producers are likely to be left without assistance in all but the most severe droughts. These severely impacted producers are not necessarily poor managers, as is sometimes assumed. They could, in contrast, be optimally prepared for drought, and simply have experienced an unfortunately-timed drought with respect to their crop plan.

Crop insurance companies also judge the validity of a claim based in part on the occurrence of similar losses in the neighboring area. It could be difficult for crop insurance adjusters to identify comparable losses with which to validate a producer's claim. A producer with valid drought losses could potentially be denied an indemnity payment because their crop plan is not synchronized with their neighbors'. Timely program delivery would not be possible if assistance were based on individual producers' circumstances. However, farm program administrators should recognize the potential for drought to generate heterogeneous impacts, even across a set of homogeneous farms.

The potential for drought to generate spillover effects from one year to another due to inter-year dynamics, a phenomenon which producers allude to, is corroborated by the model's results. A farm system with inter-year dynamics can therefore continue to experience the effects of drought after the drought itself subsides. Additionally, the effects of drought in one year can intensify the profit impact of drought in subsequent years. Although producers likely prefer prompt assistance in the event of drought, program administrators should keep in mind that the total impact of a particular year of drought might not be felt for several years, and that the impact of a multi-year drought can be more or less than the sum of its parts. The marginal profit impact of a year of drought is shown for one scenario, for example, to be 150% larger when preceded by a year of drought.

Producers face a complex set of tradeoffs when designing a drought preparedness and response plan. One important tradeoff is between maximizing the use of scarce water resources in each year of the planning horizon, and minimizing the negative profit impacts of discount and interest rates. A producer with a positive discount rate is generally expected to plant valuable crops first, which implies, for this farm system, specialization in onions in year 1. However, this strategy is not costless in a farm system with water supply uncertainty and agronomic constraints that generate inter-year dynamics. It reduces the total number of fields that can be successfully planted and the proportion of the total water allotment used over the planning horizon. It is therefore not clear intuitively whether the benefits of specialization outweigh the cost through time.

The model's results indicate that specialization in onions in year 1 is optimal, even in the presence of uncertainty and inter-year dynamics. This finding differs from the commonly-held belief that diversification is an effective drought management tool. It also contradicts the observed behavior of producers in the study area, who tend to spread the production of high value crops, such as onions, throughout the planning horizon, rather than concentrating it within one or two years. A sensitivity analysis indicates, however, that this behavior is more likely attributable to aversion to price-uncertainty for high-value crops, not water supply uncertainty. For some producers, this behavior is also attributable to agronomic constraints generated by past crop history.

Diversification is only optimal in the risk-neutral model when discount and interest rates are set to zero, or drought is defined as very severe (a water allotment of 12 acre-inches per acre, rather than 40). The hypothetical producer should, more specifically, plant as many fields to the highest valued crop in the first year as can be supported in the event of a drought. In the more probable case of less severe drought (24 acre-inches per acre), up to seven fields can be supported without risk of abandonment. Delaying the production of high value crops to reap the benefits of more complete use of scarce water resources (i.e. more net revenue from crop production) is not as profitable as concentrating the production early in the planning horizon, due to the increased cost of discounting and interest on borrowed funds. It would be difficult for a producer to weigh the relative magnitude of these tradeoffs using intuition alone.

The potential for improved water supply forecasts to reduce the impacts of water supply uncertainty receives much attention in the economics literature. Losses attributable to drought can be separated into a portion caused by the actual water shortage and a portion caused by uncertainty about the water supply. The primary effect of water supply uncertainty in the farm system modeled here is that more fall-prepared fields are abandoned than would be under certainty. This result explains why the hypothetical producer is found to enroll in the multi-peril crop insurance program's prevented planting provision. The prevented planting provision covers a portion of the losses incurred when an anticipated water shortage makes it unreasonable to follow through with a planned crop. The provision is shown to be an effective means for producers to prepare for and mitigate the profit impacts of drought, even when premiums are not subsidized. The social welfare implications of the provision are not examined, however.

The predicted effects of climate change for snowmelt-dependent farm systems include more frequent and severe drought. Producers' ability to formulate and implement optimal drought preparedness and response plans will therefore become increasingly important to the success of agricultural communities. The general public relies on these communities to provide many public goods, including open spaces and wildlife habitat. The public may also incur large expenditures if agricultural producers suffer losses due to natural disasters, such as drought, and receive assistance from the government. The ability of agricultural producers to adapt optimally to a changing climate therefore has a variety of social consequences. The impact of increased drought frequency and severity on optimal drought preparedness and response, and on profit loss associated with drought is analyzed. An increase in drought frequency has little impact on the drought preparedness plan or on profit loss attributable to drought. However, an increase in drought severity (or both severity and frequency) changes the relative importance of alternative drought preparedness tools, and substantially increases profit loss attributable to drought. The impact of climate change on the economic sustainability of agricultural communities thus depends critically on which features of the climate change. Future research on the impacts of climate change or the value of improved climate change information should investigate alternative forms of climate change to identify the range and uniqueness of optimal adjustments and impacts.

The last body of literature to which this dissertation contributes is mathematical modeling of stochastic and dynamic farm systems. The base case model illustrates the use of multi-stage discrete sequential stochastic programming (DSSP) to capture the dynamic and stochastic features of a farm system. Few studies have taken advantage of multi-stage DSSP's structure to represent both intra- and inter-year dynamics. Because the model captures both intra- and inter-year dynamics, it provides 1) a more thorough understanding of the complex tradeoffs that producers face when preparing and responding to drought, 2) a more complete picture of the impacts of drought through time, and 3) important insights about the challenges that administrators of drought assistance programs face. Lastly, it elucidates the applied aspects of optimal drought preparedness, a notion that has received increased attention in the policy arena, but whose practical form has been only vaguely discussed.

Beyond using DSSP to capture both intra- and inter-year dynamics, this dissertation also contributes to the literature by solving both a binary and continuous variables version of the model and comparing their solutions. Continuous variables are commonly used, rather than binary variables, because linear programming models are more easily solved than integer programming models, particularly when the model is stochastic. Many farm decisions, in contrast, are innately binary; for example, crops are often chosen for individual fields, rather than individual acres, or portions of an acre. A binary model represents the producer's decision problem more accurately than a continuous model, but it is also more difficult to solve. The ability of a continuous model to approximate the binary model's solution is thus examined.

The continuous model suggests similar cropping activities and timing. However, because the continuous model affords more flexibility in activities, it does not identify the same set of drought preparedness and response tools as the binary model. More importantly, drought preparedness tools that are observed on the ground are identified by the binary model, but not by the continuous model. Had the continuous model been used exclusively, one might have concluded that the activities excluded from the solution are sub-optimal, when they are in fact optimal in a more realistic model. In conclusion, factors such as field size or other discontinuities in the farm system need to be considered when choosing between a continuous versus binary (or integer) model.

The results of this dissertation shed light on several important aspects of drought management at the farm-level. However, there are many opportunities to improve and expand this analysis. A need exists to more realistically capture constraints on the producer's ability to change irrigation technologies from year-to-year, or to accommodate alternative scales of production for individual crops (i.e. machinery and labor constraints). The producer's crop mix and irrigation technology is more constrained than is assumed here; hence, expected profit and profit in dry years are likely less than those found here. A more accurate mathematical representation of yield response to deficit irrigation is also needed, such that strategic rather than season-long deficits can be modeled. Deficit irrigation plays a larger role in the response to drought than is found here.

Strategic deficit irrigation may enable producers to adjust their crop mix such that expected profit and profit in dry years are increased.

More work is also needed to better represent the continuous and updating nature of decision-making through time. Terminal values are included in the existing model to reflect that the farm continues to operate after the current planning horizon ends. However, explicit modeling of decisions in subsequent planning horizons would capture the long-term dynamics directly. This would also enable a more thorough analysis of the impact of crop history on the optimal drought preparedness strategy and the transition to that strategy. More advanced programming and a more powerful solution algorithm would be needed, however, to accommodate such additional stages in the decision problem. Additional farm programs should also be included in subsequent modeling efforts, such as loan deficiency payments, low-interest rate loans, and the conservation reserve program, to place drought preparedness and response tools in a more realistic decision context. Lastly, the modeling framework used here should be applied to other farm systems that exhibit inter-year dynamics to determine whether optimal drought preparedness and response, and the impacts of drought in these systems are affected by inter-year dynamics in ways similar to the farm system modeled in this dissertation.

Bibliography

107th United States Congress, 2nd session. 2002. *Farm Security and Rural Investment Act of 2002*. Public Law 107-171 [H.R. 2646].

Adams, R.M., K.J. Bryant, B.A. McCarl, D.M. Legler, J. O'Brien, A. Solow, and R. Weiher. 1995. "Value of Improved Long-Range Weather Information." *Contemporary Economic Policy* 13:10-19.

Adams, R.M. and S.H. Cho. 1998. "Agriculture and Endangered Species: An Analysis of Trade-Offs in the Klamath Basin, Oregon." *Water Resources Research* 34:2741-2749.

Adams, R.M., L.L. Houston, B.A. McCarl, M. Tiscareno L., J. Matus G., and R.F. Weiher. 2003. "The Benefits to Mexican Agriculture of an El Nino-Southern Oscillation (ENSO) Early Warning System." *Agricultural and Forest Meteorology* 115:183-194.

Agricultural Producers in the Vale Oregon Irrigation District. Personal communication, December 2003.

Albers, H.J. 1996. "Modeling Ecological Constraints on Tropical Forest Management: Spatial Interdependence, Irreversibility, and Uncertainty." *Journal of Environmental Economics and Management* 30:73-94.

Alston, J.M. and B.H. Hurd. 1990. "Some Neglected Social Costs of Government Spending in Farm Programs." *American Journal of Agricultural Economics* 72:149-56.

American Agricultural Economics Association Task Force. 1998. "Conceptual Issues in Cost and Return Estimates." In V. Eidman, ed(s). *Commodity Costs and Returns Estimation Handbook*. Ames, IA: American Agricultural Economics Association, pp. 1-84.

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

Antle, J.M. 1983. "Incorporating Risk in Production Analysis." *American Journal of Agricultural Economics* 65:1099-1106.

Askew, A.J. 1974. "Chance-Constrained Dynamic Programming and the Optimization of Water Resource Systems." *Water Resources Research* 10:1099-1106.

Bazza, M. 1999. "Improving Irrigation Management Practices with Water-Deficit Irrigation." In D.R. Nielsen, ed(s). *Crop Yield Response to Deficit Irrigation*. Boston, MA: Kluwer Academic Publishers, pp. 49-70.

Becker, N. 1999. "A Comparative Analysis of Water Price Support Versus Drought Compensation Scheme." *Agricultural Economics* 21:81-92.

Bernardo, D.J., N.K. Whittlesey, K.E. Saxton, and B.D. L. 1987. "An Irrigation Model for Management of Limited Water Supplies." *Western Journal of Agricultural Economics* 12:164-173.

Birge, J.R. and F. Louveaux. 1997. *Introduction to Stochastic Programming*. New York, NY: Springer-Verlag New York, Inc.

Boswell, C., J. Carr, J. Williams, and B. Turner. 1995. *Enterprise Budget: Alfalfa Hay Production, Eastern Oregon Region*. Corvallis, OR: Oregon State University Extension Service, Report No. EM 8606.

Bureau of Reclamation, U.S.D.I. 2006. *Agrimet Evapotranspiration Summaries*. Available at http://www.usbr.gov/pn/agrimet/etsummary.html, accessed August 7, 2006.

___. 2004. *Hydromet Archives Data: Reservoir Storage Content*. Available at http://www.usbr.gov/pn/hydromet/webhydarcread.html, accessed August 14, 2004.

___. 1998a. *Owyhee Project, Oregon and Idaho*. Available at http://www.usbr.gov/dataweb/html/owyhee.html, accessed August 14, 2004.

___. 1998b. *Vale Project Oregon*. Available at http://www.usbr.gov/dataweb/html/vale.html, accessed August 13, 2004.

Burke, S.M., R.M. Adams, and W.W. Wallender. 2004. "Water Banks and Environmental Water Demands: Case of the Klamath Project." *Water Resources Research* 40:W09S02, doi:10.1029/2003WR002832.

Calvin, L. 1992. *Participation in the U.S. Federal Crop Insurance Program*. Washington, D.C.: United States Department of Agriculture, Technical Bulletin Number 1800.

Charnes, A. and W.W. Cooper. 1959. "Chance-Constrained Programming." *Management Science* 5:73-79.

___. 1963. "Deterministic Equivalents for Optimizing and Satisficing under Chance Constraints." *Operations Research* 11:18-39.

Charnes, A., W.W. Cooper, and G.H. Symonds. 1958. "Cost Horizons and Certainty Equivalents: An Approach to Stochastic Programming of Heating Oil." *Management Science* 4:235-263.

Clawson, M., H.W. Ottoson, M. Duncan, and E.S. Sharp. 1980. "Task Group on Economics." In D.A. Wilhite, ed(s). *Drought in the Great Plains: Research on Impacts and Strategies*. Chelsea, MI: BookCrafters, Inc., pp. 43-59.

Cocks, K.D. 1968. "Discrete Stochastic Programming." *Management Science* 15:72-79.

Dole, R.M. 2000. "Prospects for Predicting Droughts in the United States." In D.A. Wilhite, ed(s). *Drought: A Global Assessment*. New York, NY: Routledge, pp. 83-99.

Doorenbos, J. and A.H. Kassam. 1979. *Yield Response to Water*. Rome, Italy: Food and Agriculture Organization of the United Nations.

Easterling, W.E. 1993. "Assessing the Regional Consequences of Drought: Putting the Mink Methodology to Work on Today's Problems." In D.A. Wilhite, ed(s). *Drought Assessment, Management, and Planning: Theory and Case Studies*. Boston, MA: Kluwer Academic Publishers, pp. 49-64.

Easterling, W.E. and R. Mendelsohn. 2000. "Estimating the Economic Impacts of Drought on Agriculture." In D.A. Wilhite, ed(s). *Drought: A Global Assessment*. New York, NY: Routledge, pp. 256-268.

Ehrlich, I. and G.S. Becker. 1992. "Market Insurance, Self-Insurance, and Self-Protection." In G. Dionne and S.E. Harrington, ed(s). *Foundations of Insurance Economics: Readings in Economics and Finance*. Boston, MA: Kluwer Academic Publishers, pp. 164-189.

English, M. 1990a. "Deficit Irrigation. I: Analytical Framework." *Journal of Irrigation and Drainage Engineering* 116:399-412.

___. 1990b. "Deficit Irrigation. II: Observations in Columbia Basin." *Journal of Irrigation and Drainage Engineering* 116:413-426.

English, M. and B. Nakamura. 1989. "Effects of Deficit Irrigation and Irrigation Frequency on Wheat Yields." *Journal of Irrigation and Drainage Engineering* 115:172-184.

English, M. and S.N. Raja. 1996. "Perspectives on Deficit Irrigation." *Agricultural Water Management* 32:1-14.

Farm Service Agency, U.S.D.A. 2002. *Farm Service Agency Online: What We Do and Who We Are*. Available at http://www.fsa.usda.gov/or/whatwedo.html, accessed October 26, 2004.

Featherstone, A.M., T.G. Baker, and P.V. Preckel. 1993. "Modeling Dynamics and Risk Using Discrete Stochastic Programming: A Farm Capital Structure Application." In C.R. Taylor, ed(s). *Applications of Dynamic Programming to Agricultural Decision Problems*. Boulder, CO: Westview Press, pp. 145-169.

Frederick, K.D. and P.H. Gleick. 1999. *Water & Global Climate Change: Potential Impacts on U.S. Water Resources*. Arlington, VA: The Pew Center on Global Climate Change.

Fujun, W., Q. Mengwen, W. Huaguo, and Z. Changjiu. 1999. "The Response of Winter Wheat to Water Stress and Nitrogen Fertilizer Use Efficiency." In D.R. Nielsen, ed(s). *Crop Yield Response to Deficit Irrigation*. Boston, MA: Kluwer Academic Publishers, pp. 39-48.

Garrido, A. and A. Gomez-Ramos. 2000. "Socio-Economic Aspects of Droughts." In F. Somma, ed(s). *Drought and Drought Mitigation in Europe*. Boston, MA: Kluwer Academic Publishers, pp. 197-207.

Glauber, J.W. and K.J. Collins. 2002. "Crop Insurance, Disaster Assistance, and the Role of the Federal Government in Providing Catastrophic Risk Protection." *Agricultural Finance Review* 62:81-101.

Gleick, P.H. 2000. *Water: The Potential Consequences of Climate Variability and Change for the Water Resources of the United States*. National Water Assessment Group for the U.S. Global Change Research Program. Oakland, CA: Pacific Institute for Studies in Development, Environment, and Security.

Gomez-Limon, J.A., M. Arriaza, and L. Riesgo. 2003. "An MCDM Analysis of Agricultural Risk Aversion." *European Journal of Operational Research* 151:569-585.

Green, G.P. and J.R. Hamilton. 2000. "Water Allocation, Transfers and Conservation: Links between Policy and Hydrology." *Water Resources Development* 16:197-208.

Haan, C.T. 2002. *Statistical Methods in Hydrology*. Ames, IA: Iowa State Press.

Haight, J. (Private Insurance Agent). Personal communication, January 7, 2004.

Haneveld, W.K.K. 1986. *Duality in Stochastic Linear and Dynamic Programming*. New York, NY: Springer-Verlag.

Haouari, M. and M.N. Azaiez. 2001. "Optimal Cropping Patterns under Water Deficits." *European Journal of Operational Research* 130:133-146.

Hardaker, B.J., S. Pandey, and L.H. Patten. 1991. "Farm Planning under Uncertainty: A Review of Alternative Programming Models." *Review of Marketing and Agricultural Economics* 59:9-22.

Hardaker, J.B., R.B.M. Huirne, and J.R. Anderson. 1997. *Coping with Risk in Agriculture*. New York, NY: CABI Publishing.

Hargreaves, G.H. and Z. Samani. 1984. "Economic Considerations of Deficit Irrigation." *Journal of Irrigation and Drainage Engineering* 110:343-358.

Hart, W.E., H.G. Collins, G. Woodward, and A.S. Humpherys. 1980. "Design and Operation of Gravity or Surface Systems." In M.E. Jensen, ed(s). *Design and Operation of Farm Irrigation Systems*. St. Joseph, MI: American Society of Agricultural Engineers, pp. 501-580.

Heim, R. and J. Lawrimore. 2006. *Climate of 2005 Annual Review: U.S. Drought*. Available at http://www.ncdc.noaa.gov/oa/climate/research/2005/ann/drought-summary.html, accessed October 3, 2006.

Higle, J.L. and S.W. Wallace. 2003. "Sensitivity Analysis and Uncertainty in Linear Programming." *Interfaces* 33:53-60.

Hinman, H., G. Pelter, E. Kulp, R. Gillespie, and E. Sorensen. 1997. *1997 Enterprise Budgets: Potatoes, Winter Wheat, Alfalfa Hay, Grain Corn, Silage Corn and Sweet Corn under Center Pivot Irrigation, Columbia Basin, Washington*. Pullman, WA: Washington State University Cooperative Extension, EB1667.

Hirshleifer, J. and J.G. Riley. 1992. *The Analytics of Uncertainty and Information*. Cambridge, United Kingdom: Cambridge University Press.

Hoffman, T.R. and G.S. Willett. 1998. *The Economics of Alternative Irrigation Systems in the Kittitas Valley of Washington State*. Pullman, WA: Washington State University Cooperative Extension, EB1875.

Howitt, R.E. 1995. "Positive Mathematical Programming." *American Journal of Agricultural Economics* 77:329-342.

Hueth, D.L. and W.H. Furtan. 1994. *Economics of Agricultural Crop Insurance: Theory and Evidence*. Norwell, MA: Kluwer Academic Publishers.

Iglesias, E., A. Garrido, and A. Gomez-Ramos. 2003. "Evaluation of Drought Management in Irrigated Areas." *Agricultural Economics* 29:211-229.

Intergovernmental Panel on Climate Change. 2001a. *Climate Change 2001: Impacts, Adaptation, and Vulnerability*. New York, NY: Cambridge University Press.

___. 2001b. *Climate Change 2001: Synthesis Report.* New York, NY: Cambridge University Press.

___. 1998. *The Regional Impacts of Climate Change: An Assessment of Vulnerability*. New York, NY: Cambridge University Press.

Isik, M. 2002. "Resource Management under Production and Output Price Uncertainty: Implications for Environmental Policy." *American Journal of Agricultural Economics* 84:557-571.

Jacobs, R. (Watermaster, District 9, Oregon Water Resource Department). Personal communication, December 17, 2003.

___. Personal communication, May 5, 2004.

Jaeger, W.K. 2004. "Conflicts over Water in the Upper Klamath Basin and the Potential Role for Market-Based Allocations." *Journal of Agricultural and Resource Economics* 29:167-184.

Johnson, S.R. and M.T. Holt. 1997. "The Value of Weather Information." In R.W. Katz and A.H. Murphy, ed(s). *Economic Value of Weather and Climate Forecasts*. New York, NY: Cambridge University Press, pp. 75-107.

Just, R.E. 1975. "Risk Aversion under Profit Maximization." *American Journal of Agricultural Economics* 57:347-352.

Just, R.E., L. Calvin, and J. Quiggin. 1999. "Adverse Selection in Crop Insurance: Actuarial and Asymmetric Information Incentives." *American Journal of Agricultural Economics* 81:834-849.

Kaiser, H.M. and J. Apland. 1989. "DSSP: A Model of Production and Marketing Decisions on a Midwestern Crop Farm." *North Central Journal of Agricultural Economics* 11:157-169.

Kaiser, H.M., S.J. Riha, D.S. Wilks, D.G. Rossiter, and R. Sampath. 1993. "A Farm-Level Analysis of Economic and Agronomic Impacts of Gradual Climate Warming." *American Journal of Agricultural Economics* 75:387-398.

Kanwar, S. 1999. "Does Risk Matter? The Case of Wage-Labour Allocation by Owner-Cultivators." *Applied Economics* 31:307-317.

Keith, J.E., G.A. Martinez Gerstl, D.L. Snyder, and T.F. Glover. 1989. "Energy and Agriculture in Utah: Responses to Water Shortages." *Western Journal of Agricultural Economics* 14:85-97.

Kennedy, J.O.S. 1986. *Dynamic Programming: Applications to Agriculture and Natural Resources*. New York, NY: Elsevier Applied Science Publishers.

Keplinger, K.O., B.A. McCarl, M.E. Chowdhury, and R.D. Lacewell. 1998. "Economic and Hydrologic Implications of Suspending Irrigation in Dry Years." *Journal of Agricultural and Resource Economics* 23:191-205.

King, R.P. and G.E. Oamek. 1983. "Risk Management by Colorado Dryland Wheat Farmers and the Elimination of the Disaster Assistance Program." *American Journal of Agricultural Economics* 65:247-255.

Kirda, C. 2002. "Deficit Irrigation Scheduling Based on Plant Growth Stages Showing Water Stress Tolerance." In M. Smith, ed(s). *Deficit Irrigation Practices*. Rome, Italy: Food and Agriculture Organization of the United Nations, pp. 3-10.

Kirda, C., R. Kanber, and K. Tulucu. 1999. "Yield Response of Cotton, Maize, Soybean, Sugar Beet, Sunflower and Wheat to Deficit Irrigation." In D.R. Nielsen, ed(s). *Crop Yield Response to Deficit Irrigation*. Boston, MA: Kluwer Academic Publishers, pp. 21-38.

Klauzer, J. (Clearwater Supply). Personal communication, September 2005.

Knowles, N., M.D. Dettinger, and D.R. Cayan. 2006. "Trends in Snowfall Versus Rainfall in the Western United States." *Journal of Climate* 15:4545-4559.

Knutson, C.L. 2001. "Results of a Rapid Appraisal Study: Agricultural Producers' Perceptions of Drought Vulnerability and Mitigation--Howard County, Nebraska." *Drought News Network* 13:3-6.

Kromm, D.E. and S.E. White. 1986. "Variability in Adjustment Preferences to Groundwater Depletion in the American High Plains." *Water Resources Bulletin* 22:791-801.

Kwon, C.-W., P.F. Orazem, and D.M. Otto. 2006. "Off-Farm Labor Supply Responses to Permanent and Transitory Farm Income." *Agricultural Economics* 34:59-67.

Langemeier, M.R. and G.F. Patrick. 1990. "Farmers' Marginal Propensity to Consume: An Application to Illinois Grain Farms." *American Journal of Agricultural Economics* 72:309-316.

Leathers, H. 1994. "Crop Insurance Decisions and Financial Characteristics of Farms." In W.H. Furtan, ed(s). *Economics of Agricultural Crop Insurance: Theory and Evidence*. Boston, MA: Kluwer Academic Publishers, pp. 273-291.

Leathers, H.D. and J.-P. Chavas. 1986. "Farm Debt, Default, and Foreclosure: An Economic Rationale for Policy Action." *American Journal of Agricultural Economics* 68:828-837.

Lewandrowski, J. and R. Brazee. 1992. "Government Farm Programs and Climate Change: A First Look." In J.M. Reilly and M. Anderson, ed(s). *Economics Issues in Global Climate Change: Agriculture, Forestry, and Natural Resources*. Boulder, CO: Westview Press, pp. 132-147.

Lin, W., G.W. Dean, and C.V. Moore. 1974. "An Empirical Test of Utility Vs. Profit Maximization in Agricultural Production." *American Journal of Agricultural Economics* 56:497-508.

Lomas, J. 2000. "Drought Mitigation Strategies - a Dynamic Approach." In F. Somma, ed(s). *Drought and Drought Mitigation in Europe*. Boston, MA: Kluwer Academic Publishers, pp. 247-252.

Luo, H., J.R. Skees, and M.A. Marchant. 1994. "Weather Information and the Potential for Intertemporal Adverse Selection in Crop Insurance." *Review of Agricultural Economics* 16:441-451.

Luttrell, C.B. 1989. *The High Cost of Farm Welfare*. Washington, D.C.: Cato Institute.

Mahul, O. 1999. "Optimum Area Yield Crop Insurance." *American Journal of Agricultural Economics* 81:75-82.

Maji, C.C. and E.O. Heady. 1978. "Intertemporal Allocation of Irrigation Water in the Mayurakshi Project (India): An Application of Chance-Constrained Linear Programming." *Water Resources Research* 14:190-196.

Makki, S.S. and A. Somwaru. 2001. "Farmers' Participation in Crop Insurance Markets: Creating the Right Incentives." *American Journal of Agricultural Economics* 83:662-667.

Malheur County Extension Service. 2004a. "1995 to 2004 Price and Yield for Selected Crops in Malheur County (Chart)."

___. 2004b. *Corn Silage Budget: Malheur County, Oregon*. Ontario, OR: Malheur County Extension Service, January 2004.

___. 2004c. *Dairy Quality Alfalfa Hay Budget: Malheur County, Oregon*. Ontario, OR: Malheur County Extension Service, January 2004.

___. 2004d. *Field Corn Budget: Malheur County, Oregon*. Ontario, OR: Malheur County Extension Service, January 2004.

___. 2000. *Russet Potatoes Data Sheet: Malheur County, Oregon*. Ontario, OR: Malheur County Extension Service, June 2000.

___. 2002. *Sugarbeet Budget: Malheur County, Oregon*. Ontario, OR: Malheur County Extension Service, February 2002.

___. 2004e. *Winter Wheat Budget: Malheur County, Oregon*. Ontario, OR: Malheur County Extension Service, January 2004.

___. 2003. *Yellow Onion Data Sheet: Malheur County, Oregon*. Ontario, OR: Malheur County Extension Service, May 2003.

Malheur County Oregon. 2003. *Vale Community Profile*. Available at http://www.malheurco.org/CountyProfile/CountyProfileVale.html, accessed August 13, 2004.

Mas-Colell, A., M.D. Whinston, and J.R. Green. 1995. *Microeconomic Theory*. New York, NY: Oxford University Press.

Mejias, P., C. Varela-Ortega, and G. Flichman. 2004. "Integrating Agricultural Policies and Water Policies under Water Supply and Climate Uncertainty." *Water Resources Research* 40:W07S03, doi:10.1029/2003WR002877.

Meyer, J. 2002. "Expected Utility as a Paradigm for Decision Making in Agriculture." In R.E. Just and R.D. Pope, ed(s). *A Comprehensive Assessment of the Role of Risk in U.S. Agriculture*. Boston, MA: Kluwer Academic Publishers, pp. 3-19.

Michelsen, A.M. and R.A. Young. 1993. "Optioning Agricultural Water Rights for Urban Water Supplies During Drought." *American Journal of Agricultural Economics* 75:1010-1020.

Miller, A.C. and T.R. Rice. 1983. "Discrete Approximations of Probability Distributions." *Management Science* 29:352-362.

Mjelde, J.W. and M.J. Cochran. 1988. "Obtaining Lower and Upper Bounds on the Value of Seasonal Climate Forecasts as a Function of Risk Preferences." *Western Journal of Agricultural Economics* 13:285-293.

Mjelde, J.W., H.S.J. Hill, and J.F. Griffiths. 1998. "A Review of Current Evidence on Climate Forecasts and Their Economic Effects in Agriculture." *American Journal of Agricultural Economics* 80:1089-1095.

Mjelde, J.W., J.B.J. Penson, and C.J. Nixon. 2000. "Dynamic Aspects of the Impact of the Use of Perfect Climate Forecasts in the Corn Belt Region." *Journal of Applied Meteorology* 39:67-79.

Mjelde, J.W., S.T. Sonka, B.L. Dixon, and P.J. Lamb. 1988. "Valuing Forecast Characteristics in a Dynamic Agricultural Production System." *American Journal of Agricultural Economics* 70:674-684.

Mjelde, J.W., T.N. Thompson, and C.J. Nixon. 1996. "Government Institutional Effects on the Value of Seasonal Climate Forecasts." *American Journal of Agricultural Economics* 78:175-188.

Mjelde, J.W., T.N. Thompson, C.J. Nixon, and P.J. Lamb. 1997. "Utilizing a Farm-Level Decision Model to Help Prioritize Future Climate Prediction Research Needs." *Meteorological Applications* 4:161-170.

Monke, J.D. 1995. Farmer Participation in Government Commodity Programs: A Multiyear Risk-Management Analysis. Ph.D. thesis, University of Illinois at Urbana-Champaign.

Musick, J.T. and D.A. Dusek. 1980. "Planting Date and Water Deficit Effects on Development and Yield of Irrigated Winter Wheat." *Agronomy Journal* 72:45-52.

National Assessment Synthesis Team. 2000. *Climate Change Impacts on the United States: The Potential Consequences of Climate Variability and Change*. U.S. Global Change Research Program. New York, NY: Cambridge University Press.

Neibling, H. 1997. *Irrigation Systems for Idaho Agriculture*. Moscow, ID: University of Idaho College of Agriculture, CIS1055.

Office of Communications, U.S.D.A. 2004. *USDA Drought-Related Programs*. Available at http://www.usda.gov/Newsroom/fs0199.04.html, accessed August 30, 2004.

Oregon State University Water Resources Engineering Team. 1992. *Oregon Crop Water Use and Irrigation Requirements*. Corvallis, OR: Oregon State University Extension Service, Extension Miscellaneous 8530.

Pannell, D.J., B. Malcolm, and R.S. Kingwell. 2000. "Are We Risking Too Much? Perspectives on Risk in Farm Modeling." *Agricultural Economics* 23:69-78.

Pasour, E.C., Jr. and R.R. Rucker. 2005. *Plowshares and Pork Barrels: The Political Economy of Agriculture*. Oakland, CA: Independent Institute.

Patterson, P.E., B.A. King, and R.L. Smathers. 1996a. *Economics of Low-Pressure Sprinkler Irrigation Systems: Center Pivot & Linear Move*. Moscow, ID: University of Idaho Cooperative Extension System, Bulletin No. 787.

___. 1996b. *Economics of Sprinkler Irrigation Systems: Handline, Solid Set, & Wheelline*. Moscow, ID: University of Idaho Cooperative Extension System, Bulletin No. 788.

Preckel, P.V. and E. Devuyst. 1992. "Efficient Handling of Probability Information for Decision-Analysis under Risk." *American Journal of Agricultural Economics* 74:655-662.

Rae, A.N. 1971. "An Empirical Application and Evaluation of Discrete Stochastic Programming in Farm Management." *American Journal of Agricultural Economics* 53:625-638.

Rejesus, R.M., C.L. Escalante, and A.C. Lovell. 2005. "Share Tenancy, Ownership Structure, and Prevented Planting Claims in Crop Insurance." *American Journal of Agricultural Economics* 87:180-93.

Rejesus, R.M., A.C. Lovell, B.B. Little, and M.H. Cross. 2003. "Determinants of Anomalous Prevented Planting Claims: Theory and Evidence from Crop Insurance." *Agricultural and Resource Economics Review* 32:244-58.

Rich, J. 1993. "Institutional Responses to the 1987-92 California Drought." In D.A. Wilhite, ed(s). *Drought Assessment, Management, and Planning: Theory and Case Studies*. Boston, MA: Kluwer Academic Publishers, pp. 254-262.

Risk Management Agency, U.S.D.A. 2004a. *County Actuarial Document Book: Malheur County, Oregon, 2004 Crop Year*. Available at http://www3.rma.usda.gov/apps/docbrowser/docbrowserB.cfm, accessed August 31, 2004.

___. 2003. *Irrigation and Prevented Planting*. Available at http://www.rma.usda.gov/news/2003/04/preventedplanting.pdf, accessed October 2, 2003.

___. 2006. *Premium Calculator*. Available at http://www3.rma.usda.gov/apps/premcalc/, accessed October 23, 2006.

___. 2004b. *Rma Online: Our Vision and Mission*. Available at http://www.rma.usda.gov/aboutrma/what/vision.html, accessed October 26, 2004.

Schuck, E., W.M. Frasier, and R.S. Webb. 2003. "Preliminary Summary of the 2002 Colorado Drought Survey 'Weathering Tough Times.'" *Colorado Water* 20:8-11.

Segarra, E., R.A. Kramer, and D.B. Taylor. 1985. "A Stochastic Programming Analysis of the Farm Level Implications of Soil Erosion Control." *Southern Journal of Agricultural Economics* 17:147-154.

Sherrick, B.J., P.J. Barry, P.N. Ellinger, and G.D. Schnitkey. 2004. "Factors Influencing Farmers' Crop Insurance Decisions." *American Journal of Agricultural Economics* 86:103-114.

Shock, C.C., A. Nishihara, K. Pratt, and R. Jones. 2001. *Phosphorous Content of the Malheur River*. Available at http://www.cropinfo.net/AnnualReports/2001/MalheurRiverP.htm, accessed September 23, 2004.

Smathers, R.L., B.A. King, and P.E. Patterson. 1995. *Economics of Surface Irrigation Systems*. Moscow, ID: University of Idaho, Cooperative Extension System, Bulletin No. 779.

Soil Conservation Service, U.S.D.A. and Oregon Agricultural Experiment Station. 1979. "General Soil Map, Malheur County, Oregon, Northeastern Part."

Solow, A., R.M. Adams, K.J. Bryant, D.M. Legler, J.J. O'Brien, B.A. McCarl, W. Nayda, and R. Weiher. 1998. "The Value of Improved ENSO Prediction to U.S. Agriculture." *Climatic Change* 39:47-60.

Stanger, S. (Farm Credit Services). Personal communication, August 17, 2005.

Stehlik, D. 2005. "Managing Risk?: Social Policy Responses in Time of Drought." In D.A. Wilhite, ed(s). *From Disaster Response to Risk Management: Australia's National Drought Policy*. Dordrecht, The Netherlands: Springer, pp. 65-83.

Stewart, I.T., D.R. Cayan, and M.D. Dettinger. 2004. "Changes in Snowmelt Runoff Timing in Western North America under a 'Business as Usual' Climate Change Scenario." *Climatic Change* 62:217-232.

Tannehill, I.R. 1947. *Drought: Its Causes and Effects*. Princeton, NJ: Princeton University Press.

Tapp, N., D. Thompson, N. Milham, and D. Jackson. 1998. *A Stochastic Analysis of Drought Management Strategies for Mixed Farming in the Central West of New South Wales*. Armidale, New South Wales, Australia: University of New England Armidale, Project UNE 17.

Taylor, R.G. and R.A. Young. 1995. "Rural-to-Urban Water Transfers: Measuring Direct Foregone Benefits of Irrigation Water under Uncertain Water Supplies." *Journal of Agricultural and Resource Economics* 20:247-262.

Thompson, D., D. Jackson, N. Tapp, N. Milham, R. Powell, B. Douglas, G. Kennedy, E. Jack, and G. White. 1996. *Analysing Drought Strategies to Enhance Farm Financial Viability*. Armidale, New South Wales, Australia: University of New England, Final Report.

Thompson, D. and R. Powell. 1998. "Exceptional Circumstances Provisions in Australia: Is There Too Much Emphasis on Drought?" *Agricultural Systems* 57:469-488.

Tintner, G. 1960. "A Note on Stochastic Linear Programming." *Econometrica* 28:490-495.

Toft, H.I. and P.W. O'Hanlon. 1979. "A Dynamic Programming Model for on-Farm Decision Making in a Drought." *Review of Marketing and Agricultural Economics* 47:5-16.

Torkamani, J. and M. Haji-Rahimi. 2001. "Evaluation of Farmer's Risk Attitudes Using Alternative Utility Functional Forms." *Journal of Agricultural Science and Technology* 3:243-248.

Turner, B. and M. Bohle. 1995. *Enterprise Budget: Spring Barley, South Central Region*. Corvallis, OR: Oregon State University Extension Service, Report No. EM 8591.

Turner, B.P. and G.M. Perry. 1997. "Agriculture to Instream Water Transfers under Uncertain Water Availability: A Case Study of the Deschutes River, Oregon." *Journal of Agricultural and Resource Economics* 22:208-221.

Unknown. 19--. "Group Enterprise Inventory, Region 7, Irrigation (Map)."

Vale Oregon Irrigation District (Staff). Personal communication, 2004.

___. 2004b. *United States Department of the Interior, Bureau of Reclamation, Crop and Water Data, Form 7-2045 (1992 to 2002).* Vale, OR: Vale Oregon Irrigation District.

Vlachos, E. and L.D. James. 1983. "Drought Impacts." In E. Vlachos, ed(s). *Coping with Droughts*. Chelsea, MI: BookCrafters, Inc., pp. 44-73.

Ward, F.A., R. Young, R. Lacewell, J.P. King, W.M. Frasier, J.T. McGucken, C. DuMars, J. Booker, J. Ellis, and R. Srinivasan. 2001. *Institutional Adjustments for Coping with Prolonged and Severe Drought in the Rio Grande Basin*. Las Cruces, NM: Water Resources Research Institute, Technical Completion Report No. 317.

Ward, S. (Manager, Vale Oregon Irrigation District). Personal communication, May 5, 2004.

Weisensel, W.P., G.C. Van Kooten, and R.A. Schoney. 1991. "Relative Riskiness of Fixed Vs. Flexible Crop Rotations in the Dryland Cropping Region of Western Canada." *Agribusiness* 7:551-560.

Western Drought Coordination Council. 1999. *The Western Drought Experience: The Western Drought Coordination Council's Report to the National Drought Policy Commission*. Available at http://www.westgov.org/wga/publicat/drght99.htm, accessed December 4, 2006.

Wilhite, D.A. and S.L. Rhodes. 1993. "Drought Mitigation in the United States: Progress by State Government." In D.A. Wilhite, ed(s). *Drought Assessment, Management, and Planning: Theory and Case Studies*. Boston, MA: Kluwer Academic Publishers, pp. 237-251.

Wilks, D.S. 1997. "Forecast Value: Prescriptive Decision Studies." In R.W. Katz and A.H. Murphy, ed(s). *Economic Value of Weather and Climate Forecasts*. New York, NY: Cambridge University Press, pp. 109-145.

Wojciechowski, J., G.C.W. Ames, S.C. Turner, B.R. Miller. 2000. "Marketing of cotton fiber in the presence of yield and price risk." *Journal of Agricultural and Applied Economics* 32:521-529.

Wu, J. and R.M. Adams. 2001. "Production Risk, Acreage Decisions and Implications for Revenue Insurance Programs." *Canadian Journal of Agricultural Economics* 49:19-35.

Wyse, B.J. 2004. Farm and Community-Level Impacts of Irrigation Water Supply Fluctuations: A Case Study of Malheur County, Oregon. M.S. thesis, Oregon State University.

Yevjevich, V. and E. Vlachos. 1983. "Strategies and Measures for Coping with Droughts." In E. Vlachos, ed(s). *Coping with Droughts*. Chelsea, MI: BookCrafters, Inc., pp. 77-101.

Young, C.E., M.L. Vandeveer, and R.D. Schnepf. 2001. "Production and Price Impacts of U.S. Crop Insurance Programs." *American Journal of Agricultural Economics* 83:1196-1203.

Ziari, H.A. and B.A. McCarl. 1995. "A Nonlinear Mixed Integer Program Model for Evaluating Runoff Impoundments for Supplemental Irrigation." *Water Resources Research* 31:1585-1594.

Zilberman, D., A. Dinar, N. MacDougall, M. Khanna, C. Brown, and F. Castillo. 2002. "Individual and Institutional Responses to the Drought: The Case of California Agriculture." *Water Resources Update* 121:17-23.

Appendices

Appendix A. Base case parameters and profit

Table A.1. Per-unit prices and maximum yield assumed in the base case.

Crop (yield unit)	Price per Unit ($2004)[1]	Max Yield (irrigation system)[2]
Onion (cwt)	6.00	650 (drip)
Russet Potato (cwt)	3.30	415 (furrow)
Sugar Beet (T)	39.00	31 (furrow)
Winter Wheat (bu)	3.20	130 (furrow)
Alfalfa Establishment (T)	79.00	6 (furrow)
Alfalfa Established (T)	79.00	6 (furrow)
Grain Corn (bu)	2.70	170 (furrow)
Silage Corn (T)	19.00	28 (furrow)
Barley (bu)	2.15	100 (furrow)

[1] Ten-year historical average price (1995-2004) as reported by the Malheur County Extension Service (2004a). [2] Maximum yield based on Malheur County Extension Service (2004a) and conversations with producers in the study area.

Table A.2. Cost ($2004/acre) of crop production under alternative irrigation technologies.

Crop/Irrigation	Fall Cost	Spring Cost	Opp Cost of $[1]	Econ Cost[2]
Onion				
Furrow	600	2400	210	3210
Reuse furrow	600	2480	216	3296
Drip	600	2750	235	3585
Russet Potato				
Furrow	100	1350	102	1552
Reuse furrow	100	1450	109	1659
Solid set sprinkler	100	1625	121	1846
Sugar Beet				
Furrow	150	820	68	1038
Reuse furrow	150	920	75	1145
Wheel-line sprinkler	150	940	76	1166
Center pivot sprinkler	150	940	76	1166
Winter Wheat				
Furrow	160	105	19	284
Reuse furrow	160	145	21	326
Wheel-line sprinkler	160	190	25	375
Center pivot sprinkler	160	190	25	375
Alfalfa Establishment				
Furrow	185	295	34	514
Reuse furrow	185	330	36	551
Wheel-line sprinkler	185	380	40	605
Center pivot sprinkler	185	380	40	605
Alfalfa Established				
Furrow	0	295	21	316
Reuse furrow	0	330	23	353
Wheel-line sprinkler	0	380	27	407
Center pivot sprinkler	0	380	27	407
Grain Corn				
Furrow	--	425	30	455
Reuse furrow	--	465	33	498
Center pivot sprinkler	--	510	36	546

Table A.2 (Cont.)

Crop/Irrigation	Fall Cost	Spring Cost	Opp Cost[1]	Econ Cost[2]
Silage Corn				
Furrow	--	600	42	642
Reuse furrow	--	640	45	685
Center pivot sprinkler	--	685	48	733
Barley				
Furrow	--	245	17	262
Reuse furrow	--	285	20	305
Wheel-line sprinkler	--	330	23	353
Center pivot sprinkler	--	330	23	353
Fallow	--	0	0	0

[1]Equals 1.07 times the sum of Fall and Spring Costs (i.e. 7% is the rate earned on own funds if saved rather than spent, or the interest rate on borrowed funds).
[2]Equals the sum of "Fall Cost," "Spring Cost," and "Opp Cost."

Enterprise budgets compiled for Malheur County crops were the primary source of cost data. Specific sources include the following: (Boswell et al. 1995; Malheur County Extension Service 2004b; Malheur County Extension Service 2004c; Malheur County Extension Service 2004d; Malheur County Extension Service 2000; Malheur County Extension Service 2002; Malheur County Extension Service 2004e; Malheur County Extension Service 2003; Turner and Bohle 1995). All cost data were adjusted for inflation to 2004$ using the Prices Paid Index (Crop Sector) for Commodities & Services, Interest, Taxes & Wage Rates. The following sources were used to adapt enterprise budgets for alternative irrigation technologies: (Hinman et al. 1997; Klauzer 2005; Patterson, King, and Smathers 1996a; Patterson, King, and Smathers 1996b; Smathers, King, and Patterson 1995).

Table A.3. Crop water requirements.

Crop	Crop Water Requirement (inches)*
Onion	29.0
Russet Potato	27.2
Sugar Beet	34.1
Winter Wheat	24.1
Alfalfa Establishment	41.8
Alfalfa Established	41.8
Grain Corn	27.5
Silage Corn	27.5
Barley	26.1
Fallow	0

*Crop water requirement is assumed equal to the 13-year average (1992-2004) seasonal evapotranspiration for the respective crop at the Ontario, Oregon Agrimet station (Bureau of Reclamation 2006). Average ET reflects the crop water requirement that must be met to produce the average yield observed in the study area.

Table A.4. Technical efficiency (%) of alternative irrigation technologies.

Irrigation Technology	**Technical efficiency***
Furrow	50
Reuse furrow	80
Solid set sprinkler	65
Wheel-line sprinkler	65
Center pivot sprinkler	75
Subsurface drip	90

*Technical efficiency is defined as the proportion of water delivered to the crop that reaches the crop root zone (i.e. the proportion of delivered water that does not runoff, evaporate or percolate out of the root zone). Sources: (Hoffman and Willett 1998; Neibling 1997; Oregon State University Water Resources Engineering Team 1992, p179)

Table A.5. Assumed yield response factor (k_y) for alternative crops.

Crop	Yield Response Factor (k_y)*
Onion	1.10
Russet Potato	1.10
Sugar Beet	0.80
Winter Wheat	1.00
Alfalfa Establishment	0.90
Alfalfa Established	0.90
Grain Corn	1.25
Silage Corn	1.25
Barley	1.00

*Yield response factors indicate sensitivity of yield to a water deficit of equal proportion throughout the growing season (in contrast to a water deficit during a particular growth stage). $k_y > 1$ indicate relatively drought intolerant crops; $k_y \leq 1$ indicate relatively drought tolerant crops. Source: Doorenbos and Kassam (1979, table 24).

Table A.6. Crop yield (units/acre), total revenue ($/acre), total cost ($/acre), and net revenue ($/acre) for alternative combinations of crop, irrigation technology, and deficit irrigation level.

Crop/Irrigation	Deficit[1]	Yield	Tot Rev	Tot Cost[2]	Net Rev
Onion (cwt)					
Furrow	D1	550	3300	3210	90
	D2	498	2987	3210	-223
	D3	446	2674	3210	-536
	D4	394	2361	3210	-849
	D5	341	2048	3210	-1162
	D6	289	1735	3210	-1475
Reuse Furrow	D1	550	3300	3296	4
	D2	498	2987	3296	-309
	D3	446	2674	3296	-621
	D4	394	2361	3296	-934
	D5	341	2048	3296	-1247
	D6	289	1735	3296	-1560
Drip	D1	650	3900	3585	316
	D2	588	3530	3585	-54
	D3	527	3160	3585	-424
	D4	465	2791	3585	-794
	D5	403	2421	3585	-1164
	D6	342	2051	3585	-1534
Russet Potato (cwt)					
Furrow	D1	415	1370	1552	-182
Reuse Furrow	D1	415	1370	1659	-289
Solid Set Sprinkler	D1	450	1485	1846	-361
Sugar Beet (T)					
Furrow	D1	31	1209	1038	171
	D2	29	1124	1038	86
	D3	27	1038	1038	0
	D4	24	953	1038	-85
	D5	22	867	1038	-171
	D6	20	782	1038	-256

[1]Represents the proportion of irrigation water requirement provided (D1=100%, D2=90%,…, D6=50%,D7=0%). [2]Includes a 7% opportunity cost of money; excludes opportunity cost of land and management.

Table A.6 (Cont.)

Crop/Irrigation	Deficit	Yield	Tot Rev	Tot Cost	Net Rev
Sugar Beet (T)					
Reuse Furrow	D1	31	1209	1145	64
	D2	29	1124	1145	-21
	D3	27	1038	1145	-107
	D4	24	953	1145	-192
	D5	22	867	1145	-278
	D6	20	782	1145	-363
Wheel Line	D1	31	1209	1166	43
	D2	29	1124	1166	-43
	D3	27	1038	1166	-128
	D4	24	953	1166	-214
	D5	22	867	1166	-299
	D6	20	782	1166	-384
Center Pivot	D1	26	1014	1166	-152
	D2	24	942	1166	-224
	D3	22	871	1166	-295
	D4	20	799	1166	-367
	D5	19	728	1166	-439
	D6	17	656	1166	-510
Winter Wheat (bu)					
Furrow	D1	130	416	284	132
	D2	119	381	284	98
	D3	108	347	284	63
	D4	97	312	284	28
	D5	87	277	284	-6
	D6	76	243	284	-41
Reuse Furrow	D1	130	416	326	90
	D2	119	381	326	55
	D3	108	347	326	20
	D4	97	312	326	-14
	D5	87	277	326	-49
	D6	76	243	326	-84

Table A.6 (Cont.)

Crop/Irrigation	Deficit	Yield	Tot Rev	Tot Cost	Net Rev
Winter Wheat (bu)					
Wheel Line	D1	130	416	375	42
	D2	119	381	375	7
	D3	108	347	375	-28
	D4	97	312	375	-63
	D5	87	277	375	-97
	D6	76	243	375	-132
Center Pivot	D1	110	352	375	-23
	D2	101	323	375	-52
	D3	92	293	375	-81
	D4	82	264	375	-111
	D5	73	235	375	-140
	D6	64	205	375	-169
Alfalfa-1st yr (T)					
Furrow	D1	6	474	514	-40
	D2	6	435	514	-78
	D3	5	397	514	-117
	D4	5	359	514	-155
	D5	4	320	514	-194
	D6	4	281	514	-232
Reuse Furrow	D1	6	474	551	-77
	D2	6	435	551	-116
	D3	5	397	551	-154
	D4	5	359	551	-192
	D5	4	320	551	-231
	D6	4	281	551	-270
Wheel Line	D1	7	553	605	-52
	D2	6	508	605	-97
	D3	6	463	605	-142
	D4	5	418	605	-187
	D5	5	373	605	-232
	D6	4	328	605	-277

Table A.6 (Cont.)

Crop/Irrigation	Deficit	Yield	Tot Rev	Tot Cost	Net Rev
Alfalfa-1st yr (T)					
Center Pivot	D1	7	514	605	-91
	D2	6	472	605	-133
	D3	5	430	605	-175
	D4	5	388	605	-217
	D5	4	346	605	-259
	D6	4	304	605	-300
Alfalfa-yrs 2-4 (T)					
Furrow	D1	6	474	316	158
	D2	6	435	316	120
	D3	5	397	316	81
	D4	5	359	316	43
	D5	4	320	316	4
	D6	4	281	316	-34
Reuse Furrow	D1	6	474	353	121
	D2	6	435	353	82
	D3	5	397	353	43
	D4	5	359	353	6
	D5	4	320	353	-33
	D6	4	281	353	-72
Wheel Line	D1	7	553	407	146
	D2	6	508	407	101
	D3	6	463	407	56
	D4	5	418	407	11
	D5	5	373	407	-34
	D6	4	328	407	-79
Center Pivot	D1	7	514	407	107
	D2	6	472	407	65
	D3	5	430	407	23
	D4	5	388	407	-19
	D5	4	346	407	-61
	D6	4	304	407	-102

Table A.6 (Cont.)

Crop/Irrigation	Deficit	Yield	Tot Rev	Tot Cost	Net Rev
Grain Corn (bu)					
Furrow	D1	170	459	455	4
	D2	152	410	455	-45
	D3	134	361	455	-94
Reuse Furrow	D1	170	459	498	-39
	D2	152	410	498	-88
	D3	134	361	498	-137
Center Pivot	D1	180	486	546	-60
	D2	161	434	546	-112
	D3	142	382	546	-164
Silage Corn (T)					
Furrow	D1	28	532	642	-110
	D2	25	475	642	-167
	D3	22	418	642	-224
Reuse Furrow	D1	28	532	685	-153
	D2	25	475	685	-210
	D3	22	418	685	-266
Center Pivot	D1	30	570	733	-163
	D2	27	509	733	-224
	D3	24	448	733	-285
Barley (bu)					
Furrow	D1	100	215	262	-47
	D2	92	197	262	-65
	D3	83	179	262	-84
	D4	75	160	262	-102
	D5	66	142	262	-120
	D6	58	124	262	-138
Reuse Furrow	D1	100	215	305	-90
	D2	92	197	305	-108
	D3	83	179	305	-126
	D4	75	160	305	-145
	D5	66	142	305	-163
	D6	58	124	305	-181

Table A.6 (Cont.)

Crop/Irrigation	Deficit	Yield	Tot Rev	Tot Cost	Net Rev
Barley (bu)					
Wheel Line	D1	100	215	353	-138
	D2	92	197	353	-156
	D3	83	179	353	-174
	D4	75	160	353	-193
	D5	66	142	353	-211
	D6	58	124	353	-229
Center Pivot	D1	90	194	353	-160
	D2	82	177	353	-176
	D3	75	161	353	-192
	D4	67	144	353	-209
	D5	60	128	353	-225
	D6	52	112	353	-242
Fallow					
Furrow	D7	0	0	0	0

Table A.7. Discounted and undiscounted profit (i.e. returns to land and management) ($2004) for each water supply scenario in the binary base case solution. Scenarios are grouped by the number of years of drought experienced, and then sorted within each group by discounted profit (in ascending order).

Yr1	Yr2	Yr3	Yr4	Yr5	Yr6	Discounted π	Undiscounted π
6 Years of Drought							
DRY	DRY	DRY	DRY	DRY	DRY	408,273	594,431
5 Years of Drought							
FULL	DRY	DRY	DRY	DRY	DRY	437,473	630,416
DRY	DRY	DRY	DRY	FULL	DRY	443,160	642,622
DRY	DRY	DRY	DRY	DRY	FULL	445,155	646,684
DRY	DRY	DRY	FULL	DRY	DRY	452,224	654,089
DRY	FULL	DRY	DRY	DRY	DRY	462,412	664,657
DRY	DRY	FULL	DRY	DRY	DRY	468,926	674,699
4 Years of Drought							
FULL	DRY	DRY	DRY	DRY	FULL	462,219	665,474
DRY	DRY	DRY	FULL	DRY	FULL	466,120	673,775
DRY	DRY	DRY	DRY	FULL	FULL	467,906	677,680
DRY	FULL	DRY	DRY	DRY	FULL	476,308	684,343
FULL	DRY	DRY	DRY	FULL	DRY	477,091	684,755
DRY	DRY	DRY	FULL	FULL	DRY	477,820	689,196
DRY	DRY	FULL	DRY	DRY	FULL	481,535	692,563
FULL	DRY	DRY	FULL	DRY	DRY	482,531	691,477
DRY	DRY	FULL	DRY	FULL	DRY	484,284	695,764
DRY	FULL	DRY	DRY	FULL	DRY	486,918	698,269
FULL	DRY	FULL	DRY	DRY	DRY	495,857	706,903
FULL	FULL	DRY	DRY	DRY	DRY	501,189	712,094
DRY	FULL	DRY	FULL	DRY	DRY	505,119	722,246
DRY	DRY	FULL	FULL	DRY	DRY	523,732	748,328
DRY	FULL	FULL	DRY	DRY	DRY	525,277	746,712

Table A.7 (Cont.)

Yr1	Yr2	Yr3	Yr4	Yr5	Yr6	Discounted π	Undiscounted π
3 Years of Drought							
FULL	DRY	DRY	FULL	DRY	FULL	486,863	697,613
DRY	DRY	DRY	FULL	FULL	FULL	491,716	708,882
DRY	DRY	FULL	DRY	FULL	FULL	496,893	713,628
FULL	DRY	FULL	DRY	FULL	DRY	500,644	713,469
DRY	FULL	DRY	DRY	FULL	FULL	500,814	717,955
FULL	DRY	DRY	DRY	FULL	FULL	501,836	719,813
DRY	FULL	DRY	FULL	DRY	FULL	506,878	724,738
FULL	DRY	DRY	FULL	FULL	DRY	509,880	728,989
DRY	FULL	DRY	FULL	FULL	DRY	519,054	741,360
FULL	DRY	FULL	DRY	DRY	FULL	520,603	741,961
FULL	FULL	DRY	FULL	DRY	DRY	523,933	742,845
DRY	DRY	FULL	FULL	DRY	FULL	524,205	748,998
FULL	FULL	DRY	DRY	DRY	FULL	525,935	747,152
DRY	DRY	FULL	FULL	FULL	DRY	526,112	751,548
FULL	FULL	DRY	DRY	FULL	DRY	528,539	749,606
FULL	FULL	FULL	DRY	DRY	DRY	531,460	751,204
DRY	FULL	FULL	DRY	FULL	DRY	536,474	762,236
DRY	FULL	FULL	DRY	DRY	FULL	537,886	764,575
DRY	FULL	FULL	FULL	DRY	DRY	546,214	774,853
FULL	DRY	FULL	FULL	DRY	DRY	554,160	785,537

Table A.7 (Cont.)

Yr1	Yr2	Yr3	Yr4	Yr5	Yr6	Discounted π	Undiscounted π
2 Years of Drought							
FULL	DRY	DRY	FULL	FULL	FULL	514,212	735,126
DRY	FULL	DRY	FULL	FULL	FULL	520,813	743,852
FULL	DRY	FULL	DRY	FULL	FULL	525,390	748,527
DRY	DRY	FULL	FULL	FULL	FULL	529,157	755,862
FULL	FULL	DRY	FULL	DRY	FULL	536,542	760,709
DRY	FULL	FULL	DRY	FULL	FULL	540,806	768,373
FULL	FULL	FULL	DRY	FULL	DRY	544,149	768,607
FULL	FULL	DRY	FULL	FULL	DRY	551,436	780,575
DRY	FULL	FULL	FULL	DRY	FULL	552,818	784,209
FULL	FULL	DRY	DRY	FULL	FULL	553,284	784,664
DRY	FULL	FULL	FULL	FULL	DRY	554,124	785,907
FULL	DRY	FULL	FULL	DRY	FULL	554,633	786,207
FULL	FULL	FULL	DRY	DRY	FULL	556,206	786,262
FULL	DRY	FULL	FULL	FULL	DRY	557,526	790,154
FULL	FULL	FULL	FULL	DRY	DRY	576,205	811,609
1 Years of Drought							
DRY	FULL	FULL	FULL	FULL	FULL	554,597	786,577
FULL	DRY	FULL	FULL	FULL	FULL	557,998	790,823
FULL	FULL	DRY	FULL	FULL	FULL	564,045	798,439
FULL	FULL	FULL	DRY	FULL	FULL	568,894	803,665
FULL	FULL	FULL	FULL	FULL	DRY	579,658	816,549
FULL	FULL	FULL	FULL	DRY	FULL	590,100	831,295
0 Years of Drought							
FULL	FULL	FULL	FULL	FULL	FULL	582,703	820,863

Table A.8. Irrigation water requirement and net revenue ($) per acre-inch of water requirement for alternative crop-irrigation-deficit combinations.

Crop, Irrig Tech & Deficit Level	Irrig Water Req[1]	Propor-tion Provided[2]	Irrig Efficiency[3]	Irrig Delivery[4]	Net Rev/ acre-inch
Onion (cwt)					
Furrow					
D1	25	1	0.5	50.00	1.80
D2	25	0.9	0.5	45.00	-4.95
D3	25	0.8	0.5	40.00	-13.40
D4	25	0.7	0.5	35.00	-24.25
D5	25	0.6	0.5	30.00	-38.72
D6	25	0.5	0.5	25.00	-58.99
Reuse Furrow					
D1	25	1	0.8	31.25	0.14
D2	25	0.9	0.8	28.13	-10.97
D3	25	0.8	0.8	25.00	-24.86
D4	25	0.7	0.8	21.88	-42.72
D5	25	0.6	0.8	18.75	-66.52
D6	25	0.5	0.8	15.63	-99.86
Drip					
D1	25	1	0.9	27.78	11.36
D2	25	0.9	0.9	25.00	-2.17
D3	25	0.8	0.9	22.22	-19.09
D4	25	0.7	0.9	19.44	-40.83
D5	25	0.6	0.9	16.67	-69.83
D6	25	0.5	0.9	13.89	-110.42
Rus. Potato (cwt)					
Furrow					
D1	23.2	1	0.5	46.40	-3.92
Reuse Furrow					
D1	23.2	1	0.8	29.00	-9.97

[1]Crop water requirement less 4” of effective precipitation. [2]Proportion of requirement supplied. [3]Proportion of delivered water that reaches crop root zone. [4]Actual water delivery required to meet water requirements, given the proportion provided (i.e. deficit level) and irrigation efficiency.

Table A.8 (Cont.)

Crop, Irrig Tech & Deficit Level	Irrig Water Req	Propor-tion Provided	Irrig Efficiency	Irrig Delivery	Net Rev/ acre-inch
Rus. Potato (cwt)					
Solid Set					
D1	23.2	1	0.65	35.69	-10.11
Sugar Beet (T)					
Furrow					
D1	30.1	1	0.5	60.20	2.84
D2	30.1	0.9	0.5	54.18	1.58
D3	30.1	0.8	0.5	48.16	0.01
D4	30.1	0.7	0.5	42.14	-2.02
D5	30.1	0.6	0.5	36.12	-4.72
D6	30.1	0.5	0.5	30.10	-8.50
Reuse Furrow					
D1	30.1	1	0.8	37.63	1.70
D2	30.1	0.9	0.8	33.86	-0.63
D3	30.1	0.8	0.8	30.10	-3.55
D4	30.1	0.7	0.8	26.34	-7.29
D5	30.1	0.6	0.8	22.58	-12.29
D6	30.1	0.5	0.8	18.81	-19.29
Wheel Line					
D1	30.1	1	0.65	46.31	0.92
D2	30.1	0.9	0.65	41.68	-1.02
D3	30.1	0.8	0.65	37.05	-3.46
D4	30.1	0.7	0.65	32.42	-6.59
D5	30.1	0.6	0.65	27.78	-10.76
D6	30.1	0.5	0.65	23.15	-16.60
Center Pivot					
D1	30.1	1	0.75	40.13	-3.79
D2	30.1	0.9	0.75	36.12	-6.20
D3	30.1	0.8	0.75	32.11	-9.20
D4	30.1	0.7	0.75	28.09	-13.07
D5	30.1	0.6	0.75	24.08	-18.21
D6	30.1	0.5	0.75	20.07	-25.43

Table A.8 (Cont.)

Crop, Irrig Tech & Deficit Level	Irrig Water Req	Propor-tion Provided	Irrig Efficiency	Irrig Delivery	Net Rev/ acre-inch
Winter Wheat (bu)					
Furrow					
D1	20.1	1	0.5	40.20	3.29
D2	20.1	0.9	0.5	36.18	2.70
D3	20.1	0.8	0.5	32.16	1.96
D4	20.1	0.7	0.5	28.14	1.01
D5	20.1	0.6	0.5	24.12	-0.26
D6	20.1	0.5	0.5	20.10	-2.04
Reuse Furrow					
D1	20.1	1	0.8	25.13	3.57
D2	20.1	0.9	0.8	22.61	2.43
D3	20.1	0.8	0.8	20.10	1.01
D4	20.1	0.7	0.8	17.59	-0.82
D5	20.1	0.6	0.8	15.08	-3.26
D6	20.1	0.5	0.8	12.56	-6.67
Wheel Line					
D1	20.1	1	0.65	30.92	1.34
D2	20.1	0.9	0.65	27.83	0.24
D3	20.1	0.8	0.65	24.74	-1.13
D4	20.1	0.7	0.65	21.65	-2.89
D5	20.1	0.6	0.65	18.55	-5.24
D6	20.1	0.5	0.65	15.46	-8.54
Center Pivot					
D1	20.1	1	0.75	26.80	-0.84
D2	20.1	0.9	0.75	24.12	-2.15
D3	20.1	0.8	0.75	21.44	-3.79
D4	20.1	0.7	0.75	18.76	-5.89
D5	20.1	0.6	0.75	16.08	-8.70
D6	20.1	0.5	0.75	13.40	-12.63

Table A.8 (Cont.)

Crop, Irrig Tech & Deficit Level	Irrig Water Req	Propor-tion Provided	Irrig Efficiency	Irrig Delivery	Net Rev/ acre-inch
Alfalfa-1st yr (T)					
Furrow					
D1	37.8	1	0.5	75.60	-0.52
D2	37.8	0.9	0.5	68.04	-1.15
D3	37.8	0.8	0.5	60.48	-1.93
D4	37.8	0.7	0.5	52.92	-2.93
D5	37.8	0.6	0.5	45.36	-4.27
D6	37.8	0.5	0.5	37.80	-6.15
Reuse Furrow					
D1	37.8	1	0.8	47.25	-1.63
D2	37.8	0.9	0.8	42.53	-2.72
D3	37.8	0.8	0.8	37.80	-4.09
D4	37.8	0.7	0.8	33.08	-5.82
D5	37.8	0.6	0.8	28.35	-8.15
D6	37.8	0.5	0.8	23.63	-11.42
Wheel Line					
D1	37.8	1	0.65	58.15	-0.89
D2	37.8	0.9	0.65	52.34	-1.85
D3	37.8	0.8	0.65	46.52	-3.04
D4	37.8	0.7	0.65	40.71	-4.58
D5	37.8	0.6	0.65	34.89	-6.64
D6	37.8	0.5	0.65	29.08	-9.52
Center Pivot					
D1	37.8	1	0.75	50.40	-1.81
D2	37.8	0.9	0.75	45.36	-2.93
D3	37.8	0.8	0.75	40.32	-4.34
D4	37.8	0.7	0.75	35.28	-6.14
D5	37.8	0.6	0.75	30.24	-8.55
D6	37.8	0.5	0.75	25.20	-11.92

Table A.8 (Cont.)

Crop, Irrig Tech & Deficit Level	Irrig Water Req	Propor-tion Provided	Irrig Efficiency	Irrig Delivery	Net Rev/ acre-inch
Alfalfa-yrs 2-4 (T)					
Furrow					
D1	37.8	1	0.5	75.60	2.09
D2	37.8	0.9	0.5	68.04	1.76
D3	37.8	0.8	0.5	60.48	1.34
D4	37.8	0.7	0.5	52.92	0.81
D5	37.8	0.6	0.5	45.36	0.09
D6	37.8	0.5	0.5	37.80	-0.91
Reuse Furrow					
D1	37.8	1	0.8	47.25	2.56
D2	37.8	0.9	0.8	42.53	1.93
D3	37.8	0.8	0.8	37.80	1.15
D4	37.8	0.7	0.8	33.08	0.17
D5	37.8	0.6	0.8	28.35	-1.17
D6	37.8	0.5	0.8	23.63	-3.04
Wheel Line					
D1	37.8	1	0.65	58.15	2.52
D2	37.8	0.9	0.65	52.34	1.94
D3	37.8	0.8	0.65	46.52	1.21
D4	37.8	0.7	0.65	40.71	0.28
D5	37.8	0.6	0.65	34.89	-0.97
D6	37.8	0.5	0.65	29.08	-2.71
Center Pivot					
D1	37.8	1	0.75	50.40	2.12
D2	37.8	0.9	0.75	45.36	1.43
D3	37.8	0.8	0.75	40.32	0.57
D4	37.8	0.7	0.75	35.28	-0.53
D5	37.8	0.6	0.75	30.24	-2.00
D6	37.8	0.5	0.75	25.20	-4.07

Table A.8 (Cont.)

Crop, Irrig Tech & Deficit Level	Irrig Water Req	Propor-tion Provided	Irrig Efficiency	Irrig Delivery	Net Rev/ acre-inch
Grain Corn (bu)					
Furrow					
D1	23.5	1	0.5	47.00	0.09
D2	23.5	0.9	0.5	42.30	-1.06
D3	23.5	0.8	0.5	37.60	-2.50
Reuse Furrow					
D1	23.5	1	0.8	29.38	-1.31
D2	23.5	0.9	0.8	26.44	-3.31
D3	23.5	0.8	0.8	23.50	-5.81
Center Pivot					
D1	23.5	1	0.75	31.33	-1.91
D2	23.5	0.9	0.75	28.20	-3.96
D3	23.5	0.8	0.75	25.07	-6.52
Silage Corn (T)					
Furrow					
D1	23.5	1	0.5	47.00	-2.34
D2	23.5	0.9	0.5	42.30	-3.94
D3	23.5	0.8	0.5	37.60	-5.95
Reuse Furrow					
D1	23.5	1	0.8	29.38	-5.20
D2	23.5	0.9	0.8	26.44	-7.93
D3	23.5	0.8	0.8	23.50	-11.34
Center Pivot					
D1	23.5	1	0.75	31.33	-5.20
D2	23.5	0.9	0.75	28.20	-7.93
D3	23.5	0.8	0.75	25.07	-11.36

Table A.8 (Cont.)

Crop, Irrig Tech & Deficit Level	Irrig Water Req	Propor-tion Provided	Irrig Efficiency	Irrig Delivery	Net Rev/ acre-inch
Barley (bu)					
Furrow					
D1	22.1	1	0.5	44.20	-1.07
D2	22.1	0.9	0.5	39.78	-1.64
D3	22.1	0.8	0.5	35.36	-2.36
D4	22.1	0.7	0.5	30.94	-3.29
D5	22.1	0.6	0.5	26.52	-4.52
D6	22.1	0.5	0.5	22.10	-6.25
Reuse Furrow					
D1	22.1	1	0.8	27.63	-3.26
D2	22.1	0.9	0.8	24.86	-4.35
D3	22.1	0.8	0.8	22.10	-5.72
D4	22.1	0.7	0.8	19.34	-7.48
D5	22.1	0.6	0.8	16.58	-9.82
D6	22.1	0.5	0.8	13.81	-13.10
Wheel Line					
D1	22.1	1	0.65	34.00	-4.06
D2	22.1	0.9	0.65	30.60	-5.11
D3	22.1	0.8	0.65	27.20	-6.42
D4	22.1	0.7	0.65	23.80	-8.10
D5	22.1	0.6	0.65	20.40	-10.34
D6	22.1	0.5	0.65	17.00	-13.48
Center Pivot					
D1	22.1	1	0.75	29.47	-5.42
D2	22.1	0.9	0.75	26.52	-6.64
D3	22.1	0.8	0.75	23.57	-8.16
D4	22.1	0.7	0.75	20.63	-10.12
D5	22.1	0.6	0.75	17.68	-12.73
D6	22.1	0.5	0.75	14.73	-16.39
Fallow					
Furrow					
D7	0	0	0.5	0.00	0.00

Appendix B. Description of the Gaussian quadrature procedure used to assign water quantities and probabilities (and onion prices and probabilities) to each state of nature.

Miller and Rice (1983) show that approximating a continuous distribution with a discrete number of categories that are defined as the midpoints of intervals of interest underestimates the true distribution's higher moments. They suggest an alternative way to define the discrete categories, using Gaussian quadrature. This approach is generally able to maintain the distributions more accurately than the standard midpoint approach; however, the accuracy of the Gaussian approximation varies by distribution. Preckel and DeVuyst (1992) also demonstrate that this approach performs better than alternative methods and recommend its use in discrete stochastic programming models.

Miller and Rice (1983) present two approaches. One approach is for cases in which the random variable's continuous distribution and moments are thought to be known; the other approach is for cases in which the distribution is not known. Each approach is described briefly and illustrated using historical water allocation data from the study area.

B.1 Distribution Known:

Cases in which the random variable's distribution is thought to be known involve taking the Gaussian quadrature of the distribution for a chosen N. N is the desired number of discrete categories with which to represent the continuous distribution. The statistical software package R can perform Gaussian quadrature calculations. Output from the Gaussian quadrature includes N pairs of values and probabilities, which respectively define and assign probabilities to each category.

The random variable, water allotment, is naturally censored below by zero and above by the maximum reservoir storage capacity. The beta distribution is the only distribution, to the author's knowledge, that allows censoring on both ends, so it was considered as a possible distribution for the random variable. The fit of the beta distribution needed to be tested first. Water allotment data for the study area from 1981-2004 was used to create a relative frequency histogram. Note that the beta distribution is typically expressed with bounds of [0,1]; data has to be adjusted to this scale before applying the distribution. Parameters for the beta distribution were first estimated from the data (Haan 2002, p141). The beta distribution's probability distribution function was then constructed and overlaid on the empirical relative frequency histogram (figure B.1). The degree of fit was visually judged. The beta distribution captures the major characteristics of the histogram. Proceeding, for illustrative purposes, on the assumption that the data comes from the beta distribution, a Gaussian quadrature of the parameterized beta distribution is performed for N = 2 and 3. The suggested values and probabilities for N = 2 are (16", 40%), and (39", 60%). The suggested values and probabilities for N = 3 are (10", 16%), (27", 49%), and (43", 35%).

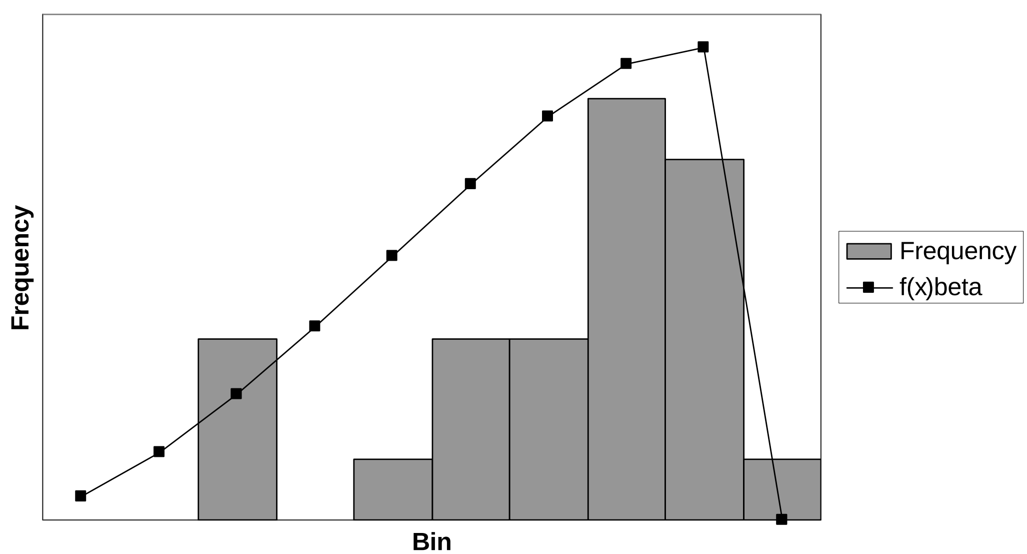


Figure B.1. Beta distribution's probability distribution function (parameterized with historical water allotment data from the study area), overlaid on a relative frequency histogram of the data.

B.2 Distribution Unknown

Cases in which the random variable's distribution is completely unknown require an alternative approach. A cumulative distribution function (cdf) is first estimated from the data. Table 3 in Miller and Rice (1983) is then used as follows: choose the desired N; find the F(x) associated with N in table 3; identify the x in the empirical cdf that correspond to the recommended F(x); assign to each x the probability suggested in table 3 for each F(x). Proceeding on the assumption that the water allotment's distribution is unknown, a cdf was estimated from the historical data (figure B.2). The suggested values and probabilities for N = 2 are (24", 50%) and (41", 50%), and those for N = 3 are (12", 25%), (36", 50%), (42", 50%).

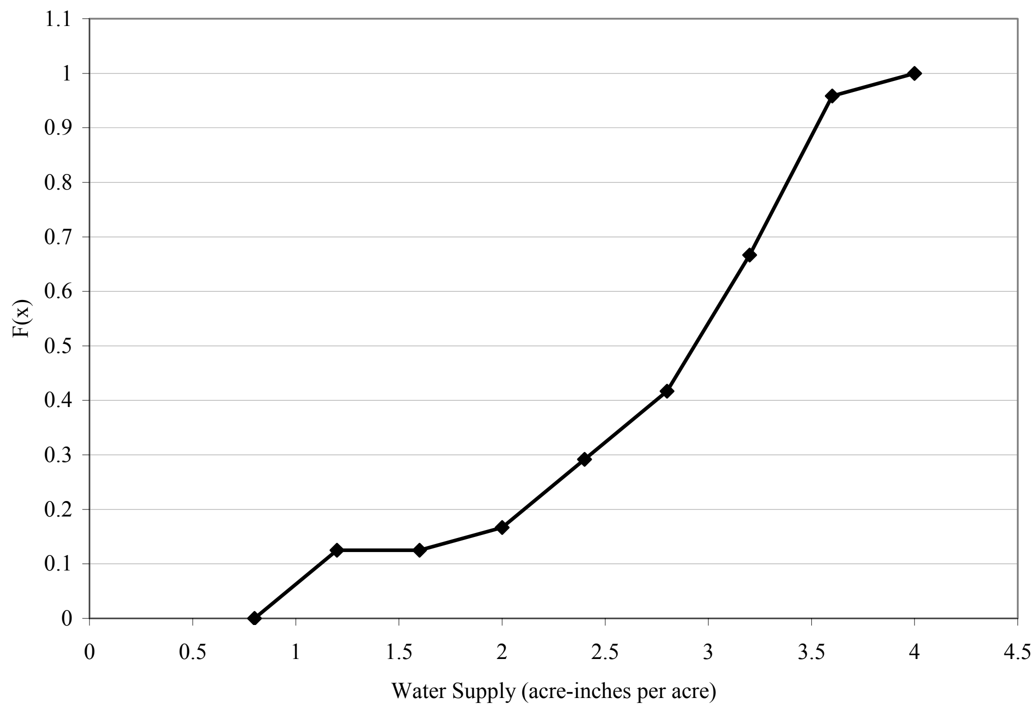


Figure B.2. Cumulative distribution function for the random variable "water supply," estimated with historical water allotment data from the study area.

Prior to being aware of this approach, interviews with producers were used to select economically meaningful values for the categories, “FULL” and “dry”. Those values were identified as 24” and 40”. Historical data was used to assign probabilities of 40% and 60%, respectively, to the categories. The Gaussian quadrature approach conveniently suggested nearly the same values, and similar probabilities. Prior analyses had been conducted at the 40 and 60% probabilities. One model was resolved with 50% probabilities in place, and the results were not significantly different. The cost of re-running all analyses with 50% probabilities in place outweighed the benefits, so the original values and probabilities were kept.

Miller and Rice’s approach does not perfectly preserve all moments of the distribution. They report that for a particular beta distribution (parameter values are not reported) the Gaussian approach (for N=2) overestimates variance by 10.5%, underestimates skew by 100%, and underestimates kurtosis by 48.3%. This performance is better, however, than the standard midpoint approach, which underestimates variance by 31.5%, underestimates skew by 100%, and underestimates kurtosis by 80.1%. The degree of improvement varies, however, by distribution.

B.3 Discrete Categories for the Onion Price

Proceeding on the assumption that onion price’s distribution is unknown, a cdf was estimated from the historical data (figure B.3). The suggested values and probabilities for N = 2 are ($2.80, 50%) and ($8.75, 50%), and those for N = 3 are ($2.50, 25%), ($5.50, 50%), ($12.25, 50%). N = 3 was chosen; however, the use of the price $5.50 resulted in no onions being planted. The price was therefore increased to $6.00, which matches the expected price assumed in the base case model. The categories used in models that incorporate price uncertainty are ‘hi’ = $12.25, ‘med’ = $6.00, and ‘lo’ = $2.50.

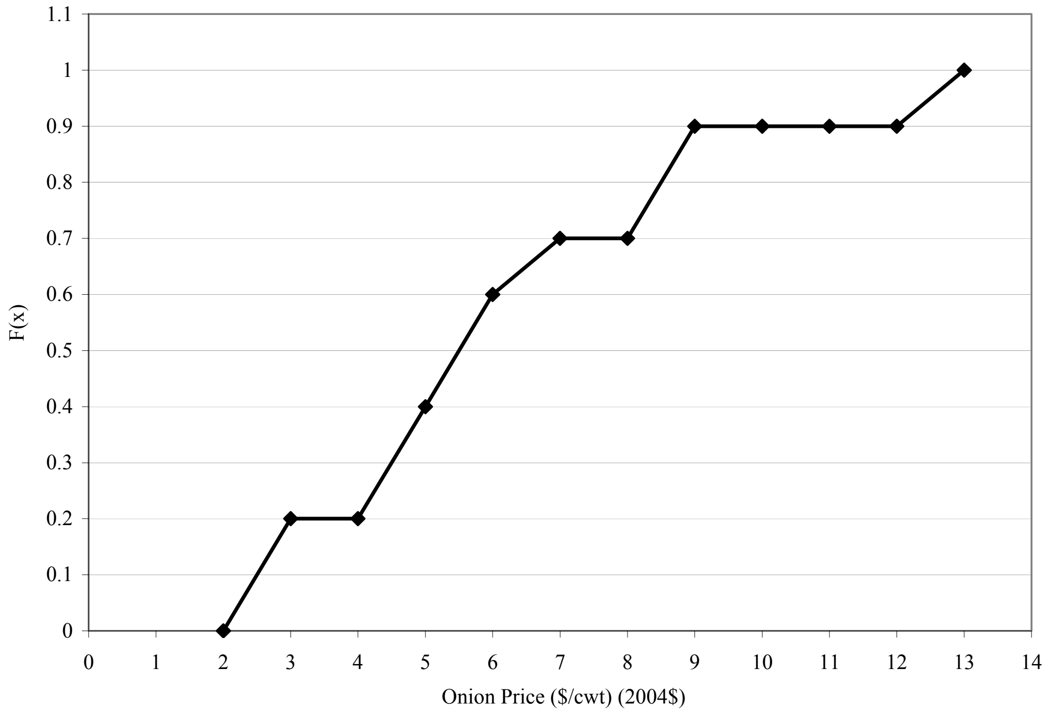


Figure B.3. Cumulative distribution function for the random variable "onion price," estimated with historical data from the study area.

Appendix C. Prevented planting model's parameters and profit.

Table C.1. Approved yields used in the calculation of a prevented planting payment.

Insured Crop (yield Unit)	**Approved Yield Per Acre**
Onion (cwt)	550
Potato (cwt)	415
Sugar beet (T)	31
Wheat (bu)	130

Table C.2. Available coverage levels for the multi-peril crop insurance contract.

Insured Crop	**Coverage Levels (%)**
Onion	50
	65
	75
Potato	75
Sugar beet	50
	65
	75
	85
Wheat	55
	65
	75
	85

Table C.3. Price election ($/unit of production) assumed for each insured crop.

Insured Crop	**Price Elected**
Onion (cwt)	3.25
Potato (cwt)	3.34
Sugar beet (T)	39.00
Wheat (bu)	3.22

Table C.4. Prevented planting coverage level assumed for each insured crop.

Insured Crop	**PP Coverage (%)**
Onion	45
Potato	25
Sugar beet	45
Wheat	60

Table C.5. Discounted and undiscounted profit (i.e. returns to land and management) ($2004) by scenario for the "subsidized prevented planting" model's solution. Scenarios are sorted by discounted profit (in ascending order).

Yr1	Yr2	Yr3	Yr4	Yr5	Yr6	Discounted π	Undiscounted π
FULL	FULL	FULL	FULL	DRY	FULL	577,023	818,768
FULL	FULL	FULL	FULL	FULL	FULL	577,719	819,723
FULL	FULL	FULL	FULL	DRY	DRY	587,111	833,060
FULL	FULL	FULL	FULL	FULL	DRY	587,808	834,016
FULL	DRY	FULL	FULL	FULL	FULL	591,589	837,423
FULL	FULL	FULL	DRY	FULL	FULL	593,457	841,405
DRY	DRY	FULL	FULL	FULL	DRY	594,659	840,008
DRY	DRY	FULL	FULL	FULL	FULL	599,603	847,012
DRY	FULL	FULL	FULL	FULL	DRY	600,244	846,666
FULL	DRY	FULL	FULL	DRY	FULL	601,013	850,348
FULL	FULL	DRY	FULL	FULL	FULL	601,431	851,304
FULL	DRY	FULL	FULL	FULL	DRY	601,678	851,715
FULL	FULL	FULL	DRY	DRY	FULL	601,814	852,820
FULL	FULL	FULL	DRY	FULL	DRY	601,959	853,450
DRY	FULL	FULL	FULL	FULL	FULL	602,003	849,158
FULL	DRY	FULL	DRY	FULL	FULL	603,967	854,431
DRY	FULL	FULL	FULL	DRY	FULL	609,294	859,062
FULL	DRY	FULL	FULL	DRY	DRY	611,101	864,641
FULL	FULL	DRY	FULL	FULL	DRY	611,520	865,596
FULL	DRY	FULL	DRY	FULL	DRY	612,469	866,476
FULL	FULL	FULL	DRY	DRY	DRY	613,307	869,103
FULL	DRY	DRY	FULL	FULL	FULL	614,424	867,800
FULL	FULL	DRY	FULL	DRY	FULL	616,081	871,564
DRY	FULL	DRY	FULL	FULL	DRY	616,675	868,343
FULL	FULL	DRY	DRY	FULL	FULL	616,859	872,351
DRY	FULL	FULL	FULL	DRY	DRY	617,820	871,141
DRY	FULL	DRY	FULL	FULL	FULL	618,435	870,835
FULL	DRY	FULL	DRY	DRY	FULL	619,111	875,154
DRY	DRY	DRY	FULL	FULL	DRY	619,604	873,681
DRY	DRY	FULL	DRY	FULL	FULL	619,649	874,457
DRY	DRY	FULL	FULL	DRY	FULL	620,381	875,893
DRY	DRY	DRY	FULL	FULL	FULL	621,557	876,448
FULL	DRY	DRY	FULL	FULL	DRY	624,513	882,093
DRY	FULL	FULL	DRY	FULL	FULL	625,018	880,865
FULL	DRY	DRY	DRY	FULL	FULL	625,595	883,016
FULL	FULL	DRY	FULL	DRY	DRY	627,574	887,846
DRY	DRY	FULL	DRY	FULL	DRY	628,151	886,502

Table C.5 (Cont.)

Yr1	Yr2	Yr3	Yr4	Yr5	Yr6	Discounted π	Undiscounted π
FULL	FULL	DRY	DRY	FULL	DRY	628,352	888,634
DRY	DRY	FULL	FULL	DRY	DRY	628,883	887,938
FULL	DRY	FULL	DRY	DRY	DRY	630,447	891,214
FULL	FULL	DRY	DRY	DRY	FULL	632,737	894,129
DRY	FULL	FULL	DRY	DRY	FULL	633,375	892,280
DRY	FULL	FULL	DRY	FULL	DRY	633,520	892,910
DRY	DRY	DRY	DRY	FULL	FULL	634,088	893,306
DRY	DRY	FULL	DRY	DRY	FULL	634,943	895,393
FULL	DRY	DRY	FULL	DRY	FULL	636,389	898,094
FULL	DRY	DRY	DRY	FULL	DRY	636,931	899,076
DRY	FULL	DRY	FULL	DRY	FULL	638,649	899,085
FULL	FULL	DRY	DRY	DRY	DRY	644,230	910,412
DRY	FULL	FULL	DRY	DRY	DRY	644,868	908,563
DRY	DRY	DRY	DRY	FULL	DRY	645,424	909,366
FULL	DRY	DRY	DRY	DRY	FULL	645,814	910,748
DRY	DRY	FULL	DRY	DRY	DRY	646,278	911,452
FULL	DRY	DRY	FULL	DRY	DRY	647,882	914,377
DRY	DRY	DRY	FULL	DRY	FULL	649,461	914,816
DRY	FULL	DRY	FULL	DRY	DRY	649,985	915,144
DRY	FULL	DRY	DRY	FULL	FULL	652,880	918,021
FULL	DRY	DRY	DRY	DRY	DRY	657,150	926,808
DRY	DRY	DRY	FULL	DRY	DRY	660,955	931,099
DRY	FULL	DRY	DRY	FULL	DRY	664,374	934,304
DRY	FULL	DRY	DRY	DRY	FULL	665,583	935,444
DRY	DRY	DRY	DRY	DRY	FULL	666,034	937,123
DRY	FULL	DRY	DRY	DRY	DRY	677,076	951,727
DRY	DRY	DRY	DRY	DRY	DRY	677,370	953,182

Table C.6. Discounted and undiscounted profit (i.e. returns to land and management) ($2004) by scenario for the “unsubsidized prevented planting” model’s solution. Scenarios are sorted by discounted profit (in ascending order).

Yr1	Yr2	Yr3	Yr4	Yr5	Yr6	Discounted π	Undiscounted π
DRY	FULL	FULL	FULL	FULL	DRY	574,026	814,098
FULL	FULL	FULL	FULL	DRY	FULL	575,409	816,760
DRY	FULL	FULL	FULL	FULL	FULL	575,785	816,590
DRY	DRY	FULL	FULL	FULL	DRY	576,854	819,004
DRY	DRY	FULL	FULL	FULL	FULL	577,639	820,115
DRY	FULL	FULL	FULL	DRY	DRY	577,914	819,431
FULL	FULL	FULL	FULL	DRY	DRY	578,314	820,876
FULL	FULL	FULL	FULL	FULL	FULL	578,775	821,377
DRY	FULL	FULL	FULL	DRY	FULL	579,673	821,923
DRY	DRY	FULL	FULL	DRY	DRY	581,487	825,358
FULL	FULL	FULL	FULL	FULL	DRY	581,680	825,493
DRY	DRY	FULL	FULL	DRY	FULL	582,272	826,470
DRY	DRY	DRY	FULL	FULL	DRY	583,858	828,296
FULL	DRY	FULL	FULL	FULL	FULL	584,039	828,177
DRY	DRY	DRY	FULL	FULL	FULL	584,642	829,408
FULL	FULL	FULL	DRY	FULL	FULL	585,681	831,086
FULL	DRY	FULL	FULL	FULL	DRY	585,816	830,694
FULL	DRY	FULL	FULL	DRY	DRY	587,404	832,836
FULL	DRY	FULL	DRY	FULL	FULL	589,230	835,319
FULL	FULL	FULL	DRY	DRY	FULL	589,569	836,419
FULL	DRY	FULL	FULL	DRY	FULL	589,630	835,988
DRY	FULL	DRY	FULL	FULL	DRY	589,963	835,693
DRY	DRY	FULL	DRY	FULL	FULL	589,976	837,086
FULL	FULL	FULL	DRY	FULL	DRY	590,704	838,203
DRY	FULL	DRY	FULL	FULL	FULL	591,722	838,186
DRY	FULL	FULL	DRY	FULL	FULL	592,892	840,295
FULL	FULL	DRY	FULL	FULL	FULL	593,546	841,374
DRY	DRY	FULL	DRY	FULL	DRY	593,713	842,380
FULL	DRY	FULL	DRY	FULL	DRY	594,253	842,436
FULL	FULL	FULL	DRY	DRY	DRY	594,592	843,535
DRY	DRY	FULL	DRY	DRY	FULL	594,941	843,895

Table C.6 (Cont.)

Yr1	Yr2	Yr3	Yr4	Yr5	Yr6	Discounted π	Undiscounted π
DRY	FULL	FULL	DRY	FULL	DRY	595,343	843,767
FULL	DRY	FULL	DRY	DRY	FULL	595,613	844,074
FULL	DRY	DRY	FULL	FULL	FULL	595,758	843,981
DRY	FULL	FULL	DRY	DRY	FULL	595,795	844,231
DRY	DRY	DRY	DRY	DRY	FULL	596,147	844,989
FULL	DRY	DRY	FULL	FULL	DRY	596,248	844,675
FULL	FULL	DRY	FULL	FULL	DRY	596,452	845,490
FULL	FULL	DRY	FULL	DRY	FULL	596,616	845,799
DRY	FULL	DRY	FULL	DRY	FULL	596,859	845,586
FULL	FULL	DRY	FULL	DRY	DRY	598,092	847,890
DRY	FULL	DRY	FULL	DRY	DRY	598,335	847,677
DRY	DRY	FULL	DRY	DRY	DRY	598,678	849,190
DRY	DRY	DRY	DRY	FULL	FULL	598,940	849,132
DRY	DRY	DRY	FULL	DRY	FULL	599,841	850,492
FULL	DRY	FULL	DRY	DRY	DRY	600,636	851,190
FULL	DRY	DRY	DRY	FULL	FULL	600,690	850,811
DRY	FULL	FULL	DRY	DRY	DRY	600,818	851,348
FULL	DRY	DRY	FULL	DRY	FULL	601,383	851,630
FULL	DRY	DRY	DRY	FULL	DRY	603,140	854,283
FULL	FULL	DRY	DRY	FULL	FULL	603,735	855,622
DRY	DRY	DRY	DRY	FULL	DRY	603,963	856,249
DRY	DRY	DRY	FULL	DRY	DRY	604,864	857,609
FULL	DRY	DRY	FULL	DRY	DRY	605,420	857,350
FULL	FULL	DRY	DRY	FULL	DRY	606,185	859,094
DRY	FULL	DRY	DRY	FULL	FULL	606,327	858,414
FULL	FULL	DRY	DRY	DRY	FULL	606,443	859,337
FULL	DRY	DRY	DRY	DRY	FULL	607,783	860,540
DRY	DRY	DRY	DRY	DRY	DRY	608,093	861,913
FULL	FULL	DRY	DRY	DRY	DRY	608,894	862,809
FULL	DRY	DRY	DRY	DRY	DRY	610,233	864,012
DRY	FULL	DRY	DRY	FULL	DRY	611,351	865,531
DRY	FULL	DRY	DRY	DRY	FULL	614,406	869,540
DRY	FULL	DRY	DRY	DRY	DRY	616,857	873,011

Appendix D. Price uncertainty model's profit.

Table D1. Discounted and undiscounted profit (i.e. returns to land and management) ($2004) by scenario for the "price uncertainty" model's solution.

Yr1	Yr1	Yr2	Yr2	Yr3	Yr3	Discounted π	Undiscounted π
DRY	LO	DRY	LO	DRY	HI	-755,400	-797,514
DRY	LO	DRY	LO	DRY	MED	-755,400	-797,514
DRY	LO	DRY	LO	DRY	LO	-755,400	-797,514
FULL	LO	DRY	LO	DRY	HI	-743,135	-784,220
FULL	LO	DRY	LO	DRY	MED	-743,135	-784,220
FULL	LO	DRY	LO	DRY	LO	-743,135	-784,220
DRY	LO	DRY	LO	FULL	HI	-726,754	-762,456
DRY	LO	DRY	LO	FULL	MED	-726,754	-762,456
DRY	LO	DRY	LO	FULL	LO	-726,754	-762,456
DRY	LO	FULL	LO	DRY	HI	-708,212	-741,604
DRY	LO	FULL	LO	DRY	MED	-708,212	-741,604
DRY	LO	FULL	LO	DRY	LO	-708,212	-741,604
FULL	LO	DRY	LO	FULL	HI	-700,439	-731,967
FULL	LO	DRY	LO	FULL	MED	-700,439	-731,967
FULL	LO	DRY	LO	FULL	LO	-700,439	-731,967
FULL	LO	FULL	LO	DRY	HI	-694,109	-726,062
FULL	LO	FULL	LO	DRY	MED	-694,109	-726,062
FULL	LO	FULL	LO	DRY	LO	-694,109	-726,062
DRY	LO	FULL	LO	FULL	HI	-679,566	-706,546
DRY	LO	FULL	LO	FULL	MED	-679,566	-706,546
DRY	LO	FULL	LO	FULL	LO	-679,566	-706,546
FULL	LO	FULL	LO	FULL	HI	-651,414	-673,809
FULL	LO	FULL	LO	FULL	MED	-651,414	-673,809
FULL	LO	FULL	LO	FULL	LO	-651,414	-673,809
DRY	LO	DRY	MED	DRY	HI	-539,224	-541,368
DRY	LO	DRY	MED	DRY	MED	-539,224	-541,368
DRY	LO	DRY	MED	DRY	LO	-539,224	-541,368
FULL	LO	DRY	MED	DRY	HI	-527,306	-528,499
FULL	LO	DRY	MED	DRY	MED	-527,306	-528,499
FULL	LO	DRY	MED	DRY	LO	-527,306	-528,499
DRY	LO	DRY	MED	FULL	HI	-509,271	-504,711
DRY	LO	DRY	MED	FULL	MED	-509,271	-504,711

Table D1 (Cont.)

Yr1	Yr1	Yr2	Yr2	Yr3	Yr3	Discounted π	Undiscounted π
DRY	LO	DRY	MED	FULL	LO	-509,271	-504,711
DRY	LO	FULL	MED	DRY	HI	-492,384	-485,884
DRY	LO	FULL	MED	DRY	MED	-492,384	-485,884
DRY	LO	FULL	MED	DRY	LO	-492,384	-485,884
FULL	LO	DRY	MED	FULL	HI	-484,611	-476,247
FULL	LO	DRY	MED	FULL	MED	-484,611	-476,247
FULL	LO	DRY	MED	FULL	LO	-484,611	-476,247
FULL	LO	FULL	MED	DRY	HI	-480,118	-472,589
FULL	LO	FULL	MED	DRY	MED	-480,118	-472,589
FULL	LO	FULL	MED	DRY	LO	-480,118	-472,589
DRY	LO	FULL	MED	FULL	HI	-463,738	-450,825
DRY	LO	FULL	MED	FULL	MED	-463,738	-450,825
DRY	LO	FULL	MED	FULL	LO	-463,738	-450,825
FULL	LO	FULL	MED	FULL	HI	-437,422	-420,336
FULL	LO	FULL	MED	FULL	MED	-437,422	-420,336
FULL	LO	FULL	MED	FULL	LO	-437,422	-420,336
DRY	LO	DRY	HI	DRY	HI	-154,164	-85,150
DRY	LO	DRY	HI	DRY	MED	-154,164	-85,150
DRY	LO	DRY	HI	DRY	LO	-154,164	-85,150
FULL	LO	DRY	HI	DRY	HI	-140,062	-69,607
FULL	LO	DRY	HI	DRY	MED	-140,062	-69,607
FULL	LO	DRY	HI	DRY	LO	-140,062	-69,607
DRY	LO	DRY	HI	FULL	HI	-125,518	-50,091
DRY	LO	DRY	HI	FULL	MED	-125,518	-50,091
DRY	LO	DRY	HI	FULL	LO	-125,518	-50,091
DRY	LO	FULL	HI	DRY	HI	-106,976	-29,239
DRY	LO	FULL	HI	DRY	MED	-106,976	-29,239
DRY	LO	FULL	HI	DRY	LO	-106,976	-29,239
FULL	LO	DRY	HI	FULL	HI	-97,366	-17,354
FULL	LO	DRY	HI	FULL	MED	-97,366	-17,354
FULL	LO	DRY	HI	FULL	LO	-97,366	-17,354
FULL	LO	FULL	HI	DRY	HI	-92,873	-13,697
FULL	LO	FULL	HI	DRY	MED	-92,873	-13,697
FULL	LO	FULL	HI	DRY	LO	-92,873	-13,697

Table D1 (Cont.)

Yr1	Yr1	Yr2	Yr2	Yr3	Yr3	Discounted π	Undiscounted π
DRY	LO	FULL	HI	FULL	HI	-78,330	5,819
DRY	LO	FULL	HI	FULL	MED	-78,330	5,819
DRY	LO	FULL	HI	FULL	LO	-78,330	5,819
FULL	LO	FULL	HI	FULL	HI	-50,178	38,556
FULL	LO	FULL	HI	FULL	MED	-50,178	38,556
FULL	LO	FULL	HI	FULL	LO	-50,178	38,556
DRY	MED	DRY	LO	DRY	HI	204,266	305,192
DRY	MED	DRY	LO	DRY	MED	204,266	305,192
DRY	MED	DRY	LO	DRY	LO	204,266	305,192
FULL	MED	DRY	LO	DRY	HI	227,071	331,393
FULL	MED	DRY	LO	DRY	MED	227,071	331,393
FULL	MED	DRY	LO	DRY	LO	227,071	331,393
DRY	MED	FULL	LO	DRY	HI	229,836	335,251
DRY	MED	FULL	LO	DRY	MED	229,836	335,251
DRY	MED	FULL	LO	DRY	LO	229,836	335,251
DRY	MED	DRY	LO	FULL	HI	237,197	345,494
DRY	MED	DRY	LO	FULL	MED	237,197	345,494
DRY	MED	DRY	LO	FULL	LO	237,197	345,494
FULL	MED	FULL	LO	DRY	HI	258,731	368,905
FULL	MED	FULL	LO	DRY	MED	258,731	368,905
FULL	MED	FULL	LO	DRY	LO	258,731	368,905
FULL	MED	DRY	LO	FULL	HI	260,002	371,695
FULL	MED	DRY	LO	FULL	MED	260,002	371,695
FULL	MED	DRY	LO	FULL	LO	260,002	371,695
DRY	MED	FULL	LO	FULL	HI	272,531	387,503
DRY	MED	FULL	LO	FULL	MED	272,531	387,503
DRY	MED	FULL	LO	FULL	LO	272,531	387,503
FULL	MED	FULL	LO	FULL	HI	291,662	409,207
FULL	MED	FULL	LO	FULL	MED	291,662	409,207
FULL	MED	FULL	LO	FULL	LO	291,662	409,207
DRY	MED	DRY	MED	DRY	HI	420,094	560,913
DRY	MED	DRY	MED	DRY	MED	420,094	560,913
DRY	MED	DRY	MED	DRY	LO	420,094	560,913
FULL	MED	DRY	MED	DRY	HI	438,008	581,128

Table D1 (Cont.)

Yr1	Yr1	Yr2	Yr2	Yr3	Yr3	Discounted π	Undiscounted π
FULL	MED	DRY	MED	DRY	MED	438,008	581,128
FULL	MED	DRY	MED	DRY	LO	438,008	581,128
DRY	MED	FULL	MED	DRY	HI	448,894	594,924
DRY	MED	FULL	MED	DRY	MED	448,894	594,924
DRY	MED	FULL	MED	DRY	LO	448,894	594,924
DRY	MED	DRY	MED	FULL	HI	453,025	601,215
DRY	MED	DRY	MED	FULL	MED	453,025	601,215
DRY	MED	DRY	MED	FULL	LO	453,025	601,215
FULL	MED	FULL	MED	DRY	HI	474,560	624,626
FULL	MED	FULL	MED	DRY	MED	474,560	624,626
FULL	MED	FULL	MED	DRY	LO	474,560	624,626
FULL	MED	DRY	MED	FULL	HI	479,504	631,912
FULL	MED	DRY	MED	FULL	MED	479,504	631,912
FULL	MED	DRY	MED	FULL	LO	479,504	631,912
DRY	MED	FULL	MED	FULL	HI	484,686	638,727
DRY	MED	FULL	MED	FULL	MED	484,686	638,727
DRY	MED	FULL	MED	FULL	LO	484,686	638,727
FULL	MED	FULL	MED	FULL	HI	507,491	664,928
FULL	MED	FULL	MED	FULL	MED	507,491	664,928
FULL	MED	FULL	MED	FULL	LO	507,491	664,928
DRY	MED	DRY	HI	DRY	HI	797,574	1,007,855
DRY	MED	DRY	HI	DRY	MED	797,574	1,007,855
DRY	MED	DRY	HI	DRY	LO	797,574	1,007,855
FULL	MED	DRY	HI	DRY	HI	828,307	1,043,758
FULL	MED	DRY	HI	DRY	MED	828,307	1,043,758
FULL	MED	DRY	HI	DRY	LO	828,307	1,043,758
DRY	MED	FULL	HI	DRY	HI	830,434	1,046,835
DRY	MED	FULL	HI	DRY	MED	830,434	1,046,835
DRY	MED	FULL	HI	DRY	LO	830,434	1,046,835
DRY	MED	DRY	HI	FULL	HI	840,270	1,060,107
DRY	MED	DRY	HI	FULL	MED	840,270	1,060,107
DRY	MED	DRY	HI	FULL	LO	840,270	1,060,107
FULL	MED	FULL	HI	DRY	HI	852,040	1,071,568
FULL	MED	FULL	HI	DRY	MED	852,040	1,071,568

Table D1 (Cont.)

Yr1	Yr1	Yr2	Yr2	Yr3	Yr3	Discounted π	Undiscounted π
FULL	MED	FULL	HI	DRY	LO	852,040	1,071,568
FULL	MED	DRY	HI	FULL	HI	861,238	1,084,060
FULL	MED	DRY	HI	FULL	MED	861,238	1,084,060
FULL	MED	DRY	HI	FULL	LO	861,238	1,084,060
DRY	MED	FULL	HI	FULL	HI	871,930	1,097,620
DRY	MED	FULL	HI	FULL	MED	871,930	1,097,620
DRY	MED	FULL	HI	FULL	LO	871,930	1,097,620
FULL	MED	FULL	HI	FULL	HI	894,735	1,123,820
FULL	MED	FULL	HI	FULL	MED	894,735	1,123,820
FULL	MED	FULL	HI	FULL	LO	894,735	1,123,820
DRY	HI	DRY	LO	DRY	HI	1,891,187	2,242,553
DRY	HI	DRY	LO	DRY	MED	1,891,187	2,242,553
DRY	HI	DRY	LO	DRY	LO	1,891,187	2,242,553
FULL	HI	DRY	LO	DRY	HI	1,920,276	2,276,128
FULL	HI	DRY	LO	DRY	MED	1,920,276	2,276,128
FULL	HI	DRY	LO	DRY	LO	1,920,276	2,276,128
DRY	HI	DRY	LO	FULL	HI	1,933,882	2,294,806
DRY	HI	DRY	LO	FULL	MED	1,933,882	2,294,806
DRY	HI	DRY	LO	FULL	LO	1,933,882	2,294,806
DRY	HI	FULL	LO	DRY	HI	1,934,116	2,293,302
DRY	HI	FULL	LO	DRY	MED	1,934,116	2,293,302
DRY	HI	FULL	LO	DRY	LO	1,934,116	2,293,302
FULL	HI	FULL	LO	DRY	HI	1,953,773	2,315,888
FULL	HI	FULL	LO	DRY	MED	1,953,773	2,315,888
FULL	HI	FULL	LO	DRY	LO	1,953,773	2,315,888
FULL	HI	DRY	LO	FULL	HI	1,962,971	2,328,380
FULL	HI	DRY	LO	FULL	MED	1,962,971	2,328,380
FULL	HI	DRY	LO	FULL	LO	1,962,971	2,328,380
DRY	HI	FULL	LO	FULL	HI	1,976,811	2,345,555
DRY	HI	FULL	LO	FULL	MED	1,976,811	2,345,555
DRY	HI	FULL	LO	FULL	LO	1,976,811	2,345,555
FULL	HI	FULL	LO	FULL	HI	1,996,469	2,368,140
FULL	HI	FULL	LO	FULL	MED	1,996,469	2,368,140
FULL	HI	FULL	LO	FULL	LO	1,996,469	2,368,140

Table D1 (Cont.)

Yr1	**Yr1**	**Yr2**	**Yr2**	**Yr3**	**Yr3**	**Discounted π**	**Undiscounted π**
DRY	HI	DRY	MED	DRY	HI	2,107,015	2,498,274
DRY	HI	DRY	MED	DRY	MED	2,107,015	2,498,274
DRY	HI	DRY	MED	DRY	LO	2,107,015	2,498,274
FULL	HI	DRY	MED	DRY	HI	2,136,104	2,531,848
FULL	HI	DRY	MED	DRY	MED	2,136,104	2,531,848
FULL	HI	DRY	MED	DRY	LO	2,136,104	2,531,848
DRY	HI	DRY	MED	FULL	HI	2,149,711	2,550,526
DRY	HI	DRY	MED	FULL	MED	2,149,711	2,550,526
DRY	HI	DRY	MED	FULL	LO	2,149,711	2,550,526
DRY	HI	FULL	MED	DRY	HI	2,149,944	2,549,023
DRY	HI	FULL	MED	DRY	MED	2,149,944	2,549,023
DRY	HI	FULL	MED	DRY	LO	2,149,944	2,549,023
FULL	HI	FULL	MED	DRY	HI	2,169,601	2,571,609
FULL	HI	FULL	MED	DRY	MED	2,169,601	2,571,609
FULL	HI	FULL	MED	DRY	LO	2,169,601	2,571,609
FULL	HI	DRY	MED	FULL	HI	2,178,800	2,584,101
FULL	HI	DRY	MED	FULL	MED	2,178,800	2,584,101
FULL	HI	DRY	MED	FULL	LO	2,178,800	2,584,101
DRY	HI	FULL	MED	FULL	HI	2,192,640	2,601,275
DRY	HI	FULL	MED	FULL	MED	2,192,640	2,601,275
DRY	HI	FULL	MED	FULL	LO	2,192,640	2,601,275
FULL	HI	FULL	MED	FULL	HI	2,212,297	2,623,861
FULL	HI	FULL	MED	FULL	MED	2,212,297	2,623,861
FULL	HI	FULL	MED	FULL	LO	2,212,297	2,623,861
DRY	HI	DRY	HI	DRY	HI	2,490,586	2,952,670
DRY	HI	DRY	HI	DRY	MED	2,490,586	2,952,670
DRY	HI	DRY	HI	DRY	LO	2,490,586	2,952,670
FULL	HI	DRY	HI	DRY	HI	2,529,439	2,998,195
FULL	HI	DRY	HI	DRY	MED	2,529,439	2,998,195
FULL	HI	DRY	HI	DRY	LO	2,529,439	2,998,195
DRY	HI	DRY	HI	FULL	HI	2,533,282	3,004,922
DRY	HI	DRY	HI	FULL	MED	2,533,282	3,004,922
DRY	HI	DRY	HI	FULL	LO	2,533,282	3,004,922

Table D1 (Cont.)

Yr1	Yr1	Yr2	Yr2	Yr3	Yr3	Discounted π	Undiscounted π
DRY	HI	FULL	HI	DRY	HI	2,544,996	3,017,470
DRY	HI	FULL	HI	DRY	MED	2,544,996	3,017,470
DRY	HI	FULL	HI	DRY	LO	2,544,996	3,017,470
FULL	HI	FULL	HI	DRY	HI	2,555,009	3,028,253
FULL	HI	FULL	HI	DRY	MED	2,555,009	3,028,253
FULL	HI	FULL	HI	DRY	LO	2,555,009	3,028,253
FULL	HI	DRY	HI	FULL	HI	2,562,370	3,038,497
FULL	HI	DRY	HI	FULL	MED	2,562,370	3,038,497
FULL	HI	DRY	HI	FULL	LO	2,562,370	3,038,497
DRY	HI	FULL	HI	FULL	HI	2,573,642	3,052,528
DRY	HI	FULL	HI	FULL	MED	2,573,642	3,052,528
DRY	HI	FULL	HI	FULL	LO	2,573,642	3,052,528
FULL	HI	FULL	HI	FULL	HI	2,597,705	3,080,505
FULL	HI	FULL	HI	FULL	MED	2,597,705	3,080,505
FULL	HI	FULL	HI	FULL	LO	2,597,705	3,080,505

Appendix E. List of electronic files provided.

Computer Program Files (GAMS):

Base case model (binary): ip_base.gms
Base case model (continuous): cont_base.gms

Model Solution Files (Excel)
Base case solution (binary): ip_base.xcl
Base case solution (continuous): cont_base.xcl