THE VALUE OF PASTURE, RANGELAND, FORAGE RAINFALL INDEX INSURANCE TO TEXAS RANCHERS

A Thesis

by

ALEKSANDRE MAISASHVILI

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

May 2010

Major Subject: Agricultural Economics

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ABSTRACT

The Value of Pasture, Rangeland, Forage Rainfall Index Insurance to Texas Ranchers.

(May 2010)

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In the beginning of the 2007 crop year, the Federal Crop Insurance Corporation (FCIC) launched the Pasture, Rangeland, Forage Rainfall Index Pilot Program (PRF-RI) for six states. This insurance is an index and not individual insurance. Risk Management Agency officials claim that PRF-RI insurance mitigates the risk because index and forage production move in the same direction. Therefore when the index is low there is the expectation that production will also be low. PRF-RI is a pilot program and ranchers are skeptical as to whether or not it is viable to purchase the insurance.

The objective of this research was to determine the economic benefits of rainfall insurance in selected counties in Texas and estimate the probability of indemnities under different types of coverage levels and index intervals.

Historical rainfall indices were simulated for all index intervals and a multivariate empirical distribution of rainfall indices were used. The model was run for alternative scenarios on the available coverage levels (90%, 85%, 80%, 75%, 70%) and relevant premium rates. Each scenario resulted in an estimate of the insurance benefits variable probability density function for a particular coverage level. Stochastic Dominance with Respect to a Function (SDRF), Stochastic Efficiency with Respect to a Function (SERF), and StopLight chart were used to rank the benefits of alternative coverage levels.

The results indicated that for all regions tested, the best alternative when purchasing PRF-RI was to buy the 90% coverage level. Probabilities of earning net indemnities decreased at lower coverage levels. December-January is a critical time period that should be taken into consideration by the ranchers. The results indicated also that insurance returns depend on the region where the policy is purchased. In southern and eastern parts of Texas net indemnities appeared to be significantly less and have lower probabilities of being positive than in West Texas. Ranchers from West Texas may be able to significantly benefit from the insurance.

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1. INTRODUCTION

1.1 General Overview

Droughts and floods cause severe income losses for rural people. Rainfall uncertainty has always been a serious challenge for ranchers. Texas is a state that is susceptible to droughts in the US and livestock and cattle-breeding has always been one of its important businesses. In 2009 drought in Texas led to an estimated $3.6 billion in crop and livestock losses and could exceed $4.1 billion (Texas AgriLife Extension Service 2009). Hedging against weather risk is a major concern for Texas ranchers.
In the beginning of the 2007 crop year, the Federal Crop Insurance Corporation (FCIC) launched Pasture, Rangeland, Forage Rainfall Index Pilot Program (PRF-RI) for six states. These states include counties in: Colorado, Idaho, North Dakota, Pennsylvania, South Carolina, and Texas. Different from the traditional crop insurance program, PRF-RI is based on rainfall index.

Using a rainfall index, within a specific area and certain time period indemnity payments are calculated as a function of shortfall from normal precipitation. Rainfall indices are obtained from National Oceanic and Atmospheric Administration (NOAA) for approximately a 12 x 12 mile grid in each insurable county.

This thesis follows the style of *American Journal of Agricultural Economics*.

Ranchers are required to select at least two, two-month time periods in which precipitation is important during the growth and production of the local grazingland species (Risk Management Agency 2009a). In 2008 and 2009, 11,962 insurance policies were sold in Texas; 5,254 and 6,708, respectively (Risk Management Agency 2009b).

The program has many advantages, it is flexible, provides timely indemnities, production records are not required, and, finally, moral hazard and adverse selection problems are minimized. The last two advantages of PRF-RI are main drawbacks for traditional crop insurance. The main disadvantage of PRF-RI is basis risk, which means that individual losses and experiences are not covered since the indemnity payment is based on an area grid index.

1.2 Statement of the Problem

The problem is that PRF-RI is a pilot program and ranchers are skeptical whether it is viable to purchase insurance or not. Six index intervals, different types of coverage levels and productivity factors make the program complicated for individual ranchers to make the right decision. Personal experience alone may not be enough to judge if PRF-RI is worthwhile for Texas ranchers. Precipitation in Texas decreases as we move from East Texas towards West Texas; however it does not necessarily mean that insuring ranchers in the western counties is always beneficial.

1.3 Objective

The objective of this research is to determine the economic benefits of rainfall insurance in selected counties in Texas and estimate the probability of indemnities under different types of coverage levels and index intervals. Monte Carlo simulation will be applied to calculate stochastic payouts for different scenarios. Several types of risk ranking methodologies will be used to rank insurance options for risk-averse ranchers. The results should help ranchers make better decisions regarding PRF-RI. The research will be useful for educational, as well as for decision making purposes.

2. BACKGROUND

2.1 The Program Overview

A Pasture, Rangeland, Forage Rainfall Index Insurance (PRF-RI) pilot program was developed by Risk Management Agency in 2007. This insurance program for pasture, rangeland or forage based on a rainfall index is available in 18 states. This section aims to provide information on the mechanics of the program, clarify the terminology used and provide an example of how the program works.

Different from traditional crop insurance programs, PRF-RI is based on overall lack of precipitation in a certain region, so individual losses are not indemnified. Losses are calculated on regional grid levels using the rainfall index. The rainfall index is based on National Oceanic and Atmospheric Administration (NOAA) data and uses an approximate 12x12 mile grid. RMA officials claim that this small grid size allows for closer correlation to individual experience. As a result, there is a possibility that the grid will cross county and state lines. According to RMA, this new program offers maximum flexibility for ranchers, as it allows them to insure only those areas that are important to their pasture program or hay operation (Risk Management Agency 2009a).

When a producer decides to purchase PRF-RI insurance, there are several steps that need to be processed. The first step for the rancher is to identify the grid in which the grazingland is located. Local insurance companies help ranchers to determine those grids after they provide the exact location of the land. If the contiguous acreage is located, for example, in three grids the acreage can be separated into two or three grids, or left all in one grid. Therefore, acreage cannot be insured in more than one grid.

The next step for the rancher is to decide which index intervals need to be insured. The crop year is divided into six, two-month index intervals. The crop year starts in February; therefore, the first index interval contains February-March and the sixth contains December-January. The insured is required to select at least two index intervals, assuming production per year is influenced by rainfall in more than one interval. Each index interval is determined separately; indemnities payable on one interval are not dependent on results from other intervals. The maximum percentage of grazingland a producer is allowed to insure in each index interval varies by state. In Texas, the maximum percentage for one index interval is 50 percent and the minimum is 10 percent of total insured acres, with the sum of all the percentages (crop type, Grid ID, index interval) equaling 100 percent of the insured acreage selected for each grid ID by crop type (Risk Management Agency 2009b).

Once a rancher decides which index intervals to insure, he or she must choose the appropriate coverage level and productivity factor to determine the **dollar amount of protection per acre.** The following factors must be included in the rancher's decision:

- A **productivity factor** is a percentage factor selected by the insured producer that allows them to individualize their coverage based on the productivity of the grazingland or hayland they operate. The percentage value is between 60 and 150 percent (Risk Management Agency 2009a). The productivity of graizngland is determined subjectively by the rancher. If the producer thinks that his grazingland is an average as productive as other ranchers' pastures in the same county, he could choose 100 percent.

- A **coverage level** ranges between 70 and 90 percent, is simply the percentage of loss against which the producer desires to be covered.
- A **county base value** is an established production value of grazingland and hayland; every county has a unique land value.
- So the **dollar amount of protection** per acre equals the product of the county base value, by the Productivity Factor (60% -150%) and the Coverage Level (70% -90%), as illustrated in Table 2.1 below:

Table 2.1. Calculation of the Dollar Amount of Protection Per Acre

County Base Value (1)	Productivity Factor (2)	Coverage Level (3)	Dollar Amount of Protection Per Acre (1x2x3)
$17.65	1.2	0.85	$18.00

- The **premium rate** is applied to each unit and equals the product of the dollar amount of protection per acre, the number of insured acres, the premium rate, and the adjustment factor. In addition, the government offers a premium rate subsidy depending on coverage level chosen. The higher the coverage level, the lower the subsidy. As illustrated in Table 2.2, the adjustment factor has a fixed value in every state and is given as 0.01. At 85 percent coverage level, the applicable subsidy is 55 percent; hence the producer has to pay 45 percent of the total premium per acre.

Table 2.2. Calculation of the Producer Premium Rate Per Acre

Dollar Amount of (1)	Premium Rate (2)	Adjustment Factor (3)	Cost to Producer Net of Subsidy (4)	Producer Premium Rate (1x2x3x4)
$18.00	$26.00	0.01	0.45	$2.10

- The **Trigger Grid Index** is calculated by multiplying the selected coverage level by the Expected Grid Index (based on historical mean accumulated precipitation by index interval, expressed as a percentage; expected grid index = 100).
- The **Final Grid Index** is based on current accumulated precipitation data for each index interval. For example, if current data represents a 30% reduction, then the final grid index will be 70.

2.2 Example

A hypothetical rancher decided to insure 500 acres of pasture. The producer may select any coverage level between 70 and 90 percent. Let’s assume that the rancher chose 85 percent. Using the same principle, the productivity factor ranges between 60 and 150 percent and it depends on the producer, since the value is based on the productivity of the land that every rancher subjectively chooses depending on his/her own discretion. Let’s assume the producer selected 120 percent productivity factor with a county base value of $17.65. The dollar amount of protection per acre would be $18, as illustrated in Table 2.1.

Assume that that the rancher chose the first and second index intervals and he decided to insure 50 percent of total grazingland in each index interval, because he knows that the minimum and maximum amount to be insured is 10 percent and 50 percent respectively. If we assume that the rancher insured totally 500 acres and chose the first and second index intervals, the insured acres in each index interval will be 250 acres.

If we combine the values that we determined, we are able to calculate the total policy protection. As illustrated in Table 2.3, it is simply the product of dollar amount of protection per acre, insured acres, and share:

Table 2.3. Calculation of the Total Policy Protection

Index Interval	Dollar Amount of Protection Per Acre	Insured Acres	Share	Policy Protection
	(1)	(2)	(3)	(1x2x3)
I	$18	250	1	$4,500
II	$18	250	1	$4,500
III				
IV				
V				
VI				
Total Policy Protection		500		$9,000

Note: Index Interval I is the beginning of the crop year and stands for February-March; Index Interval VI is the end of the crop year and stands for December-January.

The hypothetical rancher finds out that the premium rates in index interval I and II are $12 and $14 respectively. The applicable subsidy on the 85% coverage level is 55%. Given this information, we can determine the total producer premium rate, which is the product of policy protection, the premium rate, the adjustment factor and one minus the government subsidy. Table 2.4 demonstrates the calculation of the total producer premium rate.

Table 2.4. Calculation of the Total Producer Premium Rate

Index Interval	Policy Protection	Premium Rate	Adjustment Factor	Cost to Producer Net of Subsidy	Producer Premium Rate
	(1)	(2)	(3)	(4)	(1x2x3x4)
I	$4,500	$12	0.01	0.45	$243
II	$4,500	$14	0.01	0.45	$283.50
III					
IV					
V					
VI					
Total	$9,000.00				$526.50

Note: Index Interval I is the beginning of the crop year and stands for February-March; Index Interval VI is the end of the crop year and stands for December-January.

Once the final grid index is determined, indemnities will be due only if the final grid index is below the trigger grid index. Suppose that for Interval I, the final grid index is 120, which is above the trigger grid index, in this case no indemnity is due. On the other hand, let’s assume that the final grid index for interval II is 60, which is below the trigger grid index.

The indemnity is calculated by multiplying the payment calculation factor by the total policy protection for the relevant index interval. The payment calculation factor is calculated by subtracting the FGI from the TGI trigger grid index and dividing by the TGI:

$$\text{Payment Calculation Factor} = \frac{\text{(Trigger Grid Index-Final Grid Index)}}{\text{Trigger Grid Index}} = \frac{(85\text{-}60)}{85} = 0.294$$

Table 2.5. Calculation of the Indemnity Payment

Index Interval	Premium Paid	Policy Protection	Payment Calculation Factor	Indemnity
I	$243	$4,500	N/A	N/A
II	$283.50	$4,500	0.294	1,323
III				
IV				
V				
VI				
Total	$526.50	$9,000		$1,323

Note: Index Interval I is the beginning of the crop year and stands for February-March; Index Interval VI is the end of the crop year and stands for December-January.

As we see in Table 2.5, the payment calculation ratio for the first index interval is not applicable. Since the trigger grid index in the first index interval is less than the final grid index. The total amount of indemnity is $1323, which is generated from the second index interval.

3. LITERATURE REVIEW

Bhattacharya and Osgood (2008) examined potential effects of index insurance for ranchers on animal stocking decisions and possible environmental effects on long-run pasture sustainability. They suggested that index insurance based on weather is one of the tools to deal with climate risk and enhance the returns from livestock; however it might have undesired negative effects. They discuss the behavior of individual ranchers as they make ex-ante animal stocking decisions to meet a minimum return (necessary for loan repayment or consumption). Their analysis used a constrained optimization model based on minimum stocking requirements. They reviewed three possible scenarios and came up with the following results: 1) If income is non-binding, the stocking decision and pasture quality will not be affected by the introduction of insurance. 2) When income is binding two scenarios were analyzed: In the case of low rainfall, insurance promotes ranchers to make higher ex-ante stocking decisions and run more animals than optimal. Naturally, insurance would have an adverse effect on the pasture quality and its overall long-term sustainability. If income is binding in high rainfall areas, pasture will be better utilized and insurance will be beneficial only in the short term, however it might cause harmful long run effects. Their paper concluded that insurance encourages ranchers to make suboptimal decisions at the beginning of the season, which not only jeopardizes their income, but affects the pasture quality in the long run, as well as leads to overstocking.

Hazell (2001) reported the advantages and shortcomings of weather index based

insurance in developing countries. Hazell suggested that index based insurance has positive attributes if it can meet the following requirements: it is affordable to all rural people, it can reimburse catastrophic income losses and protect consumption or debt repayment ability; rainfall insurance is very practical and can be freely implemented even if there is limited data available, rain index insurance circumvents moral hazard problem that typical insurance programs face, and it requires less monitoring to control adverse selection. Hazell mentions two major pitfalls of area based insurance:
1) individuals can suffer a loss and not receive an indemnity if the actual rainfall index remains above the trigger point. This is called basis risk and significant risks are faced by the insurer. 2) When an indemnity is to be paid, all of the insured ranchers in an area must be reimbursed at the same time, so the insurer faces the prospect of having to make enormous payments.

Müller, Quaas, Baumgärtner, and Frank (2007) investigated how the access to rainfall insurance affects the grazing strategy of a farmer. A case study was investigated on a Gamis Farm in Namibia that is successful in ecological and economic terms located in the district Maltahohe. They applied a safety-first rule as the decision criteria. Precipitation was simulated stochastically and a right skewed distribution was observed, where events of low rainfall are frequent, however time to time high rainfall events occurred. Average annual net income was simulated, average income and standard deviation were calculated too. The paper revealed that farmers' optimal strategy is highly dependent on their time horizon. Farmers with a short-time horizon who require high minimum income and are more risk averse do not rest pastures, no resting means using the pasture with fully stocked livestock to generate the highest expected value of average income. Hence pastures become less sustainable and insurance would accelerate the over use of pastures. With a long-time horizon, insurance can play a positive role on pasture sustainability. The study showed that, in dry years the minimal income requirement can be reached despite resting a part of the grazing land, because an indemnity payment is available for the farmer. Therefore, in the long run it is highly likely that higher productivity of the pasture will be maintained.

Cole, Tobacman, and Topolova (2007) presented results from large-scale randomized field experiments that offered weather insurance for farmers in over 50 villages in India. The authors discuss the factors affecting decisions for purchasing rainfall insurance. Wealth appeared to be a significant factor in the decision process. Education was important variable too; educated farmers were 12% more likely to purchase insurance. Risk aversion is another predictor for the insurance purchase decision; risk-averse households were more likely to purchase insurance. Demand for insurance appeared to be very elastic with respect to the premium price.

4. THEORY

4.1 Introduction

Section 4 represents the economic theory used to model decision making under risk from which the rainfall insurance model is based. To accurately determine the most appropriate insurance type, coverage level and index intervals with an assumed level of risk preference, an appropriate economic framework must be utilized. The purpose of this section is to set up and explain this framework. The first section defines the concept of risk and outlines the various sources of risk that influence the rainfall insurance decision. Section two explains utility theory, upon which the methods for ranking risky alternative choices is based. Section three explains the three major levels of risk preference. In the final two sections, the theory behind the specific risk ranking methods of CEs stochastic efficiency and StopLight chart is explained.

4.2 Concept of Risk

In the real world the results of most decisions are associated with risk. Agricultural production is typically a risky business and decisions are made in an environment highly characterized by risk and uncertainty. In a risky environment, there are many uncertain variables at play when making a decision. Usually, it is difficult for the producer to make a decision when faced with several alternatives and, therefore, it gets complicated for them to accurately determine which is the correct choice.

There are many definitions of risk in agricultural economic analysis.

Hardaker et al. (2004a) describe risk as undertaking any action involving uncertain consequences. Risk is an imperfect knowledge where the probabilities of the possible outcomes are known. Risk is the part of a business decision, the manager cannot control (Richardson 2008). Uncertainty, however exists when these probabilities are not known. Lien (2001) provides two additional interpretations of risk: the chances of bad outcomes and the variability of outcomes. Uncertainty is not analogous or equivalent to risk. Uncertainty, unlike risk, cannot be portrayed by a probability distribution. A risky decision is one for which there is no single sure outcome and forces beyond the farmer's control affect and determine the probability of the outcome.

Hardaker et al. (2004a) define six specific types of risk observed in agricultural production. *Production risk* comes from the unpredictable nature of weather and uncertainty about the performance of crops, livestock and pasture. Moreover, production risk also includes the fact that prices of farm inputs and outputs are seldom known for certain when production decision must be made. *Price risk* include risks that come from unpredictable supply and demand changes and currency exchange rates. *Institutional risk* is a risk that the government usually brings on with the introduction of various rules and policies. Within institutional risk is sub-categories of *political risk* (risk of unfavorable policy changes), *sovereign risk* (risk that foreign governments will fail to uphold commitments such as trade agreements), and *relationship risk* (risk steaming from issues between business partners or other trading organizations). *Human/personal risk* is a risk that develops within those operating the farm. Crises such as death and/or divorce of those operating the farm may threaten the existence of the operation. If one of the owners becomes seriously ill, production could be lost or significantly altered, which may in turn reduce returns. Losses in this category may also be a result of carelessness by the farmer or farm workers in using inputs such as machinery or handling livestock. *Business risk* is the combination of production, market, institutional, and personal risk. This type of risk affects the business independent of how it is financed. Business risk impacts the farm business performance in terms of the net cash flow generated or net farm income earned. *Financial risk* results from the method used to finance the farm. There is risk when the farm uses borrowed funds to provide some of the capital for the operation of the farm. In this case, some of the operating profit must be allocated towards meeting the interest charges on the borrowed funds. Similarly, financial risk exists when: funds are borrowed and interest rates unexpectedly rise, the loan is called-off by the lender, and there is a limited or lack of availability of loan finance when required by the farm.

Food and Agriculture Organization of the United Nations (FAO) (1997) also includes 3 external sources of risk in agricultural production. *Natural environment risk* is a risk from short-term weather conditions (drought, flood, frost, and storms) and long-term climate factors (climate change leading to increased variability from issues such as the Greenhouse Effect). Natural hazards such as earthquakes, landslides, wildfires, and ever-changing incidences of pests and diseases are also included as sources of natural environment risk. These risk factors directly impact yields, which further indirectly impact prices through a change in supply. *Economic environment* risks come from uncertainty about market demand and supply which in turn influences prices of inputs and outputs, inflation and interest rates which affect long-term planning, and productivity resulting from the availability for new technology. *Social environment risks* are risks that occur over the long-term, as the availability and competence of farm labor is affected by changes in lifestyle and education. Other social events, such as war, are included in this type of risk as they could also severely impact a farm production.

4.3 Risk Aversion

Weather is the main risk in rainfall insurance. Weather is unpredictable and uncontrollable. Excess amounts or lack of precipitation could reduce the pasture quality.

Individuals' approaches toward risk influence many of the decisions they make. There are three types commonly used to characterize a decision makers' attitude toward risk. An individual is typically characterized as being either risk averse, risk neutral, or risk preferring (Nicholson and Snyder 2008)[1]. An individual who is risk averse usually prefers a level of income that is certain compared to a risky income that has the same expected value. That individual has a diminishing marginal utility of income or wealth. One who is risk averse can be described by their willingness to pay a certain amount of wealth to avoid the risk involved in a gamble (Nicholson and Snyder 2008). Similarly, the greater the variability of income, the more the person would be willing to pay to avoid the risky situation.

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[1] We only analyzed risk neutral and risk averse individuals; however the research by Halter (1978) showed that some ranchers appeared risk takers.

In agriculture, it is assumed that the majority of farmers are risk averse (Hardaker, Hurine, and Anderson 1997). For example, farmers are willing to buy production insurance, adopt farming systems that are more diversified and pay less attention to decisions that are based solely on profit. For an individual who is risk averse, losses are weighted more heavily than gains. When a decision maker exhibits a risk neutral attitude they are defined as being indifferent between a level of income that is certain and an uncertain income with the same expected value. If the individual shows a preference for risk or a "risk loving" attitude, they prefer an uncertain income to a level of income that is certain, no matter if the expected value of the uncertain income is less than that of the certain income.

The general assumption of risk aversion is that more money is preferred to less which is illustrated mathematically by:

(1) $U^{(1)}(w)>0$,

where $U^{(i)}(w)$ is the i-th derivative of the utility function U and w represents wealth. If the first derivative of the utility function is positive, then it is the case that the decision maker prefers more to less (Nicholson and Snyder 2008). Similarly, if the second derivative of the utility function is negative, this implies that the decision maker is risk averse. If the second derivative of the utility function is equal to zero the decision maker is assumed to be risk neutral and if it is positive they are characterized as having a risk preferring attitude (Nicholson and Snyder 2008).

The farmers' level of risk preference is an important factor in any decision analysis. Risk averse behavior by agricultural producers not only affects the decisions they make but also further impacts society: if a farmer is risk averse, they may avoid the efficient allocation of farm resources (Hardaker et al. 2004a). For instance, if a farmer has an aversion to risk, they may be slow to adopt new and improved but untried technologies. Farmers might wait until significant time passes before they actually decide to try more advanced and improved technologies (Pride and Ferrell 2008). All economic models that include risk are more solid and robust because they provide a better prediction of an individual producer's behavior.

Among three types of risks decision makers can be defined risk averse, risk neutral, or risk loving. Moreover, individuals can also be classified based on their degree of risk preference. For example, two decision makers may both be risk averse but one may be more risk averse than other. The degree of a person's risk aversion depends on the nature of the risk and on the person's wealth. One method to find out the degree of risk aversion is to measure the curvature of an individual's utility function (Hardaker et al. 2004a). Since the utility function is described only up to a positive linear transformation, measuring risk aversion using the decision maker's utility function can be fairly difficult to accomplish. Therefore, a measure needs to be used that is constant for a positive linear transformation.

Arrow (1965) and Pratt (1964) developed a more simplistic means for estimating the degree of risk aversion given the fact that the utility function is only defined up to a positive linear transformation. Meyer(1977) clarifies that the degree of risk aversion can be measured by the coefficient $R_a(w)$ or equivalently the absolute risk aversion function represented by equation (2):

$$(2) \qquad R_a(w) = \frac{-U''(w)}{U'(w)}$$

Within equation (2), it is implied that the absolute risk aversion coefficient will decrease as the level of wealth increases. This is because it is assumed that individuals are more willing to take on risk as their level of wealth increases. This equation demonstrates the negative ratio of the second and first derivatives of the utility of wealth (U(w)) function. If the resulting sign of equation (2) is positive, it is implied that the decision maker prefers risk, and zero value indicates a risk neutral attitude. In addition, the resulting coefficient obtained from equation (2) measures the curvature of the utility function and is not affected by any positive linear transformation. Adding a constant will also have no impact on the numerator or the denominator. The numerator and/or denominator will only be affected when they are multiplied by a constant but regardless their ratio will remain the same.

The absolute risk aversion function, $R_r(w)$, merely provides a local measure of risk aversion. Therefore, at different levels of wealth, the degree of risk aversion will vary (Hardaker et al. 2004a). Arrow (1965) and Pratt (1964) provided three different classifications as to how the degree of risk aversion varies with increasing levels of wealth. A utility function will display either constant, increasing, or decreasing absolute risk aversion over some domain of wealth if and only if, over the interval, $R_a(w)$ remains constant, increases, decreases with an increase in wealth (Jehle and Reny 2001). The first classification, decreasing Absolute Risk Aversion (DARA), imposes the restriction that the decision maker is less averse to taking small risks at higher levels wealth (Jehle and Reny 2001). The second case, Constant Absolute Risk Aversion (CARA) states that the decision maker does not have a change in their willingness to accept a gamble at higher levels of wealth. In this second case, preferences are unchanged if a constant amount is added to or subtracted from all payoffs (Hardaker et al. 2004a). In addition preferences among risky prospects are unchanged for all payoffs (Hardaker et al. 2004a). In addition preferences among risky prospects are unchanged if all payoffs are multiplied by a positive constant. The final classification, Increasing Absolute Risk Aversion (IARA) describes the case where the more wealth the decision maker has, the more averse they become to accepting the small gamble.

When there is no information available regarding the decision maker's exact risk preference or level of risk aversion an assumption must be made. Arrow (1965) suggested using the relative risk aversion coefficient, $R_a(w)$, to define risk preference and a value of 1.0 as the most common attitude toward risk. The constant relative risk aversion function for $R_r(w) = 1$, which is the "everyone's utility function" stated by Daniel Bernoulli (1738). However in 1992, Anderson and Dillon found that this was too strong of an assumption and they proposed a scale for classifying the degree of risk aversion which is based on the magnitude of the relative risk aversion coefficient. Table 4.1 presents the classifications of risk aversion proposed by Anderson and Dillon (1992).

Table 4.1. Classification of Risk Aversion

Rr (w)	Degree of Risk Aversion
0.0	Risk Neutral
0.5	Hardly Risk Averse
1.0	Somewhat Risk Averse
2.0	Rather Risk Averse
3.0	Very Risk Averse
4.0	Extremely Risk Averse

If from the classification above, a value for R_r (w) can be established that is assumed to be more or less constant for a local variation in wealth then a value of R_a (w) can be derived using equation (3):

$$(3) \qquad R_a\ (w) = \frac{R_r\ (w)}{w}$$

Hardaker et al. (2004a) suggest that the choice of the exact form of the utility function is rarely important in decision analysis provided the degree of risk aversion is consistently represented. Therefore, if the risk aversion coefficients are derived using the classification represented in Table 4, then they can be used with reasonable confidence in almost any utility function.

4.4 Expected Utility

When an individual faces a decision and involves risky consequences, a framework should be developed in a way that the various alternatives can be compared. This framework is termed Decision Analysis Under Risk. When an individual faces a decision that is not certain, the probability distributions for each of the risky alternatives must be made for decision making (Anderson, Dillon, and Hardaker 1977). Utility theory plays a significant role in decision making under risk. When making a choice among risky alternatives, an individual is expected to select the alterative that provides the highest expected utility (Nicholson and Snyder 2008).

The central theorem of utility analysis is known as Bernoulli's principle or the expected utility theorem. As far back as 1738, Daniel Bernoulli wrote about Subjective Expected Utility (SEU) hypothesis, which states that in order to assess risky alternatives the decision makers' utility function for any given outcome is required (Hardaker et al. 2004b). The expected utility theory is the most commonly used framework for analyzing decision making under risk. Decision analysis is often complicated by the fact that for a single risky choice different individuals will have varying attitudes toward the level of risk represented by the decision. However, Hardaker et al. (2004b) state that the SEU hypothesis continues to be the most suitable theory for the assessment of risky choices. The SEU hypothesis is based on four principle axioms (Hardaker et al. 2004a). The first axiom, *completeness*, implies that a person either prefers one of two risky prospects (a_1 and a_2) or is indifferent between them. The second axiom, *transitivity*, follows from ordering but expands to include additional risky prospects, thus a_1, a_2, and a_3. Transitivity states that if a person prefers a_1 to a_2 (or is indifferent between them) and prefers a_2 to a_3 (or is at the same time indifferent between them), then this same individual will either be indifferent between or prefer a_1 to a_3. The third axiom, *continuity*, infers that if an individual is faced with a risky prospect involving both a good and bad outcome, this individual will take the risk only if the chance of getting the bad outcome is low enough. This axiom can also be explained by saying, if an individual prefers a_1 to a_2 to a_3 then a subjective probability P (a_1) exists that is not zero or one. Further, a probability exists where this individual is indifferent between a_2 and a lottery yielding a_1 with a probability P (a_1) and a_3 with a probability 1 – P (a_1). Lastly, the *independence* axiom states that the preference between a_1 and a_2 is independent of a_3. That is, if a_1 is preferred to a_2, and a_3 is separate risky prospect, then a lottery with a_1 and a_3 as outcomes will be preferred to a lottery with a_2 and a_3 as outcomes when

$P(a_1) = P(a_2)$.

The SEU hypothesis (Bernoulli's principle) can be established based on these four axioms. These axioms measure both preference and subjective probability (Hardaker et al. 2004a). If a decision makers' preferences are consistent with these four axioms, a utility function, U, can be established for that decision maker which associates a single utility value U (a_j) with any risky prospect. In turn, the utility function has three basic properties. First, utilities can be used to rank risky alternatives. Therefore the alternative with the highest utility can be assumed to be the preferred option. This is represented by stating:

if a_1 is preferred to a_2 then $U(a_1) > U(a_2)$.

Secondly, the utility of a risky prospect is in fact the decision maker's expected utility for that prospect. This can also be defined by equation (5):

(5) $U(a_j) = \sum_i U(a_j \mid S_i) P(S_i)$.

Here the expected value is calculated from the utility values of the consequences weighted by the corresponding subjective probabilities. Lastly, the utility function is only defined up to a positive linear transformation. In other words it has an arbitrary origin and scale.

The SEU hypothesis is important as it unities the three foundations of decision making under risk (FAO 1997). Decision analysis is based on the SEU theory because the chances of bad versus good outcomes can only be evaluated and compared if the decision maker's relative preferences for such outcomes are known (Hardaker et al. 2004b). The SEU hypothesis states that the decision maker's utility function for these outcomes is needed to assess risky alternatives because the shape of the utility function is what defines the decision maker's attitude toward risk. The FAO (1997), further states that the SEU hypothesis is significant in decision analysis as it brings together three important elements of risky decision making. These three elements include: the decision maker's personal preferences about possible outcomes, the decision maker's personal degrees of belief in the occurrence of these possible outcomes, and the decision maker's personal responsibility and accountability for whatever decision is taken. Since the expected utility theorem brings together these aspects of decision making, it allows for risky prospects to be ranked in order of preference. The risky prospect with the highest expected utility is determined to be the most preferred choice.

In agricultural economic studies such as this rainfall insurance model, where there are alternative risky decisions and an assumed utility function, the SEU hypothesis is valuable as it states that the level of utility can be calculated depending on the degree of risk aversion (r) and the stochastic outcome of the output variable x. This is computed using equation:

$$(6) \qquad U(x,r) = \int U(x,r)\, f(x)\, dx \ .$$

Following this computation, U is calculated for selected values of r in the range of r_1 to r_2. In addition, CEs can be established for every value of U by applying equation:

(7) $CE\ (x,r) = U^{-1}\ (x,r)$.

4.5 Certainty Equivalents

Using the SEU theory, the concept of CEs can be inferred. When decision analysis is based on financial outcomes it is useful to compare CEs with the expected value of the risky prospect to determine the risk attitude of the decision maker (Hardaker et al. 2004a). When a decision maker is faced with a decision with risky payoffs, there is a sum of money for sure that would make the decision maker indifferent between whether taking the risk or accepting the sure sum of money. This sure sum of money is referred to as the *CE*. The CE is the lowest price for which the decision maker would be willing to sell a desirable risky prospect or equivalently, the highest amount that the decision maker would be willing to pay to get rid of an undesirable risky prospect. For the same risky alternative, the CE can vary between individuals because, in general, people have different attitudes toward risk. Figure 4.1 is used to provide a graphical representation that can be used to explain an individual's attitude toward risk.

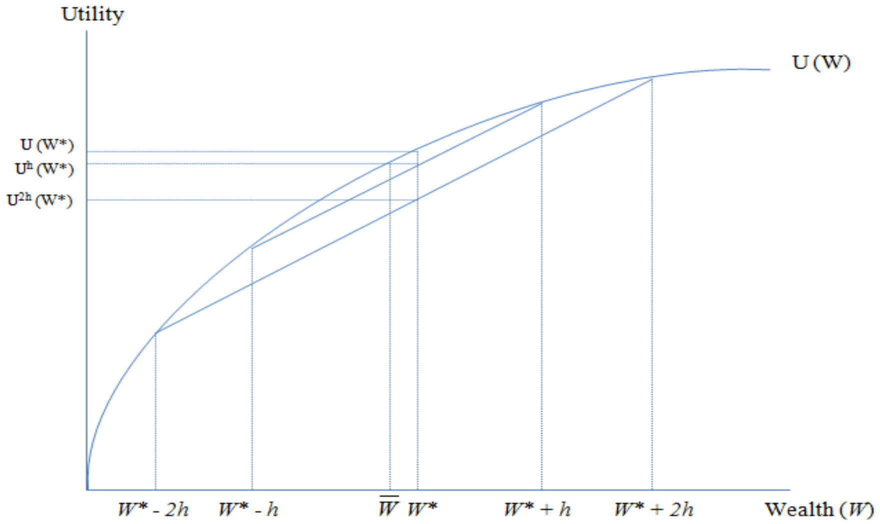

Figure 4.1. Individual’s attitude towards risk. Adapted from: Nicholson and Snyder 2008

In the figure above, *W** represents an individual’s current wealth and *U (W)* is a von Neumann-Morgenstern utility index that reflects how he or she feels about various levels of wealth. In the figure, *U (W)* is drawn as a concave function of *W* to reflect the assumption of a diminishing marginal utility. It is assumed that earning extra money receives less enjoyment as total wealth increases. For example, if a risk averse individual is offered two fair gambles: a 50-50 chance of winning or losing \$*h* of a 50-50 chance of winning or losing \$2*h*. The utility of present wealth is *U(W*)*. The expected utility if he or she participates in gamble 1 is given by $U^h(W^*)$:

$$U^h(W^*) = \frac{1}{2}\,\mathrm{U}\left(\mathrm{W}^*+\mathrm{h}\right) + \frac{1}{2}\,\mathrm{U}\left(\mathrm{W}^*-\mathrm{h}\right),$$

and the expected utility of gamble 2 is given by $U^{2h}(W^*)$:

$$U^{2h}(W^*) = \frac{1}{2}\,\mathrm{U}\left(\mathrm{W}^*+2\mathrm{h}\right) + \frac{1}{2}\,\mathrm{U}\left(\mathrm{W}^*-2\mathrm{h}\right).$$

It is geometrically clear that:

$$U\ (W^*) > U^h\ (W^*) > U^{2h}\ (W^*)$$

We can conclude that , this risk averse person will prefer his or her current wealth to that wealth combined with a fair gamble and will prefer a small gamble to a large one. The reason for this is that winning a fair bet adds to enjoyment less than losing hurts (Nicholson and Snyder 2008). As a matter of fact, this person might be willing to pay some amount to avoid participating in any gamble at all. We can notice that, a certain wealth of $\overline{W}$provides the same utility as does participating in gamble 1.This person would be willing to pay W^*-$\overline{W}$ in order to avoid participating in the gamble. This explains why people buy insurance. They are giving up a small, certain amount (the insurance premium) to avoid the risky outcome they are being insured against (Nicholson and Snyder 2008).

4.6 Efficiency Criteria

In applied agricultural economic research, risk is generally represented by a probability distribution. Risk assessment requires coming to grips with both probabilities and preferences for outcomes held by the decision maker (Hardaker et al. 2004a). The probability distributions associated with various risky choices are often quantitatively compared using methods of stochastic efficiency. These methods are highly accepted as means of evaluating risky alternatives, as they only require two assumptions regarding a decision makers’ preference for risk (FAO 1997). These assumptions include the decision makers’ level of risk aversion and the associated functional form of the utility function.

If a decision makers' utility function is unknown or unavailable, efficiency criteria is very helpful as it allows researchers to rank risky alternatives (Hardaker et al. 2004a). Although SEU hypothesis had been criticized because hypothesis is not consistent with the theory in certain risky choice situations (e.g., Allais 1984), Hardaker et al. (2004b), argue that the SEU hypothesis remains the most appropriate theory for prescriptive assessment of risky choices. In order to avoid the need to elicit a specific single-valued utility function, stochastic dominance and efficiency criteria have been developed. There is an important trade-off to be made in conducting a stochastic dominance analysis. When fewer restrictions are placed on the utility function, the results will be more applicable, but the criterion in selecting between alternatives will be less powerful.

First-degree stochastic dominance (FSD) has the fewest restrictive preference assumptions of all stochastic dominance methods. As stochastic dominance goes further into Second-degree stochastic dominance (SSD), third-degree stochastic dominance (TSD), SDRF, and SERF, more restrictive preference assumptions are imposed (Anderson, Dillon, and Hardaker 1977). FSD has an assumption that more wealth is preferred to less and have absolute risk aversion with respect to wealth, $r_a(w)$, between the bounds $-\infty < r_a(w) < +\infty$ (King and Robison 1984).

Following FSD, SSD is the next most discriminating efficiency method. The SSD adds the assumption that the decision maker has an aversion to risk. In terms of the utility function over the range of [a, b], the basic assumption surrounding SSD is that the utility function is monotonically increasing and strictly concave, or equivalently $U_1(x) > 0$ and $U_2(x) < 0$, where $U_1(x)$ and $U_2(x)$ are the first and second derivatives of the utility function. The absolute risk aversion bounds are $0 < r_a(w) < +\infty$.

TSD has an additional assumption, which infers that the third derivative of the utility function is positive, $U_3(x) > 0$. This assumption implies that as individuals become wealthier they become less risk averse.

SDRF and SERF are used more frequently to rank risky decisions in applied research, as they have stronger discriminatory power than FSD, SSD, TSD. For SDRF the absolute risk aversion bounds are reduced to $r_L(w) \leq r_a(w) \leq r_U(w)$, and ranking of risky scenarios is defined for all decision makers whose absolute risk aversion function lies anywhere between lower and upper bounds $r_L(w)$ and $r_U(w)$, respectively (Hardaker et al. 2004a). SDRF uses a pairwise comparison between alternatives to discover whether one alternative dominates another. SDRF also requires assumptions to be made regarding the form of decision makers' utility function. Usually the negative exponential utility function is assumed for convenience. Moreover, when using SDRF one can expect that pairwise SDRF may not isolate the smallest possible efficient set (Hardaker et al. 2004a). SDRF establishes an efficient set by only selecting the alternatives that are dominated in a pairwise comparison (Hardaker et al. 2004b).

SERF is arguably more transparent in application than SDRF and offers a more simplistic method of ranking risky alternatives. SERF method selects the efficient options, as it simultaneously compares all possible alternatives to each other. The SERF sets a specific range of risk preferences and ranks each preference with a utility efficient alternative. The SERF compares all alternatives based on certainty equivalents (CEs) for a specific range of risk preference. Moreover, when there is no information available about the decision makers' preferences, the SERF method can be used for that situation. Like SDRF, the SERF also requires an assumption regarding the specific form of the utility function and relevant measure of risk aversion (Hardaker et al. 2004a). There are several possible utility functions for the SERF: power utility function, the logarithmic utility function, and the negative exponential utility function. When dealing with SDRF method, it might depend on the choice of a utility function. SERF can be applied for any utility function as long as the inverse function can be calculated. However, it is suggested that the SERF will yield the best result when CARA function is adopted or equivalently a negative exponential function (Hardaker et al. 2004b). CARA has one main advantage, the coefficients of absolute risk aversion can be applied to consequences measured in terms of wealth or income (Anderson and Hardaker 2003).

4.7 StopLight Chart

The StopLight table develops the probability ranking tables. The StopLight chart summarizes the probabilities that the scenarios will be less than the lower target value (in red) and the probabilities that the risky alternatives will exceed a maximum target value (in green). The probability of each scenario falling between the two targets is reported in the table in yellow (Richardson 2008). StopLight facilitates the ranking of scenarios by providing a table of the probabilities as well as graphically showing the probabilities of each range. The StopLight chart is simpler for those decision makers' who are not trained in the use of SERF and stochastic dominance.

5. METHODOLOGY

5.1 Simulation

In the literature review section, four major studies have been reviewed that addressed weather risk. In all four studies a simulation method was a critical component of the research. The reason is that a simulation is the best method that can be used in the research to truly incorporate thoroughness and feasibility of a particular risky action. A simulation has many advantages that support this argument: A deterministic model uses single-point estimates. Each random variable in the model is assigned a “best guess” estimate. Several alternatives of each input variable are manually chosen (such as best case, worst case), and the results recorded for each so-called “what if” scenario. However, Monte Carlo simulation uses random sampling of probability distribution functions as model inputs; simulation produces hundreds of possible outcomes instead of a few discrete scenarios. The results provide probabilities of different outcomes occurring. The results show not only what could happen, but how likely each outcome is. Simulation makes creating graphs easy for different outcomes and the corresponding chances of occurrence. This is a crucial component for communicating findings to the decision makers.

If simulation is compared with mathematical programming, mathematical programming models are simulations in some cases. They can represent the mathematical relationships necessary to describe an economic or business system. However, they seldom incorporate risk, they solve for the optimal answer and give the normative answer of what ought to be. Simulation models, on the other hand, incorporate risk and answer the positive question of what is the likely outcome (Richardson 2009). To conclude the description of simulation it is defined as the process of solving a mathematical simulation model representing an economic system for a set of exogenous variables (Richardson 2008). A simulation model is solved a large number of times to statistically represent all possible combinations of the random variables in the system. Therefore, the results of simulation are a large number of key output variables (KOVs) of interest to the decision makers. The values of simulated model represent an empirical estimate of the stochastic distribution for a random variable, thus the risk is incorporated with variable.

5.2 Distributions

In agriculture, making a decision based only on highest net return without considering a risk is unrealistic. Agriculture is a risky environment and each alternative of net return is represented by a distribution.

There are two broad categories of probability distributions: parametric and nonparametric. Common parametric distributions include the uniform and normal distribution. Nonparametric distributions include the discrete uniform and empirical distribution. Those distributions are applied to variables for which the information available regarding their distribution is unknown. In other words, those distributions allow the data to define the shape of the distribution.

Probability distributions are also known as univariate or multivariate. Univariate distributions have one variable while multivariate distributions refer more than one random variable. In most cases variables are correlated to each other, multivariate distributions are the rule in economic analysis models (Richardson et al. 2000).

If two random variables are correlated and their correlation is ignored in simulation, the model will either over or under state the risk, hence the results of the simulation will be biased. Rainfall indices in each index interval are correlated, therefore to capture the historical correlation among the rainfall indices from different index intervals, the probability distributions associated with these random variables are estimated as multivariate empirical probability distributions.

5.3 Data

The PRF-RI is based on almost 50 years of data from NOAA. The historical index values are available for 12x12 mile grids. Index intervals and sample year are stated as the percent of normal. Information on rainfall indices, PRF-RI premium rates and government subsidies for each insurable county are available on the RMA website (http://prfri-rma-map.tamu.edu/default.aspx).

5.4 Model Development

The first part of the research is the input data which are historical rainfall indices starting in year 1948. The data includes six two-month index intervals for selected counties in Texas. The first step of the model is to simulate the historical rainfall indices for all index intervals. A multivariate empirical distribution of rainfall indices will be used for the following reasons: 1) Empirical distribution allows the data to define the shape of distribution and it avoids forcing a specific distribution on the variables. 2) The empirical distribution can be simulated multivariate to capture the historical correlation between index intervals. 3) Multivariate empirical distribution is closed form distribution and it eliminates the possibility of the simulated values exceeding values observed in history (Ribera, Hons, and Richardson 2004), hence negative rainfall indices will not be observed.

Validation is the second step of the model development. Validation is the process used to ensure that the historical rainfall indices are simulated correctly and the simulated indices demonstrate the appropriate properties of the parent distribution. Cumulative distribution function (CDF) and Probability distribution function (PDF) will be developed from the simulated values and compare to the historical data to ensure that they have the same shape throughout the range of the data. The 2-Sample Hotelling T-Squared multivariate test will be used to statistically test if the collective means of a multivariate random sample are generated from the same distribution as the historical distribution. The complete homogeneity test will be used to compare mean vector and the covariance matrix for the simulated values simultaneously to their corresponding values in the historical data series. Student's t-test will be used to validate if the correlation coefficients between the simulated variables and the assumed correlation matrix are statistically equal.

Verification is the process of verifying that all of the equations in the model appropriately calculate what they are supposed to calculate. The mathematical accuracy of the equations will be checked separately. All equations will be checked to ensure that the correct variables are included and multiplied by the appropriate coefficients and added or subtracted correctly.

Choosing which two 2-months index intervals are most appropriate to be insured is a complex process. One of the solutions to this problem is to develop a portfolio analysis. All combinations of two 2-month index intervals will be simulated separately and two types of risk ranking methods will be applied to rank which two index intervals are the most viable. Stochastic Dominance with Respect to a Function, Stochastic Efficiency with Respect to a Function, and StopLight chart will be used to rank the alternative pairs of indices.

Scenario analysis is an alternative strategy or policy action. Each scenario in a simulation is unique because it is based on a different set of assumptions for the exogenous variables. The model will be simulated for 500 iterations to estimate the parameters for the benefit function assuming that coverage level is 90 percent associated with its premium rate. The 500 iteration simulation for this pair of values consisted of one scenario for the model and one value for the PDF of the benefit variable. The model will also be run for alternative scenarios on the remaining coverage levels (85%, 80%, 75%, 70%) and relevant premium rates. Therefore each scenario results in an estimate of the insurance benefits variable PDF for a particular coverage level.

How will it address the objective of the problem? The study is not to develop or predict anything or make decisions whether the insurance in particular county is viable or not. The purpose of this model is to estimate distributions of the insurance payoffs for alternative options so the decision maker can make a better decision. Every rancher makes a rational decision based on past experience and personal discretion. This study aims to answer the question: will ranchers make a better decision having used this study or not? Applied simulation model will answer many questions that ranchers might face now.

6. RESULTS

6.1 South San Antonio, Bexar County, TX Grid ID 39650

Rainfall index data is given from 1948 through 2008 and is divided by index intervals I through VI. The first index interval includes February-March and sixth includes December-January. A multivariate empirical distribution was applied to the data; six index intervals were simulated and the simulated, stochastic variables for 500 iterations were analyzed. Table 6.1 shows the summary statistics for the simulated data over the six index intervals.

Table 6.1. Summary Statistics for the Six Index Intervals for South Bexar County Grid ID 39650

Index Intervals	I	II	III	IV	V	VI
Mean	99.19	98.99	99.14	100.22	98.42	98.74
StDev	56.88	51.54	69.51	56.66	66.19	82.56
CV	57.35	52.07	70.12	56.53	67.25	83.61
Min	2.50	9.89	13.99	17.19	2.79	5.79
Max	320.20	250.21	320.62	250.51	285.02	540.04

Note: Index Interval I is the beginning of the crop year and stands for February-March; Index Interval VI is the end of the crop year and stands for December-January.

The model was validated to ensure the random variables were simulated properly and to demonstrate the properties of their parent distributions. Several tests were performed to validate random input variables. Specifically, “Hotelling’s T-Squared Test” was used to test whether the simulated vector of means for the multivariate distribution is equal to the vector of means for the original distribution. The Hotteling’s T-Squared

Test failed to reject the null hypothesis that the vector of means is equal to the vector of means for the random variables. In other words, the simulated means were found to be statistically equal to the input data mean. A Correlation test was performed using a Student’s t-test to determine if the historical correlation matrix used to simulate the multivariate distribution is appropriately reproduced by the simulated variables. None of the correlation coefficients for any two simulated variables were statistically different from the historical correlation coefficient at the 99 percent level.

The model was also validated by visually inspecting the minimum and maximum random values to ensure that they are reasonable given the assumed means. Also, the minimum and maximum fractional deviates in the empirical probability distributions were validated visually to ensure they are practical. While these tests are non-statistical, they help to ensure that the coefficient of variation, minimum, and maximum of the simulated values are equal to the historical data.

The next step is to calculate the net returns per acre for each index interval. In South San Antonio, the county base value, the premium rate and the applicable government subsidy are given by RMA. A productivity factor of 120 and a coverage level of 70 percent were chosen for simplicity. Again these choices are completely up to the rancher, and he/she subjectively chooses based on his/her subjective expectations.

The net returns for each index interval were calculated using the same principle that had been applied in the hypothetical example.[2]

After we generated the stochastic benefits per acre for the six index intervals, the next step was to conduct the portfolio analysis. The rancher must insure the pasture in at least two index intervals. For simplicity, we generated the payoffs for two index intervals. If we take into account all possibilities of six index intervals and the rancher decides to select two index intervals, there are a total of fifteen possible combinations. Table 6.2 shows the portfolio combinations given two index intervals selected at a time.

Table 6.2. Fifteen Possible Combinations of Index Intervals for 50% Coverage of Two Intervals at a Time Used as Portfolios for Picking the Best Combination of Intervals

	Feb-Mar	Apr-May	June-July	Aug-Sep	Oct-Nov	Dec-Jan
Portfolio 1	0.5	0.5	0	0	0	0
Portfolio 2	0.5	0	0.5	0	0	0
Portfolio 3	0.5	0	0	0.5	0	0
Portfolio 4	0.5	0	0	0	0.5	0
Portfolio 5	0.5	0	0	0	0	0.5
Portfolio 6	0	0.5	0.5	0	0	0
Portfolio 7	0	0.5	0	0.5	0	0
Portfolio 8	0	0.5	0	0	0.5	0
Portfolio 9	0	0.5	0	0	0	0.5
Portfolio 10	0	0	0.5	0.5	0	0
Portfolio 11	0	0	0.5	0	0.5	0
Portfolio 12	0	0	0.5	0	0	0.5
Portfolio 13	0	0	0	0.5	0.5	0
Portfolio 14	0	0	0	0.5	0	0.5
Portfolio 15	0	0	0	0	0.5	0.5

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[2] Given any combinations of coverage levels and productivity factors, it would not change the final outcome. As for combination we chose 70 percent of coverage level and 120 percent of a productivity factor.

For the fifteen possible combinations the net return is simulated per acre using the stochastic rainfall index values. Each index interval is insured for 0.5 acre. The results for simulating net benefits for the fifteen portfolios are summarized in Table 6.3.

Table 6.3. Summary Statistics for Comparing Fifteen Portfolios of Index Intervals for South Bexar County Grid ID 39650

	P 1	P 2	P 3	P 4	P 5	P 6	P 7	P 8	P 9	P 10	P 11	P 12	P 13	P 14	P 15
Mean ($/acre)	0.95	1.06	0.82	1.18	1.08	1.08	0.84	1.20	1.10	0.96	1.32	1.22	1.08	0.98	1.33
StDev ($/acre)	2.27	2.18	1.93	2.48	2.42	2.21	1.93	2.58	2.46	2.02	2.65	2.31	2.58	2.36	2.84
CV (%)	239.89	205.51	235.25	209.81	223.72	204.14	228.42	215.05	223.56	210.24	201.10	189.49	239.97	241.21	212.52
Min ($/acre)	-0.81	-0.95	-0.79	-0.98	-0.92	-0.91	-0.75	-0.94	-0.88	-0.89	-1.08	-1.02	-0.92	-0.86	-1.04
Max ($/acre)	9.84	9.01	9.36	9.89	10.76	9.83	8.45	11.59	10.05	7.94	10.69	10.28	8.95	9.24	10.76

Note: P stands for Portfolio.

Portfolio fifteen, 50% V and 50% VI had the highest mean followed by portfolio three. Figure 6.1 shows the SERF rankings for the simulated portfolios.

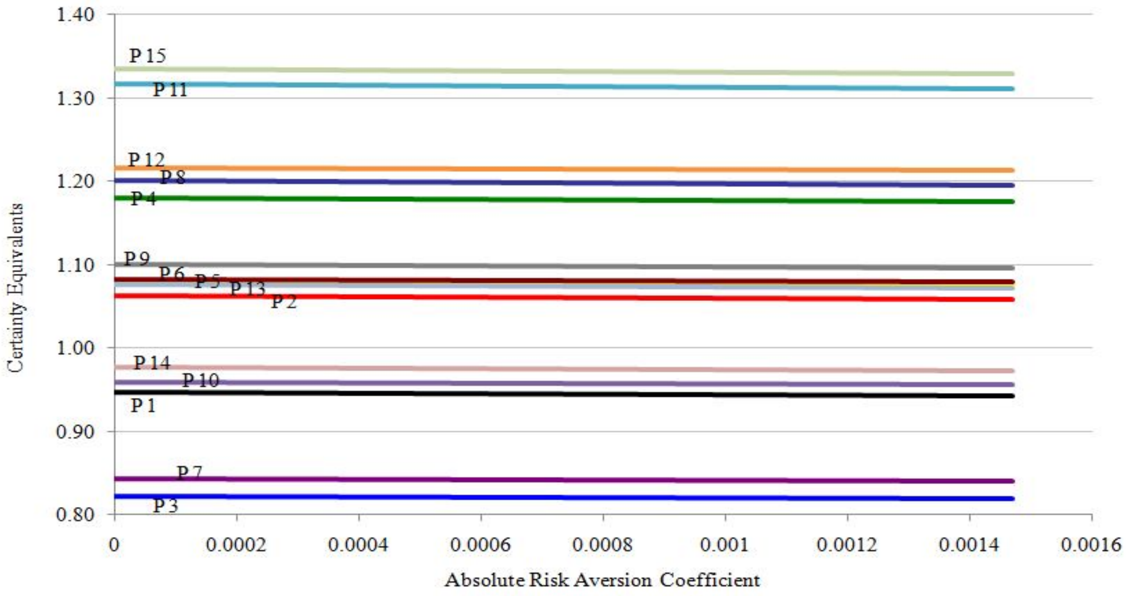

Figure 6.1. SERF ranking of fifteen portfolios for determining the best index intervals for a risk averse decision maker in South Bexar County Grid ID 39650

The fifteenth portfolio - the fifth and sixth index intervals - ranked as the most preferred assuming a negative exponential utility function across risk intervals for a risk neutral to an extremely risk averse producer.[3] Initially this might suggest that the rancher should have picked corresponding index intervals during the spring time when the rainfall is critical for pasture; but the portfolio fifteen is winter when the grass is not growing. Implying that, they want to maximize returns of insurance indirect to ranch operations. Next the decision maker must choose the appropriate coverage level. The higher the coverage level, the higher the premium rate and the lower the government subsidy. Five

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[3] Maximum ARAC was calculated by division of half of the pasture land value in Texas into 4.0 which represents the relative risk aversion coefficient for an extremely risk averse decision maker.

scenarios were analyzed for coverage levels between 70% and 90%. Each coverage level has a unique premium rate and an applicable government subsidy rate. The net return simply equals the sum of indemnity payments in the fifth and sixth index intervals, less the premium rate. The net return was simulated for five alternative insurance coverage levels, 70%, 75%, 80%, 85%, and 90% using the stochastic index values for the fifth and sixth index intervals.

Table 6.4 and Figure 6.2 confirm the summary statistics and the CDF chart of the five insurance scenarios respectively. Note that in the first scenario, where the coverage level is 70%, the maximum amount that the rancher can lose is $1.04 per acre (Table 6.4). The maximum net indemnity per acre the rancher can receive under the 70% coverage level is $10.76, which is less than the other alternative coverage levels. At the higher coverage levels, the premiums (minimum per acre) increases and the maximum net return increases. The summary statistics show that insurance level that is calculated for the 90% coverage level, has the possibility of losing $2.26 per acre and gaining as much as $13.48 per acre. The CDF chart shows that insurance scenario at 90% has the lowest left and the highest right tails (Figure 6.2). In other words, the higher the coverage level, the higher the possibility to earn indemnities.

Table 6.4. Summary Statistics of Net Returns Per Acre from Simulating Five Insurance Levels Using Portfolios for Ranchers in South Bexar County Grid ID 39650

	Insurance 70%	Insurance 75%	Insurance 80%	Insurance 85%	Insurance 90%
Mean ($/acre)	1.33	1.56	1.67	1.91	1.98
StDev ($/acre)	2.84	3.11	3.39	3.66	3.92
CV (%)	212.52	199.13	203.47	191.83	197.44
Min ($/acre)	-1.04	-1.23	-1.57	-1.81	-2.26
Max ($/acre)	10.76	11.56	12.20	12.95	13.48

Note: Net Return = Indemnity - Premium.

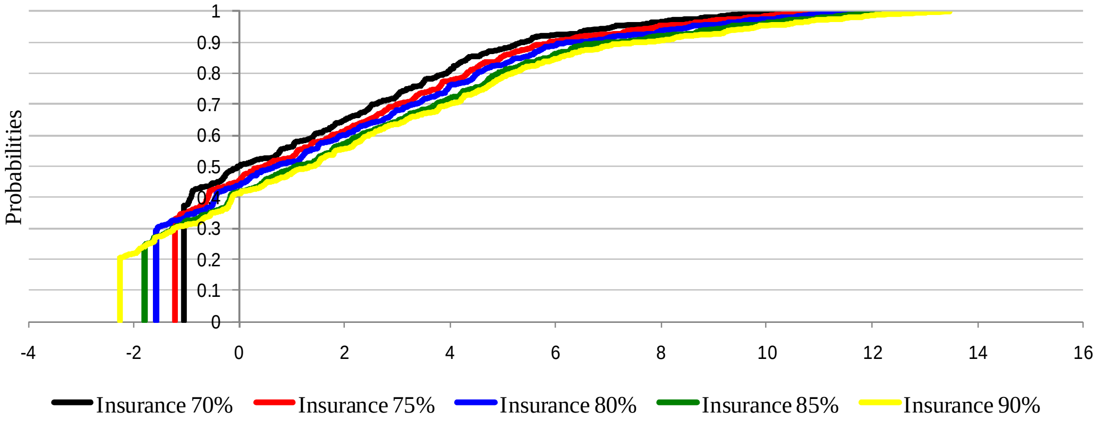


Figure 6.2. Cumulative distribution functions of per acre net returns for five insurance levels using portfolio index intervals for ranchers in South Bexar County Grid ID 39650

In Figure 6.3, the StopLight chart summarizes the probabilities that the outcomes for the insurance scenarios will be less than a lower target and the probabilities that the risky alternatives’ outcomes will exceed a maximum target (Richardson 2008).

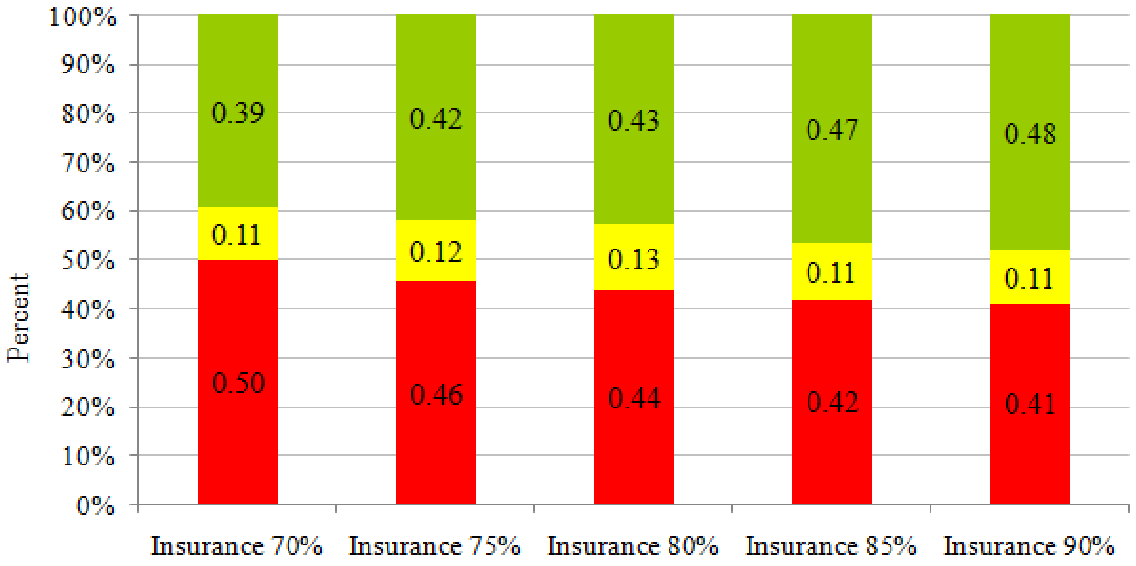


Figure 6.3. StopLight chart summarizing the probabilities of net returns to range insurance for ranchers in South Bexar County Grid ID 39650. Red light shows the probabilities that net return falls below zero; the yellow areas show the probabilities that the net return for an insurance level will fall between 0 and $1.54 per acre; and the green area shows the probabilities that the net return will be greater than $1.54 per acre

The StopLight chart shows the probabilities of each range, which is very helpful in ranking risky alternatives for a decision maker not trained in the use of SERF and stochastic dominance. The red area shows us the probabilities that the benefit falls below zero; the yellow areas show the probabilities that the net benefit for an insurance level will fall between 0 and $1.54 per acre; and the green area shows the probability that the net benefit will be greater than $1.54. A risk averse decision maker is expected to select the insurance policy that has the lowest probability that the overall benefit falls below zero. Based on the probabilities of target values, we can see that if the 90 percent coverage level policy is chosen, there is a 41 percent chance that the net benefit will fall below zero and a 59 percent chance that the rancher will receive indemnity payments that exceed the premium. If the rancher decides to choose the 70 percent coverage level, the probability that the producer will not get any indemnities or that the payment will be less than the premium paid is 50%. Similarly, we can compare other alternative coverage levels and their respective probabilities. Based on the StopLight results, the decision maker is expected to insure the pasture using the fifth and sixth index intervals and choose the 90 percent coverage level.

Figures 6.4 and 6.5 show the SERF and the SDRF ranking methods applied to the simulated data for the insurance coverage level scenarios respectively. Both utility - based rankings systems ranked insurance policy 5 — the 90 percent coverage level — as the most preferred.

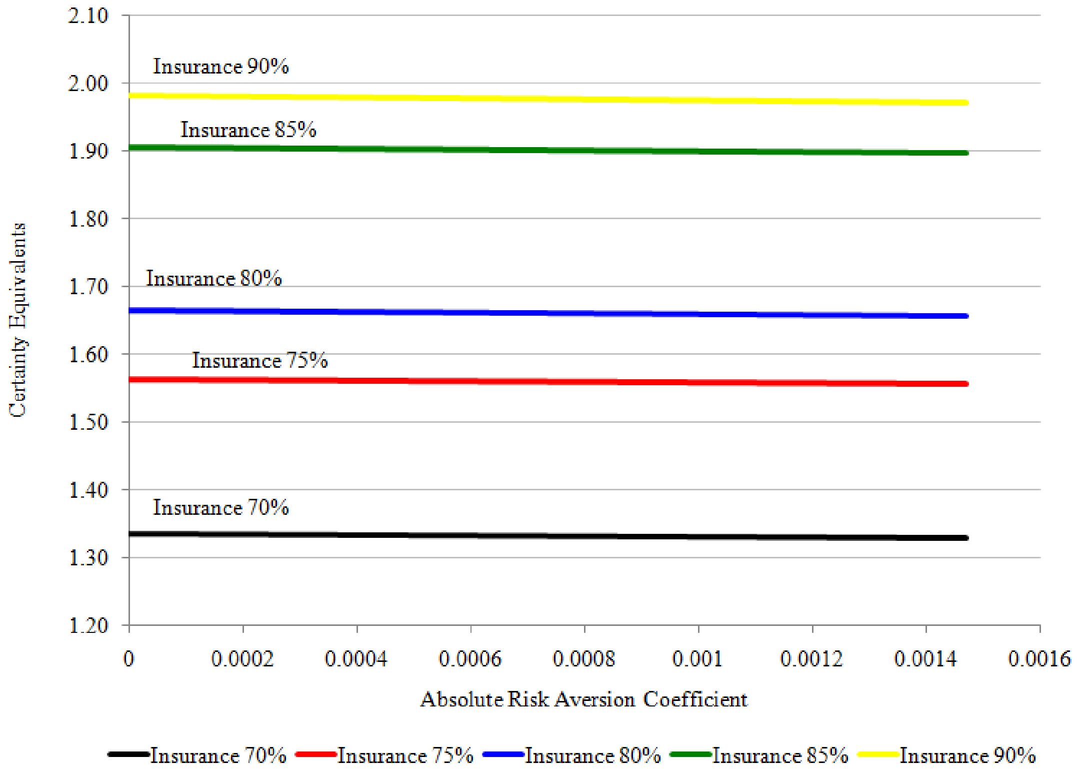


Figure 6.4. SERF ranking of five range insurance policies for ranchers in South Bexar County Grid ID 39650 for risk averse decision makers

Efficient Set Based on SDRF at

	Lower RAC	**0**
	Name	Level of Preference
1	Insurance 90%	Most Preferred
2	Insurance 85%	2nd Most Preferred
3	Insurance 80%	3rd Most Preferred
4	Insurance 75%	4th Most Preferred
5	Insurance 70%	Least Preferred

Efficient Set Based on SDRF at

	Upper RAC	**0.00147**
	Name	Level of Preference
1	Insurance 90%	Most Preferred
2	Insurance 85%	2nd Most Preferred
3	Insurance 80%	3rd Most Preferred
4	Insurance 75%	4th Most Preferred
5	Insurance 70%	Least Preferred

Note: RAC stands for Risk Aversion Coefficient and SDRF for Stochastic Dominance with Respect to a Function.

Figure 6.5. SDRF ranking of five range insurance policies for ranchers in South Bexar County Grid ID 39650 for risk averse decision makers

The same analysis was applied to three other locations — Robstown, Henrietta and Andrews. The results of that analysis follow in sections 6.2 - 6.4.

6.2 Robstown, Nueces County, TX Grid ID 41580

Validation

The simulated rainfall indices for Robstown were validated in the same way as in the previous case to ensure that they were simulated properly. The Hotteling's T-Squared test failed to reject the null hypothesis that the simulated means were statistically equal to the input data means. According to the Student's t-test, none of the correlation coefficients for any two simulated variables were statistically different from the historical correlation coefficients at the 99 percent level.

The model was also validated by visually checking coefficient of variation, the minimum and maximum random values to ensure that they are reasonable given the assumed means. Also, the minimum and maximum fractional deviates in the empirical probability distributions were validated visually to ensure they are realistic.

Portfolio Analysis

The county base value, the premium rate and the applicable government subsidy are given by RMA. As in the previous case, a productivity factor of 120 and a coverage level of 70 percent were chosen.

The fifteen possible combinations of the 6 intervals were analyzed and net return was simulated per acre for each portfolio. Each index interval is insured for 0.5 acre. The results for simulating net returns for the fifteen portfolios are summarized in Table 6.5. Portfolio five, 50% I and 50% VI had the highest mean followed by portfolio fifteen.

Table 6.5. Summary Statistics for Comparing Fifteen Portfolios of Index Intervals for Nueces County Grid ID 41580

	P 1	P 2	P 3	P 4	P 5	P 6	P 7	P 8	P 9	P 10	P 11	P 12	P 13	P 14	P 15
Mean ($/acre)	0.75	0.79	0.69	0.84	0.94	0.64	0.54	0.69	0.79	0.58	0.72	0.82	0.63	0.73	0.87
StDev ($/acre)	1.81	1.78	1.55	1.85	1.94	1.70	1.27	1.64	1.76	1.45	1.64	1.74	1.49	1.52	1.83
CV (%)	242.79	226.95	223.91	221.48	207.47	267.79	234.05	239.19	223.90	249.00	226.84	211.00	236.17	208.11	208.93
Min ($/acre)	-0.71	-0.77	-0.62	-0.73	-0.77	-0.70	-0.55	-0.66	-0.70	-0.60	-0.71	-0.75	-0.56	-0.60	-0.71
Max ($/acre)	7.01	6.75	6.29	7.08	7.27	7.67	4.99	8.30	7.05	6.26	7.45	7.18	5.87	5.89	7.26

Note: P stands for Portfolio.

Figure 6.6 shows the SERF rankings for the simulated portfolios. The fifth portfolio — the first and sixth index intervals — was ranked as the most preferred assuming a negative exponential utility function across risk intervals for a risk neutral to an extremely risk averse producer.

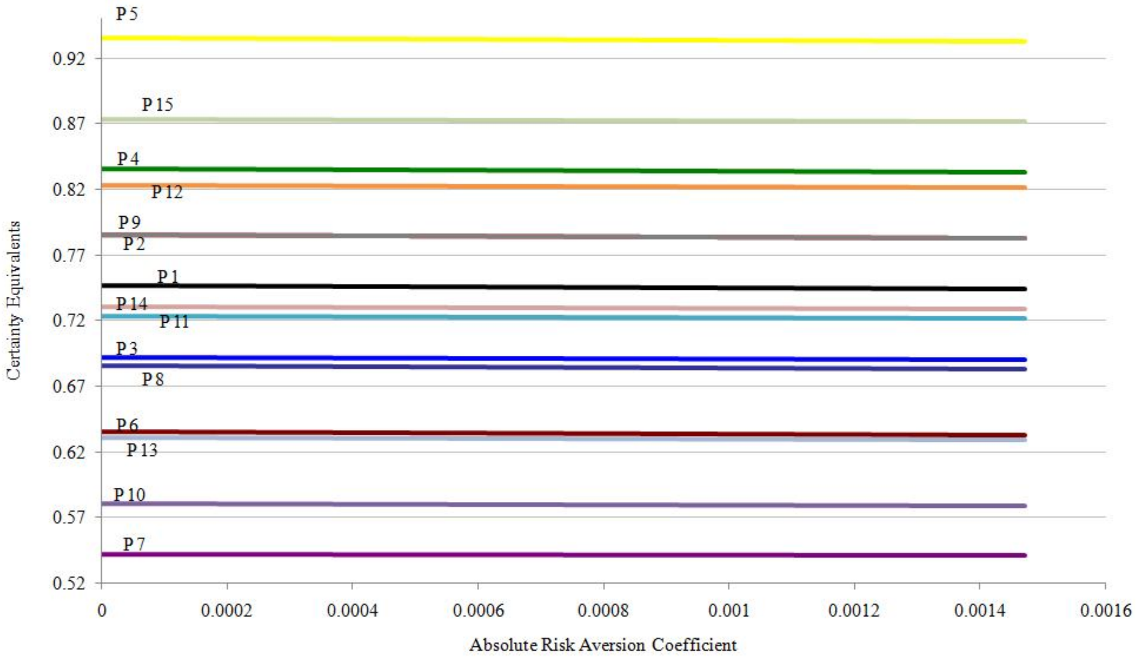


Figure 6.6. SERF ranking of fifteen portfolios for determining the best index intervals for a risk averse decision maker in Nueces County Grid ID 41580

Benefits

After finding out that the first and sixth index intervals are the driest four months, five insurance scenarios — with their respective premium rates and applicable subsidies for coverage levels between 70% and 90% — were analyzed using the stochastic index values for the first and sixth index intervals. As mentioned above, the higher the coverage level the higher the premium rate and the lower the government subsidy. The net return was simulated for five alternative coverage levels using the stochastic rainfall index values.

Table 6.6 and Figure 6.7 show the summary statistics and the CDF chart of net returns for the five insurance scenarios, 70%, 75%, 80%, 85%, 90% for the fifth and sixth index intervals.

Table 6.6. Summary Statistics of Net Returns Per Acre from Simulating Five Insurance Levels Using Portfolios for Ranchers in Nueces County Grid ID 41580

	Insurance 70%	Insurance 75%	Insurance 80%	Insurance 85%	Insurance 90%
Mean ($/acre)	0.94	1.08	1.16	1.33	1.38
StDev ($/acre)	1.94	2.15	2.36	2.56	2.77
CV (%)	207.47	198.51	203.59	192.69	201.08
Min ($/acre)	-0.77	-0.90	-1.14	-1.31	-1.62
Max ($/acre)	7.27	7.81	8.25	8.75	9.12

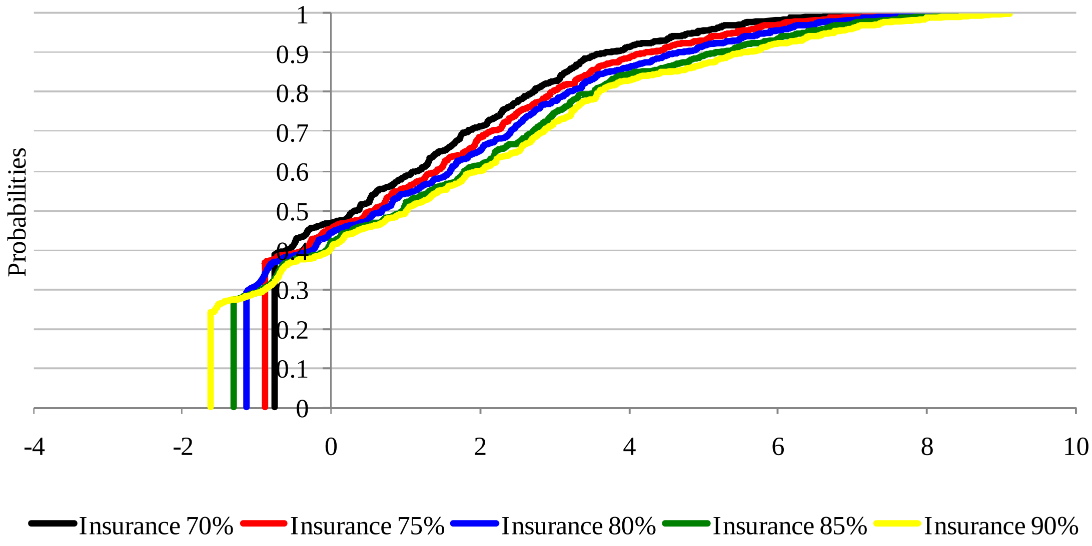


Figure 6.7. Cumulative distribution functions of per acre net returns for five insurance levels using portfolio index intervals in Nueces County Grid ID 41580

Note that in the first insurance policy where, the coverage level is 70%, the maximum amount that the rancher can lose is $0.77 per acre (Table 6.6). The maximum positive net indemnity per acre the rancher can receive under the 70% coverage level is $7.27, which is considerably less than one observed in South San Antonio at the 70% coverage level. The reason is that the minimum precipitation observed in South San Antonio is much lower than one observed in Robstown. The summary statistics show that insurance policy 5, which is calculated for the 90% coverage level, has the possibility of losing $1.61 per acre and gaining as much as $9.12 per acre. The CDF chart shows the insurance policy 5 has the lowest left and the highest right tails (Figure 6.7).

In Figure 6.8, the StopLight chart is summarized. As mentioned above, the StopLight chart is very helpful in ranking risky alternatives for a decision maker not trained in the use of SERF and stochastic dominance.

Figure 6.8. StopLight chart summarizing the probabilities of net returns to range insurance for ranchers in Nueces County Grid ID 41580. Red light shows the probabilities that net return falls below zero; the yellow areas show the probabilities that the net return for an insurance level will fall between 0 and $1.11 per acre; and the green area shows the probabilities that the net return will be greater than $1.11 per acre

The red area shows us the probabilities that the net return falls below zero; the yellow areas show the probabilities that the net return will fall between 0 and $1.11 per acre; and the green area shows the probability that the net benefit will be greater than $1.11. The decision maker is expected to select the insurance scenario that has the lowest probability that the overall net benefit falls below zero. Based on the probabilities of target values, we can see that if 90 percent coverage level is chosen, there is a 40 percent chance that the net return falls below zero and a 60 percent chance that the rancher will receive indemnity payments that will exceed the premium. If the rancher decides to choose the 70 percent insurance coverage level, the probability that the producer will not get any positive net indemnities or that the payment will be less than the premium paid is 47%. Similarly we can compare other alternative insurance policies and their respective probabilities. Based on the StopLight results, the decision maker is expected to insure the pasture in the first and sixth index intervals and choose the 90 percent coverage level.

Figures 6.9 and 6.10 show the SERF and the SDRF ranking methods applied to the simulated data for the five types of insurance policy scenarios. Both utility based rankings systems ranked insurance policy 5 – the 90 percent coverage level — as the most preferred one.

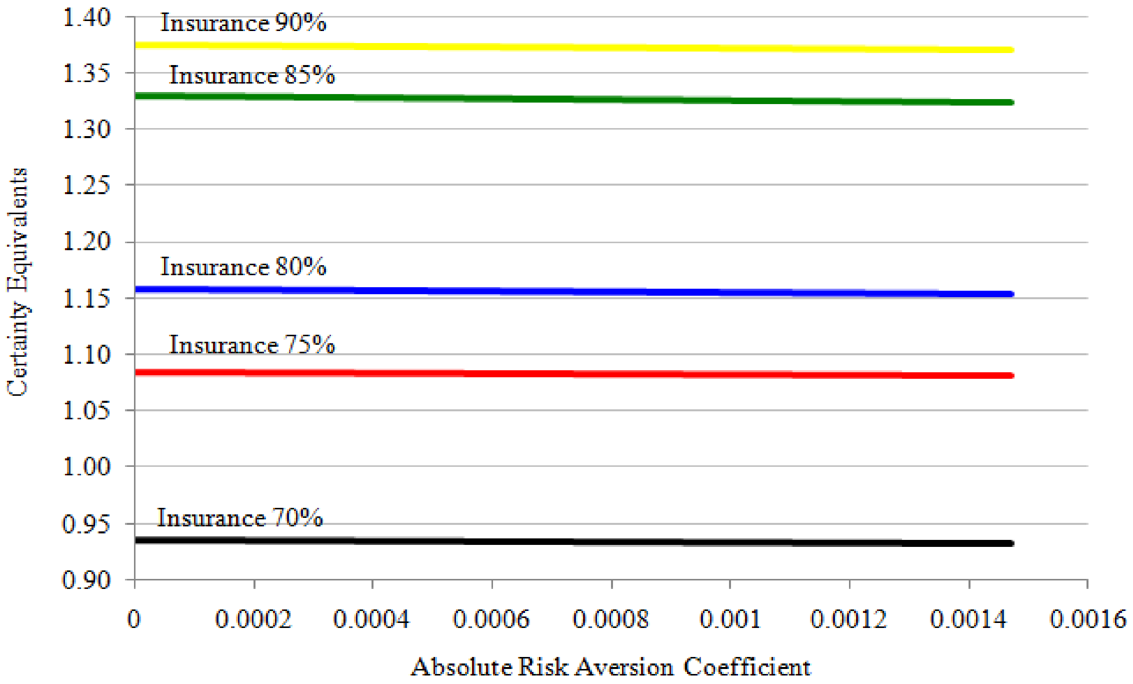


Figure 6.9. SERF ranking of five range insurance policies for ranchers in Nueces County Grid ID 41580

	Efficient Set Based on SDRF at	
	Lower RAC	**0**
	Name	Level of Preference
1	Insurance 90%	Most Preferred
2	Insurance 85%	2nd Most Preferred
3	Insurance 80%	3rd Most Preferred
4	Insurance 75%	4th Most Preferred
5	Insurance 70%	Least Preferred

	Efficient Set Based on SDRF at	
	Upper RAC	**0.00147**
	Name	Level of Preference
1	Insurance 90%	Most Preferred
2	Insurance 85%	2nd Most Preferred
3	Insurance 80%	3rd Most Preferred
4	Insurance 75%	4th Most Preferred
5	Insurance 70%	Least Preferred

Note: RAC stands for Risk Aversion Coefficient and SDRF for Stochastic Dominance with Respect to a Function.

Figure 6.10. SDRF ranking of five range insurance policies for ranchers in Nueces County Grid ID 41580

If we compare these final two study regions, some interesting results can be noticed. Robstown is drier than South San Antonio. The probability of receiving net positive indemnities in Robstown is slightly higher than in South San Antonio. However, since the county base value in Nueces County is significantly lower than in Bexar County and at the same time premium rates in Robstown are higher than in South San Antonio, which precludes earning a higher amount of indemnities than in South San Antonio. Both regions share the sixth interval as one of the most preferred one.

6.3 Henrietta, Clay County, TX Grid ID 33873

Henrietta in Clay County is the third region for the model. So far, we have discussed two regions located basically in the southern part of Texas, whereas Henrietta is located on the north side of the state. Based on that, the results of the study might be more or less different than the other two areas.

Validation

The simulated rainfall indices were validated to ensure that they were simulated properly. The Hotteling's T-Squared test failed to reject the null hypothesis and the simulated means were found to be statistically equal to the input means. Using a Student's t-test, a Correlation test was performed and none of the correlation coefficients for any two simulated variables were statistically different from the historical correlation coefficient at the 99 percent level.

The benefits per acre were calculated for each index interval. Given the county base value, the premium rate and the applicable government subsidy, a productivity factor of 120 and a coverage level of 70 percent were tested fixed for simplicity.

Portfolio Analysis

The portfolio analysis was conducted and the payoffs per acre were generated for two index intervals. The results of all fifteen combinations for two index intervals with 0.5 acre in each are summarized in Table 6.7.

Table 6.7. Summary Statistics for Comparing Fifteen Portfolios of Index Intervals for Clay County Grid ID 33873

	P 1	P 2	P 3	P 4	P 5	P 6	P 7	P 8	P 9	P 10	P 11	P 12	P 13	P 14	P 15
Mean ($/acre)	0.32	0.35	0.40	0.45	0.50	0.35	0.40	0.45	0.50	0.43	0.48	0.53	0.52	0.57	0.62
StDev ($/acre)	1.02	1.04	1.23	1.23	1.28	0.99	1.12	1.14	1.21	1.23	1.21	1.19	1.37	1.38	1.46
CV (%)	318.90	293.94	309.76	276.63	257.01	280.12	282.03	255.16	243.20	284.65	252.22	224.08	261.28	240.67	234.19
Min ($/acre)	-0.36	-0.43	-0.49	-0.51	-0.49	-0.34	-0.40	-0.42	-0.40	-0.48	-0.50	-0.48	-0.55	-0.53	-0.55
Max ($/acre)	5.35	4.85	5.94	5.51	6.02	4.84	4.67	5.85	4.91	5.42	5.97	6.19	5.43	5.56	5.24

Note: P stands for Portfolio.

Figure 6.11 shows that, portfolio fifteen has been ranked as the most preferred alternative — 50% V and 50% VI — assuming a negative exponential utility function, which has the highest mean, followed by portfolio 14 – 50% IV and 50% VI; and by portfolio 12 – 50% III and 50% VI.

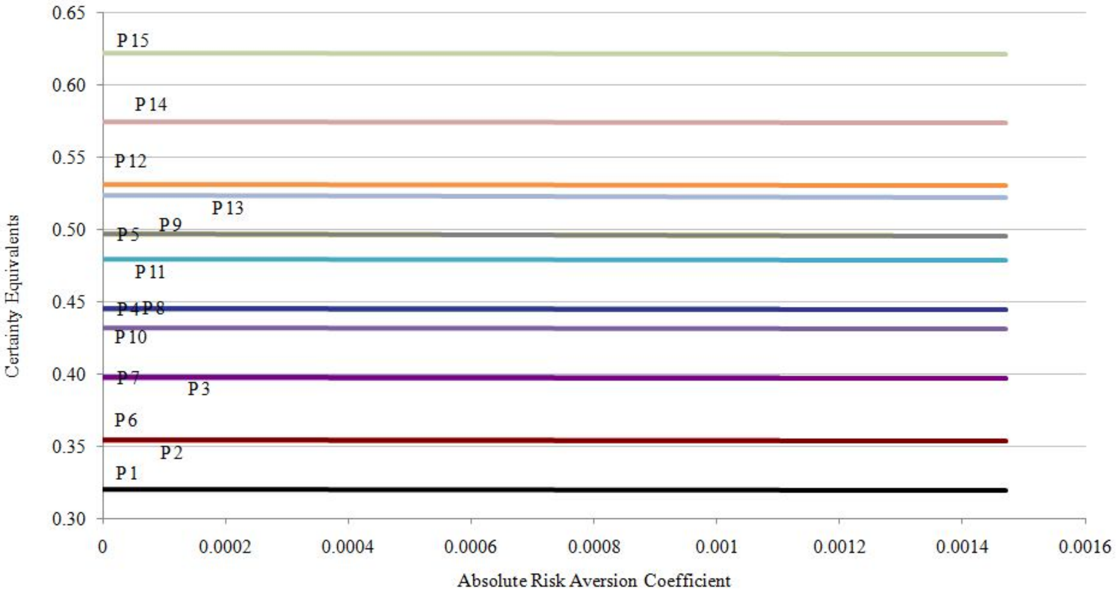


Figure 6.11. SERF ranking of fifteen portfolios for determining the best index intervals for a risk averse decision maker in Clay County Grid ID 33873

As we see, all three top ranked portfolios have the sixth index interval in common. Implying that, 6th index interval is the most critical time period that should be taken into consideration by the ranchers.

Benefits

Five insurance scenarios were analyzed for coverage levels between 70% and 90% using the fifth and sixth index intervals. For each scenario the net return of insurance policy was calculated and simulated using the stochastic rainfall index values. Those results are summarized in Table 6.8**.** We observe that the maximum payoffs per acre for each coverage levels are relatively lower than results in previous cases. The maximum net return per acre that might be received at 90% coverage level is significantly lower than the maximum benefit that can be earned in South San Antonio and in Robstown at the 70% insurance coverage level. This result can be linked to one main factor: the county base value in Henrietta is significantly lower than county base values in South San Antonio and in Robstown. The maximum amount of loses at the 70% insurance coverage level is $0.55 per acre and the highest net indemnity that can be earned on the same policy level is $5.24 per acre. As expected, at higher insurance coverage levels payoffs increase. At 90% coverage level the largest amount that can be lost is $1.17 per acre. While the possibility of earning the maximum net payoffs is as much as $6.91 per acre.

Table 6.8. Summary Statistics of Net Returns Per Acre from Simulating Five Insurance Levels Using Portfolios for Ranchers in Clay County Grid ID 33873

	Insurance 70%	Insurance 75%	Insurance 80%	Insurance 85%	Insurance 90%
Mean ($/acre)	0.62	0.74	0.79	0.93	0.98
StDev ($/acre)	1.46	1.63	1.79	1.95	2.11
CV (%)	234.19	220.30	226.37	209.80	214.32
Min ($/acre)	-0.55	-0.64	-0.82	-0.94	-1.17
Max ($/acre)	5.24	5.72	6.12	6.57	6.91

Figure 6.12 illustrates the CDF chart of net returns for five insurance scenarios. As in previous studies, the insurance policy at 90% has the lowest left and the highest right tails.

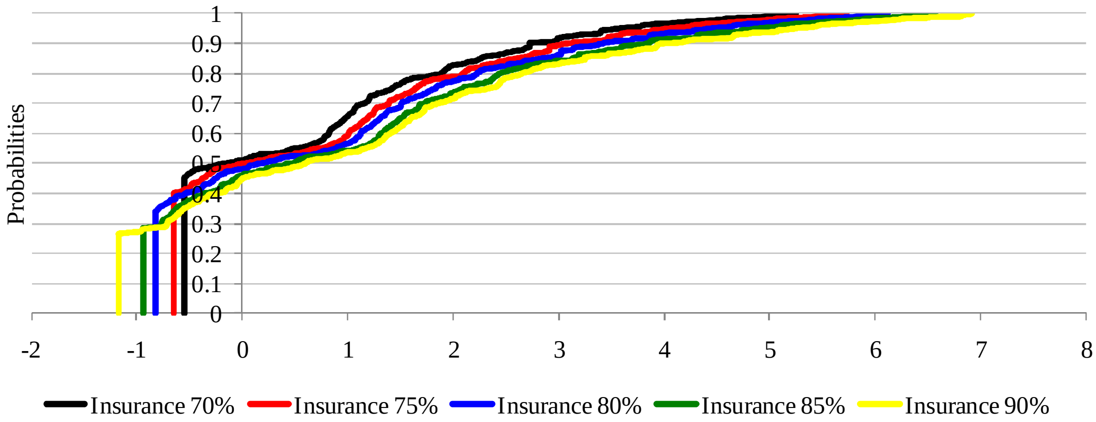


Figure 6.12. Cumulative distribution functions of per acre net returns for five insurance levels using portfolio index intervals for ranchers in Clay County Grid ID 33873

The StopLight chart is summarized in Figure 6.13. The red area shows the probabilities that the net benefit falls below zero; the yellow area shows the probabilities that the net benefit will fall between 0 and $0.74 per acre; and the green area shows the probability that the net benefit will be greater than $0.74. At the 85% and 90% insurance coverage levels, there are respectively 46% and 45% probabilities of not receiving any indemnities or indemnities that are less than $0.74/acre. Practically there is no difference between the 85% and 90% coverage levels and the decision maker might be indifferent between these two coverage levels. Similarly there is very small difference between the payoff probabilities for the70% and 75% insurance coverage levels. The probabilities of not earning any net indemnities or receiving indemnities that are less than the premium paid is 51% and 50%, respectively. For the 70% and 75% insurance coverage levels the decision maker usually is expected to select the insurance policy that has the lowest probability that the overall benefit falls below zero, but since the difference between 85% and 90% insurance coverage levels is very small, the choice for different risk averse individuals becomes more subjective.

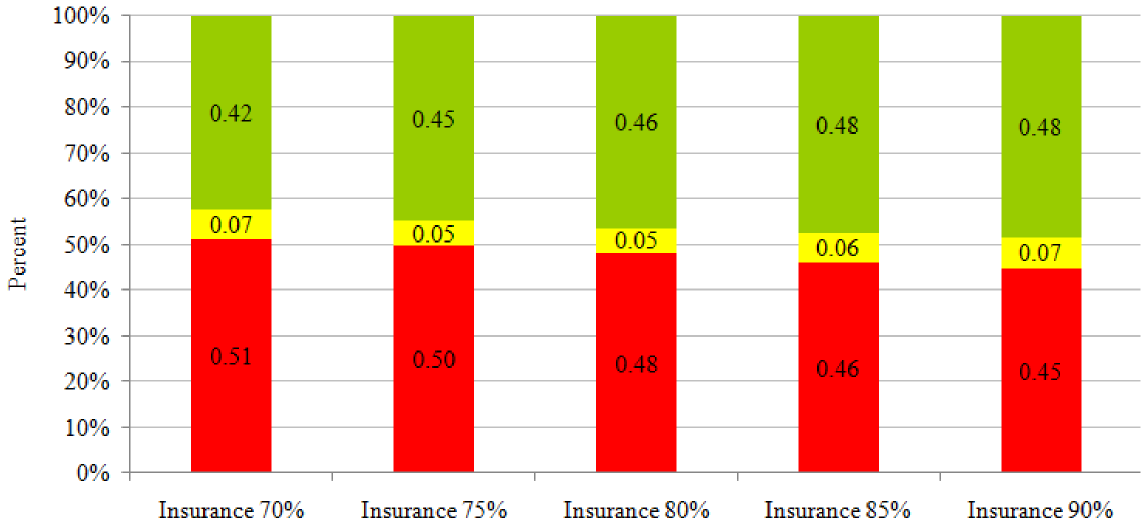


Figure 6.13. StopLight chart summarizing the probabilities of net returns to range insurance for ranchers in Clay County Grid ID 33873. Red light shows the probabilities that net return falls below zero; the yellow areas show the probabilities that the net return for an insurance level will fall between 0 and $0.74 per acre; and the green area shows the probabilities that the net return will be greater than $0.74 per acre

Figures 6.14 and 6.15 show the SERF and the SDRF ranking methods applied to the simulated data for the insurance coverage level scenarios. Both utility based rankings systems ranked insurance policy 5 — the 90 percent coverage level — as the most preferred one.

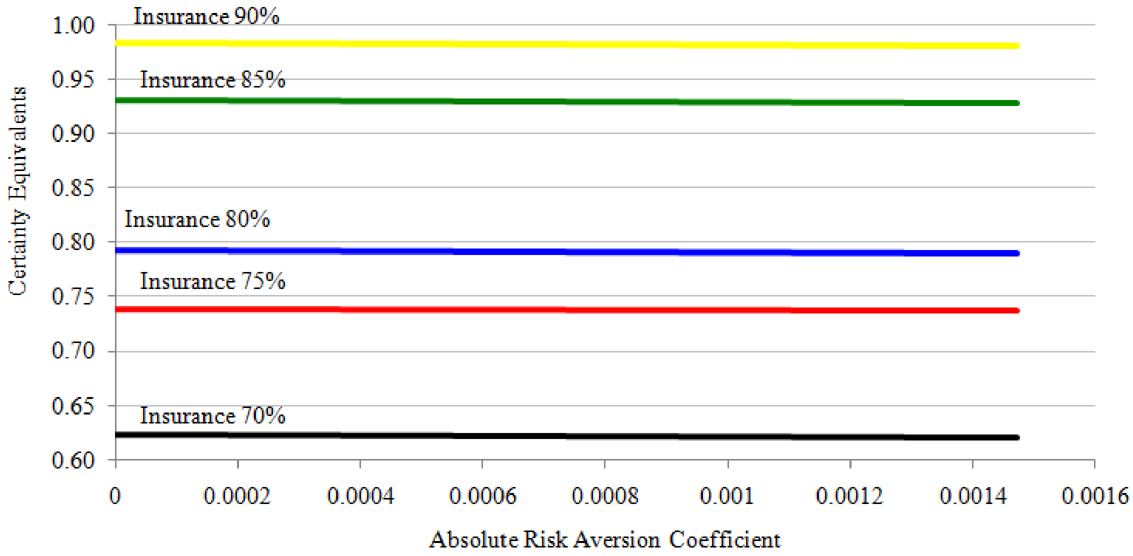
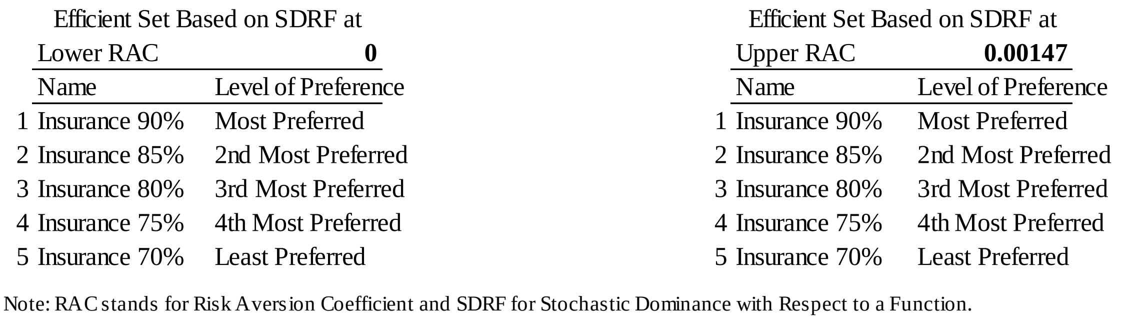


Figure 6.14. SERF ranking of five range insurance policies for ranchers in Clay County Grid ID 33873



Efficient Set Based on SDRF at
Lower RAC **0**

	Name	Level of Preference
1	Insurance 90%	Most Preferred
2	Insurance 85%	2nd Most Preferred
3	Insurance 80%	3rd Most Preferred
4	Insurance 75%	4th Most Preferred
5	Insurance 70%	Least Preferred

Efficient Set Based on SDRF at
Upper RAC **0.00147**

	Name	Level of Preference
1	Insurance 90%	Most Preferred
2	Insurance 85%	2nd Most Preferred
3	Insurance 80%	3rd Most Preferred
4	Insurance 75%	4th Most Preferred
5	Insurance 70%	Least Preferred

Note: RAC stands for Risk Aversion Coefficient and SDRF for Stochastic Dominance with Respect to a Function.

Figure 6.15. SDRF ranking of five range insurance policies for ranchers in Clay County Grid ID 33873

6.4 Andrews, Andrews County, TX, Grid ID 35781

The last area that was studied is Andrews, located in the extreme western part of the state. The rainfall map of Texas shows that, this part of the state is much drier compared to the other areas. Thus, calibrating one of the areas for this part of the state is interesting to see whether there will be a significant difference in net returns.

Validation

The Hotteling's T-Squared test failed to reject the null hypothesis, hence the simulated means were found to be statistically the equal to the input data means. None of the correlation coefficients for any two simulated variables were statistically different from the historical correlation coefficients at the 99 percent level.

The net returns per acre were simulated for each index interval. Given the county base value, the premium rate and the applicable government subsidy, a productivity factor of 120 and a coverage level of 70 percent were used simplicity.

Portfolio Analysis

The portfolio analysis was conducted and the payoffs per acre were generated for two index intervals. Table 6.9 shows us the summary statistics for all fifteen combinations simulated for two index intervals with 0.5 acre in each.

Table 6.9. Summary Statistics for Comparing Fifteen Portfolios of Index Intervals for Andrews County Grid ID 35781

	P 1	P 2	P 3	P 4	P 5	P 6	P 7	P 8	P 9	P 10	P 11	P 12	P 13	P 14	P 15
Mean ($/acre)	0.65	0.53	0.62	0.80	0.91	0.34	0.43	0.61	0.72	0.31	0.49	0.60	0.58	0.69	0.87
StDev ($/acre)	1.28	1.14	1.20	1.47	1.54	0.96	1.05	1.22	1.27	0.93	1.10	1.25	1.30	1.35	1.52
CV (%)	196.30	214.80	191.76	183.30	168.50	282.35	241.61	198.72	176.05	300.10	224.82	208.38	223.62	194.88	173.75
Min ($/acre)	-0.57	-0.51	-0.58	-0.72	-0.76	-0.35	-0.42	-0.56	-0.61	-0.36	-0.50	-0.54	-0.56	-0.61	-0.75
Max ($/acre)	4.87	4.27	5.23	5.08	5.26	4.31	4.24	5.15	4.88	4.26	4.54	4.66	4.76	5.08	5.26

Note: P stands for Portfolio.

Figure 6.16 illustrates from the SERF ranking that portfolio five is the most preferred alternative — 50% Dec, Jan and 50% Feb, Mar — assuming negative exponential utility function. It has the highest mean, followed by portfolio 15 – 50% V and 50 VI; and by portfolio 4 – 50% I and 50% V.

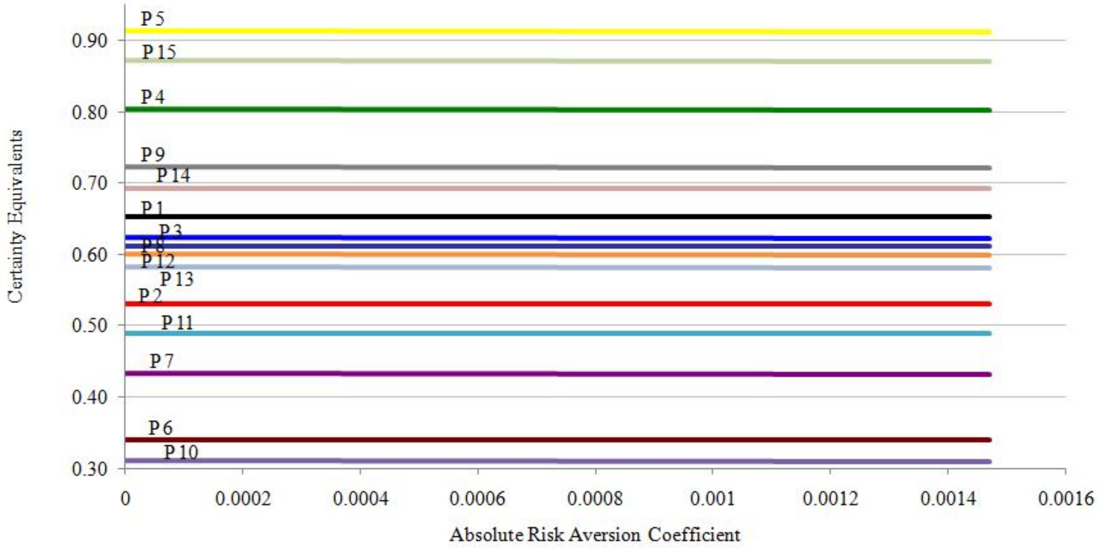


Figure 6.16. SERF ranking of fifteen portfolios for determining the best index intervals for a risk averse decision maker in Andrews County Grid ID 35781

Benefits

Using the first and sixth index intervals, five insurance scenarios were analyzed for coverage levels between 70% and 90%. Insurance policies were simulated for the five alternative insurance coverage levels using the stochastic rainfall index values and the results are summarizes in Table 6.10.

Table 6.10. Summary Statistics of Net Returns Per Acre from Simulating Five Insurance Levels Using Portfolios for Ranchers in Andrews County Grid ID 35781

	Insurance 70%	Insurance 75%	Insurance 80%	Insurance 85%	Insurance 90%
Mean ($/acre)	0.91	1.04	1.07	1.19	1.20
StDev ($/acre)	1.54	1.68	1.82	1.96	2.10
CV (%)	168.50	161.69	170.06	165.13	174.93
Min ($/acre)	-0.76	-0.87	-1.08	-1.20	-1.45
Max ($/acre)	5.26	5.60	5.84	6.16	6.35

The range of net benefit loss is relatively smaller than in South San Antonio and Robstown and similar to Henrietta. Since this area is considered to be drier than the regions that we have already discussed, the premium rates for Andrews are much higher than in the other areas. The probabilities of earning net indemnities are significantly higher than in the other three areas due in part to the higher premiums. The maximum level amount of losing at the 70% insurance coverage level is 0.76$ per acre and the highest net indemnity that can be earned for the same insurance coverage level is $5.26 per acre. As expected, at higher coverage levels the net payoffs increase. The summary statistics show that at the 90% insurance coverage level the largest amount that can be lost is $1.45 per acre and the maximum net indemnity that can be earned is $6.34 per acre.

In Figure 6.17**,** the StopLight chart summarizes the net returns of five insurance policies which are unlike the previous cases. The red area shows the probabilities that the net benefits fall below zero; the yellow areas show the probabilities that the net benefits will fall between 0 and $1.04 per acre; and the green area shows the probability that the net benefit will be greater than $1.04 per acre. As we expected, since the region is dry, the probabilities of earning net indemnities logically should be higher. On the other hand, since the premium rate is very high, it might offset the possibility of the indemnity exceeding the premium rate. However the StopLight chart illustrates that at 85% and 90% insurance coverage levels, there is a 67% probability of receiving indemnity payments which will exceed the $1.04/acre level. The probability is much higher for that region and the interesting fact is that, the decision maker might be somehow indifferent between choosing 85% and 90% insurance coverage levels. Similarly there is no difference between 75% and 80% coverage levels. Both coverage levels yield the same (65%) probability of earning indemnity payments which will exceed $1.04/acre. For the 70% insurance coverage level, the probability of earning positive net returns is 63%, which is still much higher than indemnities that could be obtained at maximum coverage levels in other studied areas.

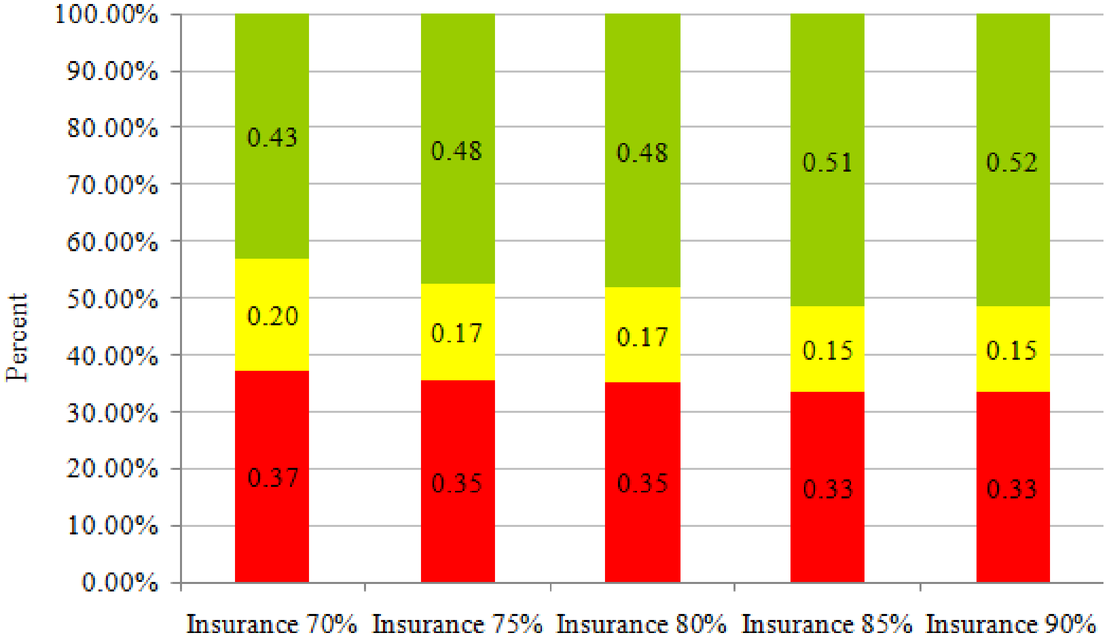


Figure 6.17. StopLight chart summarizing the probabilities of net returns to range insurance for ranchers in Andrews County Grid ID 35781. Red light shows the probabilities that net return falls below zero; the yellow areas show the probabilities that the net return for an insurance level will fall between 0 and $1.04 per acre; and the green area shows the probabilities that the net return will be greater than $1.04 per acre

Figures 6.18 and 6.19 show the SERF and the SDRF ranking methods applied to the simulated data for the insurance coverage level scenarios. Both utility based rankings systems ranked insurance policy 5 – the 90 percent coverage level — as the most preferred one.

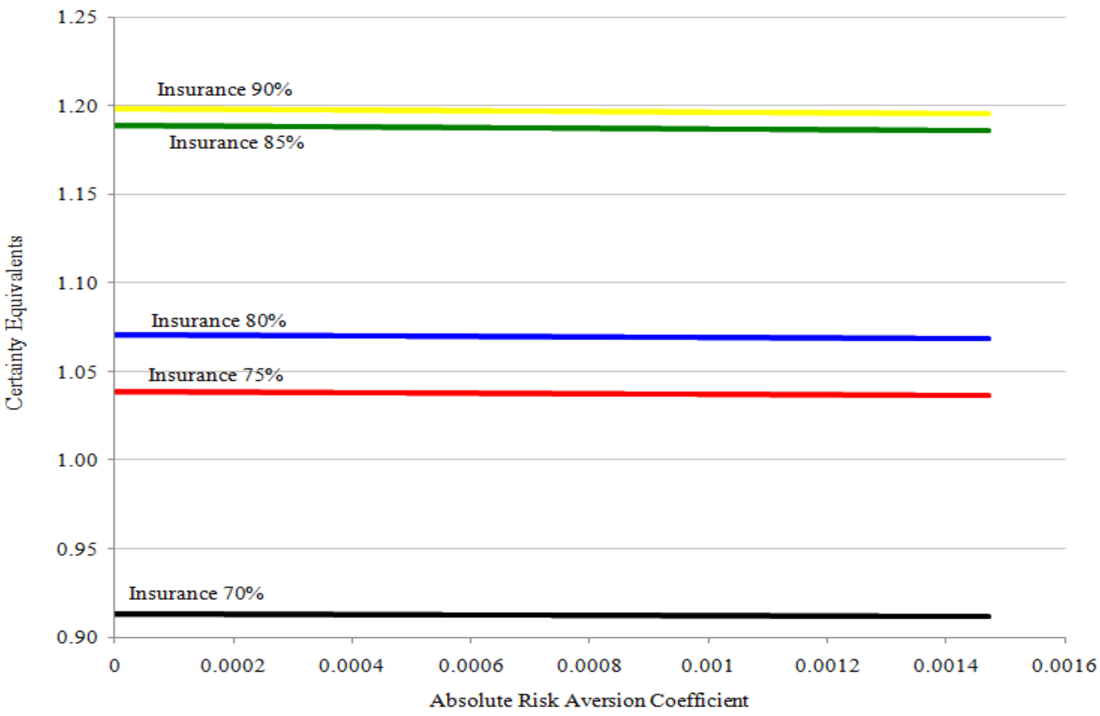


Figure 6.18. SERF ranking of five range insurance policies for ranchers in Andrews County Grid ID 35781

	Efficient Set Based on SDRF at	
	Lower RAC	**0**
	Name	Level of Preference
1	Insurance 90%	Most Preferred
2	Insurance 85%	2nd Most Preferred
3	Insurance 80%	3rd Most Preferred
4	Insurance 75%	4th Most Preferred
5	Insurance 70%	Least Preferred

	Efficient Set Based on SDRF at	
	Upper RAC	**0.00147**
	Name	Level of Preference
1	Insurance 90%	Most Preferred
2	Insurance 85%	2nd Most Preferred
3	Insurance 80%	3rd Most Preferred
4	Insurance 75%	4th Most Preferred
5	Insurance 70%	Least Preferred

Note: RAC stands for Risk Aversion Coefficient and SDRF for Stochastic Dominance with Respect to a Function.

Figure 6.19. SDRF ranking of five range insurance policies for ranchers in Andrews County Grid ID 35781

7. SUMMARY

The purpose of this research was to estimate the economic benefits of PRF-RI insurance in four counties of Texas. Probabilities of net indemnities were estimated under different types of coverage levels and index intervals. Monte Carlo simulation was applied and stochastic payouts were calculated for different insurance policies. SERF, SDRF, and StopLight Chart ranking methodologies were applied to rank insurance options for risk-averse ranchers. Four counties were analyzed: Bexar, Nueces, Henrietta, and Clay. One Grid ID was studied in each county.

In South San Antonio, Grid ID 39650 the fifth and sixth index intervals were ranked as the most preferred months to purchase insurance. The net return was simulated for five alternative insurance coverage levels, 70%, 75%, 80%, 85%, and 90% using the stochastic index values for the fifth and sixth index intervals. At the 70% coverage level, the maximum amount that the rancher can lose is $1.04 per acre, the average net indemnity is $1.33 per acre, and the maximum net indemnity per acre the rancher can receive is $10.76. At the higher coverage levels, the maximum net indemnity increased. For the 90% coverage level, PRF-RI insurance has the possibility of losing $2.26 per acre, gaining as much as $13.48 per acre, and the average net payoff is $1.98 per acre. At the 70% coverage level, the probability that the producer will get net indemnities is 50%. However at 90% coverage level the probability of earning net indemnities increases to 59%. The SERF and the SDRF ranking methods ranked the 90% coverage level as the most preferred followed by: 85%, 80%, 75%, and 70%.

In Robstown, Grid ID 41580 the first and sixth index intervals were ranked as the most preferred months to insure. At the 70% coverage level the maximum amount that the rancher can lose is $0.77 per acre, the largest net indemnity per acre the rancher can receive under the 70% coverage level is $7.27, and the average net indemnity is $0.94 per acre. For the 90% coverage level, the greatest lose is $1.61 per acre, the largest net indemnity is $9.12 per acre, and the average net payoff is $1.38 per acre. For the 70% coverage level, the probability of earning net indemnities is 53%. At the 90% insurance level, the probability of receiving net payoffs is 60%. The SERF and the SDRF ranking systems ranked the 90% coverage level as the most preferred followed by: 85%, 80%, 75%, and 70%.

In Henrietta, Grid ID 33873the fifth and sixth index intervals were ranked as the most preferred alternative. At 70% insurance coverage level, the maximum amount of lose is $0.55 per acre, the highest net indemnity that can be earned for the same insurance coverage is $5.24 per acre, and the average net return is $0.62 per acre. At higher insurance coverage levels payoffs increase. At the 90% coverage level, the maximum amount that can be lost is $1.17 per acre, the largest net payoff is as much as $6.91 per acre, and the average net indemnity is $0.98 per acre. For the 70% and 75% insurance coverage levels, the probabilities of earning net indemnities are 49% and 50% respectively. At the 85% and 90% insurance coverage levels, the probabilities of earning net indemnities are 54% and 55%. The SERF and the SDRF ranking systems ranked the 90% coverage level as the most preferred followed by: 85%, 80%, 75%, and 70%.

In Andrews, County Grid ID 35781, the first and sixth index intervals were ranked as the most preferred. At the 70% coverage insurance level, the maximum net lose is $0.76 per acre, the highest net indemnity that can be earned for the same insurance coverage level is $5.26 per acre and the average net indemnity is $0.91 per acre. For the 90% insurance coverage level the largest amount that can be lost is $1.45 per acre, the average net indemnity is $1.20 per acre, and the maximum net indemnity that can be earned is $6.34 per acre. For the 70% insurance coverage level, the probability of earning positive net payoffs is 63%. At the 85% and 90% coverage levels the probability of earning net indemnities is 67%. The SERF and the SDRF ranking systems ranked the 90% coverage level as the most preferred followed by: 85%, 80%, 75%, and 70%.

These results have implications for risk averse ranchers who are considering purchasing PRF-RI insurance. The results indicated that for all regions tested, the best alternative when purchasing PRF-RI was to buy the 90% coverage level. Probabilities of earning net indemnities decreased at lower coverage levels. All four top ranked portfolios have the sixth index interval in common. Implying that, December-January is a critical time period that should be taken into consideration by the ranchers.

The results indicated also that insurance returns depend on the region where the policy is purchased. In Southern and Eastern parts of Texas net indemnities appeared to be significantly less and have lower probabilities of being positive than in West Texas. Ranchers from West Texas may be able to significantly benefit from the insurance.

The best method for ranking scenarios is largely dependent upon the situation and the individual decision maker. Ranking the alternative scenarios using more than one method is beneficial as it provides the decision maker with more resources for making a better decision. However these results from the simulations should not be interpreted as the best alternative for all ranchers. Each rancher is individual and equipped with varying levels of experience, assets and liabilities, as well as risk and income preferences. The results of the simulation are intended to help ranchers make a better decision on the consequences of the various insurance policies presented.

Further research is strongly recommended since only four counties were analyzed and one Grid ID was studied in each county. Because there are many counties in Texas eligible for PRF-RI and each county has several Grid IDs, expanding the research to other areas would be beneficial. The model showed that one index interval in Andrews County had high probabilities of earning net payoffs, however Andrews County contains twelve Grid IDs and the results in each Grid ID might be different. Besides West Texas has other relatively dry regions which could be analyzed to fully capture the viability of the rainfall insurance in those areas. Even though Texas has some areas where insurance looks beneficial, PRF-RI insurance is launched in seventeen other states. Expanding the research to other states would offer an opportunity to test the feasibility of PRF-RI insurance under alternative climatic conditions.

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