COMPARATIVE ANALYSIS OF THE PROFIT RISK IN THE CULTIVATION OF ENERGY BEET IN NORTH DAKOTA

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Asanka Sanjeewa Wijesinghe

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Asanka Sanjeewa Wijesinghe

The Supervisory Committee certifies that this ***disquisition*** complies with North Dakota State University's regulations and meets the accepted standards for the degree of

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SUPERVISORY COMMITTEE:

David Ripplinger
Chair

Dragan Miljkovic

Zhulu Lin

Approved:

04/15/2016
Date

William Nganje
Department Chair

ABSTRACT

Energy beet is a promising ethanol feedstock as it did not compromise the food security given it is not used as a food or feed. Although the technological and financial feasibility studies were available the risk of yield and profit aspect is not considered in the previous studies. Hence this study focuses on the cost of private risk bearing of a representative energy beet grower comparing to the other crops in North Dakota. The lowest risk premium is reported for the dry land production at the Langdon Research and Extension Centre (REC). Further in Langdon energy beet has the lowest risk premium (0.733USD/acre) comparing to the conventional crops. Hence a risk averse farmer can opt for energy beet in Langdon. The certainty equivalent is highest in Oakes irrigated experiment site followed by Carrington irrigated REC. Hence in irrigated sites energy beet can be a financially appealing crop for farmers.

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DEDICATION

This thesis is dedicated for the farmers all around the world.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF ABBREVIATIONS

REC...Research and Extension Centre.

RFS……………………………………………….Renewable Fuel Standards

WLS………………………………………………Weighted Least Squares

LIST OF SYMBOLS

E	Expectation operator
u, $\boldsymbol{\varepsilon}$	Error term
x	A vector of inputs
y	A vector of outputs
β	Coefficient
δ	Partial derivative operator
π	Profit

LIST OF APPENDIX TABLES

LIST OF APPENDIX FIGURES

1. INTRODUCTION

1.1. Background

In the previous few decades renewable energy became the center of debate of sustainable development mainly due to the dwindling fossil fuel resources and the contribution of fossil fuel combustion to global warming by their enhanced greenhouse gas emission (Hoffert, et al., 2002, Ogeden et al*., 2004,* Ragauskas et al. 2006, Solomon et al., 2007 and Balat and Balat , 2009). Apart from these reasons biomass which has become a prominent renewable energy feedstockis considered as a viable option for the promotion of domestic rural economies (Balat and Balat, 2009). Renewable energy can be defined as energy derived from a wide spectrum of self-replenishing energy sources such as sunlight, wind, hydropower, geothermal power, biomass such as energy crops, agricultural and industrial waste, and municipal waste (Sayigh, 1999 and Bull, 2001).

Ethanol has become a widely used liquid biofuel which is used with motor gasoline, shifting the dependence on unstable crude oil supply and decreasing the greenhouse gas emission. Ethanol production technology is improving to use economically less valuable and more environmental friendly feedstocks. Policy makers are interested in reducing the dependence on food crops such as corn in ethanol production. In this context energy beet has gained the attention of the policy makers, economists and ethanol refiners as a viable feedstock for the ethanol production. A fundamental issue here is the nexus between the supply by the energy beet producers and the demand for energy beet by the ethanol refiners. In order to ensure a sustainable production of ethanol there should be a continuous supply of energy beet in adequate quantities and qualities. Farmers' decision making on the adoption of a new crop involves a careful consideration of the financial returns and the risk of the returns. Hence in this study we attempt to determine the risk of energy beet adoption and map it with the profit risk of other conventional crops.

1.1.1. Biomass as a renewable energy source

Currently biomass energy is among the most promising and most heavily subsidized renewable energy sources and they have the potential to replace fossil fuel consumption by the transport sector by producing liquid biofuel (Field et al., 2008). Further biofuel produced by biomass is among the strategically most important sustainable fuel sources and it is the most environmentally friendly energy source (Nigam and Singh, 2011).

The most widely used liquid biofuels for transport sector are ethanol and biodiesel. Ethanol is the most widely used bio-alcohol fuel (Environmental Protection Agency (EPA) of USA, 2015). Ethanol in the global transport sector is used after blending with gasoline. The most common blending rates are E10, E22, and E85. The European Commission aims to replace 10% of its transport fuels with renewable fuels like ethanol by 2020. The extremes are in Nordic countries, as an example Sweden is aiming to be completely free of fossil fuels by 2020. The US has set a goalof164 billion liters per year of ethanol in petrol blends by 2022 while Canada aimed for 45% of the country's gasoline consumption to contain 10% ethanol by 2010. In the developing countries, India has a national biofuels policy to replace 20% of its fuels by biofuels by 2017 while Philippine have mandated a 10% ethanol mix in gasoline since 2007 (Biofuels Association of Australia, 2014).

1.1.2. Drive for biofuel in USA

The main source of energy consumed by the USA is petroleum. The total US petroleum consumption in 2013 was 18.9 million barrels per day (bbl/d). This amount was 36% of all the energy consumed by USA. The main petroleum type used in USA is gasoline and the demand for gasoline is mainly from the transportation sector. About 8.774 million barrels of gasoline were used in 2013 which was nearly 47% of the total petroleum consumption of USA. More than 70% of the petrol and other liquids consumed by USA are demanded by the transport sector. Hence liquid bio- fuel like ethanol is important as a substitute to the fossil fuels used in the transport sector of USA. In the recent decade the ethanol production in USA grew substantially. It grew by more than seven fold in 2013 comparing to 2000. In 2013 the total ethanol production in USA was 13.3 billion gallons and contributed $44 billion in to gross domestic product.

Ethanol blended gasoline or gasohol received the attention mostly after the oil price crisis in 1970s (Ragauskaset al., 2006, Solomon et al., 2007 and Rendleman and Shapouri, 2007). Corn was used to produce ethanol initially and many farm groups began to see ethanol as a way to maintain the price of corn and even to revitalize the rural economy in USA (Rendleman and Shapouri, 2007). Further government provided attractive subsidies for the corn ethanol production (Tyner, 2008). The legislative mandates for the ethanol production incented the ethanol production. Renewable Fuel Standard (RFS) is a mandatory minimum volume of biofuels to be used in the national transportation fuel supply of USA. The Congress of the United States first established the RFS in 2005 with the enforcement of the Energy Policy Act of 2005 (Public Law 109-58) and it required under the initial RFS program (RFS1) that 7.5 billion gallons of renewable fuel to be blended into gasoline by 2012. The RFS is administered by the Environmental Protection Agency (EPA). EPA issued its final rule for administering RFS1 in April 2007. Energy Independence and Security Act of 2007 (Public Law 110-140) required EPA to revise the goals set by RFS1 to increase the amount of renewable fuel to be blended with transporting fuel from 9 billion gallons in 2008 to 36 billion gallons in 2022. EPA finalized revisions to the RFS program in February 2010. This expanded RFS is referred to as RFS2.

1.1.3. Biofuel pathways

Biofuel production in USA is composed of different feedstocks, production processes and finally different fuel types. A specific combination of these three components is called as a biofuel pathway (Environmental Protection Agency, 2014). A feedstock is a type of renewable biomass that is converted into the renewable fuel. The production process is the type of technology used to convert renewable fuel into renewable fuel like hydrotreating, gastification and upgrading and transesterification. Following Hamelinck and Faaij (2006), conversion technologies can be identified based on the feedstock type. Biodiesel are produced by esterification of the vegetable oils obtained by pressing or extracting of the oil plants. Also vegetable oils are directly used as bio-oil. Starch crops are subjected to hydrolysis to convert them to sugar and then they are fermented to obtain ethanol.

The feedstocks used to produce biofuel in the world and USA are mostly food crops like corn, and soybean. Potential energy crops include woody crops and grasses/herbaceous plants (all perennial crops), starch and sugar crops, and oilseeds (McKendry, 2002).In USA soybean remains the largest biodiesel feedstock while corn remains the largest ethanol feedstock (US energy information administration, 2014). Renewable Fuel Standards 2 (RFS2) includes four biofuel categories with specific volume mandates and lifecycle GHG emission reduction threshold levels. Among them the advanced biofuels have a greater significance due to food safety and concerns on environmental sustainability.

1.1.4. Advanced biofuels and energy beet

The EISA of 2007, which is the precursor for RFS2 defines the term ‘advanced biofuel’ as *“…renewable fuel, other than ethanol derived from corn starch, that has lifecycle greenhouse gas emissions, as determined by the Administrator (EPA) that are at least 50 percent less than* *baseline lifecycle greenhouse gas emissions."* Further according to the EISA 2007,biofuels eligible to be considered as an advanced biofuel are, ethanol derived from cellulose, hemicelluloses or lignin and ethanol derived from sugar or starch (other than corn starch), ethanol derived from waste material including crop residue, other vegetative waste material, animal waste, food waste, yard waste, biomass-based diesel, biogas (including landfill gas and sewage waste treatment gas) produced through the conversion of organic matter from renewable biomass, butanol or other alcohols produced through the conversion of organic matter from renewable biomass, and other fuel derived from cellulosic biomass.

Further the renewable fuel standard (RFS) established by Congress in 2005 has imposed a ceiling to the amount of ethanol produced from corn at 15 billion gallons enhancing the prospect of using energy beets for ethanol production. Sugar beet (*Beta vulgaris*) is growing around the world due to its multiple uses. Russian Federation is the largest sugar beet producer in the world while second and third places go to France and USA. Sugar beet growing for food production began in the United States starting about 1870. Once a viable industry was established, sugar beets were grown in 26 states (Cattanach et al, 1991). Upper Midwest states, Minnesota and North Dakota accounted for 58% of the national sugar beet acreage of USA in 2013/14. Minnesota accounts for 39% of the acreage while North Dakota accounts for 19%.Other leading sugar beet cultivating states are Idaho, Michigan, Nebraska, Wyoming and Montana. Similarly two upper Midwest states, Minnesota and North Dakota, produced 51% of the national sugar beet production of (Cattanach et al, 1991).

1.2. Purpose of the study

1.2.1. Rationale for the study

Energy beets can be considered as one of the viable feedstock alternative for advanced biofuel production over corn on which 97% of the US ethanol production depends, due to its less impact on food supply and as it can be qualified as an advanced biofuel feedstock. Under the EISA of 2007, biofuel from sugar beets qualifies as an “advanced biofuel.” EISA mandates production of 15 billion gallons of advanced biofuels annually by 2022. In the US three projects are reportedly underway to build energy beet biofuel plants in North Dakota (ND), Pennsylvania, and California (Anderson, 2011).

Under the above background, the current study focuses on the farmers’ decision of the adoption of energy beet. A risk averse farmer would adopt a crop with higher returns and less risk. The economic feasibility of sugar beet ethanol production is widely addressed in the literature (USDA, 2006, Outlaw et al., 2007, Yoder et al., 2009 and Maung and Gustafson, 2011). However it is important to incorporate the riskiness of returns to the analysis as most farmers are risk averse the decision making process the risk of return is also an important factor (Antle, 1987, Chavas, 2004 and Gollier, 2001). Hence this study focuses on the measurement of risk of adopting energy beet. It can be assumed that if the return is higher and the risk is lower than the conventional crops farmers will adopt the crop. This farmers’ willingness to adopt energy beet is really important since to ensure the sustainability of the energy beet ethanol refinery, farmers should allocate acreage for energy beet. If 10 to 20 million gallon per year ethanol refineries are to be built in North Dakota, more than half a million acres of farmland in the state will need to be used to grow energy beets (Maung and Gustafson, 2011).

1.2.2. Problem statement and research question

As a risk averse farmer considers the risk of returns in adopting a new crop the profit risk of adopting energy beet comparing to other conventional crops is needed be addressed . With this background research question of the study is, what is the relative position of the profit risk in adopting energy beet comparing to the conventional crops in North Dakota? The conventional crops considered are corn, soybean and wheat.

Adoption decision of farmers on non-conventional crops like biofuel crops is mostly evaluated using the common Net Present Value (NPV) theoretical approach. However it is important to incorporate the risk in adoption of new crops due to the fact that farmers are risk averse. The purpose of the study is to measure the risk of the adoption of energy beet. In risk literature risk premium is defined as the cost of private risk bearing (Chavas et al., 2009). Antle (1983) and Antle and Goodger (1984) proposed a flexible moments-based approach to model the firm's stochastic technology based on the moments of the probability distribution of output. This moment-based approach is widely used in the risk literature and provides the conceptual and empirical framework for the current study.

1.3. Objectives and hypotheses

The overall objective is to evaluate the cost of private risk bearing (risk premium) of adopting energy beet and its relative position comparing to the conventional crops. The specific objectives are:

1. To determine the factors affecting mean, variance, and skewness of the profit distributions of energy beet, corn, soybean, and wheat;
2. To measure the cost of private risk bearing in cultivation of energy beet, corn, soybean and wheat; and

3. To compare the risk premium of the cultivation of energy beet, corn, soybean and wheat.

With these specific objectives several hypotheses can be outlined. One is that irrigation increases the expected yield. Further it can be hypothesized that irrigation decreases the variance and increase the skewness. This is due to the fact irrigation can insulate a crop system from water stresses. Although the expected effect of the time trend is ambiguous we can hypothesize that time trend has the similar effects as irrigation. Further considering the heterogeneity of the locations the expected return, variance and skewness can be significantly different from location to location. This study utilized the data of the experimental trials conducted by the research and experimental stations of North Dakota State University. Hence the locations are the Carrington and Langdon Research and Experimental Centers (REC) and Oakes irrigated research site.

1.4. Organization of the thesis

The first chapter is the introduction to the study which is followed by the literature review. In the literature review the current knowledge on the risk measurement and crop adoption are presented with relevance to the conceptual and empirical approach used by the study. The third chapter presents a detailed methodology illustrating the theoretical, empirical, and econometric models used. In the fourth chapter results are presented with a discussion of the results which is followed by the last chapter, the conclusion.

2. LITERATURE REVIEW

The Energy Independence and Security Act in 2007 mandates that by 2022, 136 billion liters of ethanol should be produced in US. Significantly it mandates that 60.6 billion liters should be derived by lignocellulosic biomass which is around 45% of the mandated ethanol volume. Lignocellulosic biomasses have become an attractive biomass comparing to corn as lignocellulosic biomasses do not compromise the human food and animal feed consumption, due to soil conservation effects of perennial lignocellulosic biomasses and due to their greenhouse gas reduction (Hagerdal et al., 2006 and Qualls et al., 2012). Although the utilization of non-conventional biomass in ethanol production is attractive the financial profitability of bioenergy production is influenced by the crop producer’s willingness to adopt these non-conventional crops (Altman and Sanders, 2012 and Jensen et al., 2007). In this chapter a literature review is presented on the acquired knowledge over the factors influencing new crop adoption, methods of evaluation and the role of risk and its measurement.

2.1. New crop adaptation: approaches and determinants

In this section the approaches to investigate the determinants of crop adopting decision of farmers are reviewed. A particular emphasize is given on the adopting decision of energy crops due to the relevance to the study.

2.1.1. Factors affecting farmers’ decision on energy crop production

The sustainable biofuel industry requires a sustainable supply of feedstocks. Producer willingness and ability to supply biomass could be key barriers to bioenergy industries (Altman and Sanders, 2012 and Qualls et al., 2012). Hence the requirement of an assessment of the factors influencing the commercialization of energy crop production is highlighted in the literature (Jansen et al., 2007, Styles *et al*., 2008, Bocqueho and Jacquet, 2010, Paulrud and Laitila, 2010 and Qualls et al., 2012).

The literature is dominated by the assessments related to lignocellulosic biomasses like switchgrass and miscanthus (Jansen et al., 2007, Styles et al., 2008, Bocqueho and Jacquet, 2010, Paulrud and Laitila, 2010 and Qualls et al., 2012). However the assessments related to energy beets are rare (USDA, 2006, Yonderet al., 2009 and Maung and Gustafson, 2011). The key factor that focused in these studies that affects the farmer's decision making on the adoption of energy crops is the financial viability. The net present value (NPV) of the investment on energy crops is considered in many studies **(**Bocqueho and Jacquet, 2010).Pointing the theoretical weaknesses in NPV Bocqueho and Jacquet (2010) have considered the impact of liquidity constraints and risk preferences also.

Adoption of a new crop or a new variety can be related farmers' agricultural innovation adoption. The studies on the perennial energy crop adoption have shown that a farmer's liquidity constraint is a significant determinant in adoption decision (Bocqueho, 2008, Jansenet al., 2007 and Sherrington et al., 2008). Farm size, farmer's debt, and extra farm income are considered as proxies for liquidity constraints. Apart from these financing constraints, the central role of uncertainty and risk in the agricultural innovation adoption decision making process is highlighted in many studies (Marra et al., 2003, Flaten et al., 2005 and Greiner et al., 2009).

In the context of energy beet, the cost-benefits analysis is dominating. The conclusion that can be arrived at is, that scholars have considered that NPV is the key determinant in energy beet adoption decisions and energy beet refinery establishment decision. Maung and Gustafson (2011) examined the financial feasibility of producing ethanol biofuel from sugar beets in central North Dakota. Yonder et al. (2009) have presented a comprehensive study on the feasibility of a sugar beet-based ethanol industry in the state of Washington. They concluded that sugar beet production fails to cover total production costs in the state of Washington and noted the weak competence of sugar beet to compete with other irrigated crops in the state.

Reviewing of the literature about the crop adoption decision of farmers shows that the researchers have mostly concerned the financial aspect. However the importance of the consideration of uncertainty and risk is also highlighted. This is common for the studies related to sugar based energy crops also. There is a lack of a comprehensive studies on the farmers' decision making process based on uncertainty and risk.

2.1.2. Approaches in the evaluation of new crop adoption decision

The common focus is upon the farmers' adoption of agricultural innovation. New technology is an umbrella term for new breeds, technical innovations like machinery, post-harvest technologies, and new crops. Scholars from various disciplines have focused on this adoption behavior of farmers. Adesina and Baidu-Forson (1995) noted that anthropologists and sociologists have played a lead role in this area and they have used qualitative methods to conclude that farmer's subjective assessments of agricultural technologies influence adoption behavior. However economists' approach to these studies was based on access to information concept. As examples, extension, education, and media exposure are typically used by economists' in their models of the determinants of adoption decisions (Adesina and Baidu-Forson, 1995).Bocqueho and Jacquet (2010) noted that many studies related to switchgrass and miscanthus has approached to the adoption problem from an environmental point of view. Also the economic efficiency of these crops is also addressed. Apart from these farmers' approaches, recent crop adoption studies have taken the form of financial cost benefits analysis (Yonder et al., 2009 and Bocqueho and Jacquet, 2010).

Based on the above mentioned studies, it can be seen that there are several approaches to the crop adoption problem as anthropologists' farmers' subjective perception based approach, Economists' access to information approach and economic efficiency approach and the financial cost benefit approach. In financial cost benefit approach the most common theoretical approach is the net present value (NPV) approach derived from producer theory (Bocqueho and Jacquet, 2010). However this approach has two severe weaknesses. The first one is the assumption of a risk-neutral farmer or the deterministic assumption. The second one is the ignorance of liquidity. The importance of uncertainty and risk aversion in the agricultural innovation adoption decision making process is highlighted in the literature (Marra et al., 2003, Flaten et al., 2005, Greiner et al., 2009 and Thomas et al., 2011). Hence the uncertainty and risk in economic analysis of crop adoption can be considered as important aspects.

2.1.3. The role of risk in farmers' adoption of crops

As mentioned earlier the importance of uncertainty and risk aversion in the agricultural innovation adoption decision making process is highlighted in many studies. Most importantly most decision makers are risk averse (Antle, 1987, Chavas, 2004 and Gollier, 2001). In line with the traditional financial viability studies the mean return can be used to evaluate the economics implications of decision making based on the expected pay off. But most of the farmers consider about the risk exposure and it can be hypothesized that farmers adopt less risk ventures. Hence in economic evaluations of famers' adoption decisions, the implications of risk must be incorporated.

Risk is important in two different ways according to the risk literature. Although the variance is considered as the traditional measure of risk, Kim and Chavas (2003) and Chavas et al. (2009) incorporate skewness into the analysis due to the importance of the "down side" risk exposure. The down-side risk means the exposure to unanticipated low incomes (Chavas et al., 2009). Hence in evaluating the economic implications, risk skewness also should be focused. In this review, so far the focus is given into the various approaches used to evaluate the farmers' crop adoption decision. As the economic analysis is more important that approach is more focused and the importance of risk is documented. As this review found that there is a lack of consideration of risk aspects in energy crops in general and the energy beet in particular, risk adjusted economic analysis is warranted in the evaluation of the farmers' energy beet adoption decision. The next sections of this review is devoted for a comprehensive review of the theories in risk analysis.

2.2. Economic measurement of risk

As risk is an important aspect in the farmers' decision making it is warranted in been incorporated to any economic analysis crop adoption and a review of the risk concept and measurement is required. Chavas (2004) defined risk as the term representing any situation where some events are not known with certainty. However in risk literature, the terms risk and uncertainty can be found and according to Chavas (2004) there is no consensus whether they are equivalent or different. The risk corresponds to events that can be associated with given probabilities and uncertainty corresponds to events for which probability assessments are not possible in the school of thought where there is a distinction between these two terms. However Chavas (2004) questioned the ability to distinct risk and uncertainty based on the probability and introduces a working definition as a risky event to be any event that is not known for sure ahead of time. In this study the term risk is defined following Chavas (2004).

Chavas (2004) presents three reasons for the existence of risk as, the inability to control and/or measure precisely some causal factors of events, the limited ability to process information and the cost of information can take many forms. In this section the various approaches in risk measurement is reviewed. Chavas (2004) provides a comprehensive review over the different approaches.

2.2.1. Approaches in risk management

Probability theory plays a central role in risk assessments. Although ambiguity theory shows that there is a potential difficulty in assigning a probability to an event by individuals (Schmeidler 1989), probability theory provides more useful framework in risk assessment than the alternative theories (Chavas, 2004). However the probability is useful in risk assessment if and only if the probabilities can be empirically estimated. Due to the central role of probability, the question of risk measurement becomes a question of measuring the probability distribution functions.

Chavas (2004) provides empirical approaches used in the estimation of probability functions. In the case of repeatable events, repeated experiments can generate sample information. However in common non-repeatable events the solution is the individual interviews relying on the individual subjective probabilities. Two approaches for these interviews are reference lotteries and the fractile method. More details are available in Chavas (2004). Another approach is Bayesian analysis which relies on both sample information and prior information about uncertain prospects.

With this background the search for a relevant economic theoretical framework which is appropriate for the risk assessment is a requirement. Production economics literature provides ample amount of studies that assume that farmers' behavior is based on profit maximization. However Lin *et al.* (1974) argue that this assumption has serious drawbacks and an investigation for alternative approaches is warranted. Further, they showed that the Bernoullian utility formulations provide the greatest accuracy in predicting actual planned crop patterns followed by lexicographic formulation and they concluded that the profit maximization showed the poorest predictive power. Further, utility maximization framework is a more common theoretical approach in risk assessment studies (Antle, 1987 and Kim and Chavas, 2003).

2.2.2. The expected utility model

Based on the probability application to risk, the individuals make probability assessments to the risky exposure. The next question is that given a risky exposure what will be the decision of an individual? The expected utility model gives a theoretical framework in answering this question. This model was developed by von Neumann and Morgenstern and it is the dominant model used to evaluate the decision making under uncertainty (Chavas, 2004). This was a result of the "St. Petersburg Paradox" which led to the understanding that maximization of expected reward/wealth is not a satisfactory representation of decision making under risk.

The answer to the question that "if not the maximization of expected reward then what?" was the expected utility hypothesis. Expected utility hypothesis can be outlined as this; "A decision maker has risk preferences represented by a utility function $U(a)$ and the decision maker makes decisions so as to maximize expected utility $EU(a)$, where E is the expectation operator based on the subjective probability distribution of a. The existence of the utility function is discussed by Chavas (2004) in details.

The expected utility model provides a formal theory of decision-making under risk and each decision-maker has a utility function representing his/her risk preferences. The nature of risk preferences is represented by various risk preferences in the risk literature. The most important concepts are the risk premium and risk aversion in the context of risk measurement. Risk premium provides a monetary measure for the cost of private risk bearing (Pratt, 1964). The purpose of interest in this study also is to estimate a monetary measure of crop risk and evaluate the riskiness. As we have reviewed the theoretical framework that allows the measurement of risk it is important to review the useful aspects of risk premium and risk aversion.

2.2.3. Risk premium: measurements and risk aversion

The measurement of the monetary value is important in the context of risk assessments. Based on Chavas (2004) measurement can be done by income compensation tests. They involve finding the change in sure income that would make the decision-maker indifferent to a change in risk exposure. Although there are many ways of defining such compensation tests, Chavas (2004) discusses three monetary valuations of risk including risk premium. The risk premium is used intensively in the risk literature following Pratt (1964) as a monetary measure of the cost of risk (Antle 1987, Kim and Chavas, 2003 and Chavas et al., 2009). A comprehensive definition to the risk premium is provided by Chavas (2004).

The risk premium, R, is defined as the sure amount of money a decision maker would be willing to receive to become indifferent between receiving the risky return ‘‘a’’ (a monetary return) versus receiving the sure amount [E(a)-R], where E(a) is the expected value of ‘‘a.’’ Hence R is the monetary amount satisfying the indifference relationship, $\{w+a\} \sim \{w + E(a) - R\}$. Under the expected utility model, this implies that R is the solution to the implicit equation $EU (w + a) = U(w+ E(a)-R)$. Given a proper definition of the risk premium, the risk aversion concept can be introduced. Intuitively, a decision-maker is risk averse if he/she is willing to pay a positive amount of money (as measured by a positive risk premium: $R > 0$) to eliminate risk (by replacing the random variable ‘‘a’’ by its mean). This positive willingness-to-pay means that he/she is made worse off by risk exposure (Chavas, 2004). Under risk aversion the decision maker always choose to obtain the highest possible expected profit for a given variance or the least possible variance for a given expected profit (Anderson et al., 1977). Empirical evidences shows that most of the farmers are risk averse (Bardsley and Harris, 1987, Binswanger, 1981, Antle 1987 and Chavas, 2004). Further empirical evidences indicate that famers exhibit decreasing absolute risk aversion (Binswanger, 1981, Chavas and Holt, 1996). This means that famers are averse to “downside risk” or low returns (Antle, 1987 and Kim and Chavas, 2003).

The concept of downside risk aversion leads to a more comprehensive risk assessment than the traditional mean variance analysis. The main strength in mean-variance analysis is that estimation of mean and variance from sample information has a long history in statistics and in econometrics. Further, mean-variance analysis appeals as a strong framework in applied risk analysis due the flexibility of been void of restriction on risk preferences, providence of insights to mean-variance trade off and the broad applicability to the variety of risk events (Chavas, 2004). However due the relevance of the concept of downside risk aversion mean-variance analysis becomes ineffective. The alternative approach suggested in the risk literature is the moments-based approach (Antle, 1983 and Antle and Goodger, 1984).

The moments-based approach is important in the analysis of risk in aggregate level. Antle (1987) provides an approach for both the estimation of relevant moments of profit distribution and the translation of the moments into the cost of risk, and risk premium. Kim and Chavas (2003) and Chavas et al., (2009) provided a framework to analyse risk using experimental yield trials. The importance of this framework is, with the lack of data to estimate the individual risk preferences, their approach gives us a framework to evaluate the risk of energy beet cultivation in North Dakota using the experimental data of the trials conducted by NDSU research stations. With this background it is important to review the moments-based approach in risk assessment.

2.3. Moments-based approach

Antle (1983) and Antle and Goodger (1984) proposed a flexible moments-based approach to model the firm's stochastic technology based on the moments of the probability distribution of output. This approach is flexible as it does not impose restrictions on the relationship between the decision variables and the moments of the probability distribution of the output. Although econometric moment models were used before Antle (1983) and Antle and Goodger (1984), the multiplicative error econometric production functions might be inappropriate due to the imposed restrictions on the effects of inputs they can have on output variance (Antle, 1983). Hence the flexible model by Antle (1983) and Antle and Goodger (1984) is important as there is no restriction on the functional relationship between decision variables and the moments of the probability distribution outputs.

The moment based approach to the production economics has a sound theoretical foundation. In this approach, the output distributions can be shown as a unique function of their moments. Further, the output distribution can be approximated to the n^{th} degree using the first n moments. Hence, according to Antle (1983), the moments of the output distribution function can be used to uniquely identify and to approximate the desired degree of the stochastic structure of the technology and the producer's objective function. Antle (1987) used the moment-based approach of Antle (1983) and Antle and Goodger (1984) to estimate the producer's risk attitudes econometrically and concluded that econometric risk attitude estimation is possible under less restrictive moment-based approach. Further Myers (1989) stated that econometric methods are more advantageous as data originate from actual economic decisions than from hypothetical questions during interviews and surveys and as the results can provide a consistency check on risk attitudes estimated using other methods.

The important of the moment-based approach to this study is that we can approximate the risk premium using this approach. Antle (1987) estimated the risk attitudes of a producer population. He estimated the Arrow-Pratt risk coefficient and the downside risk coefficient. Using these risk preference coefficients, the risk premium can be approximated following Chavas (2004), Chavas (2009) and Kim and Chavas (2003). Kim and Chavas (2003) extended the mean-variance analysis to the third central moment, skewness. Under risk aversion, decision makers are adversely affected by the higher variance of returns. In down-side risk aversion, decision makers are negatively/positively affected by an increase/decrease of the skewness of return. Hence incorporating the third central moments to the economic assessment of risk is important.

2.3.1. Empirical estimated of risk premium and econometric methods

Empirical estimate of risk premium is given by Chavas (2004), Chavas (2009), and Kim and Chavas (2003) based on the moment-based approach by Antle (1983) and Antle and Goodger (1984). Antle (1987) proposed the approach for both the estimation of relevant moments of profit distribution and the translation of the moments into the cost of risk, and risk premium. In the first step the moments of the profit distribution are modeled as a function of input variables. The stochastic nature of the profit can be estimated from stochastic yield, output prices. Further yield is stochastic as a function of input and weather. In economic literature, risk preferences are also estimated as an intermediary step. However, data restriction motivated an approach to bypass this step. Chavas (2009) and Kim and Chavas (2003) hypothesized the risk preference as exhibiting constant relative risk aversion (CRRA). Given the empirical evidence that most farmers are risk averse and downside risk averse, CRRA risk preference specification seems reasonable.

Econometric estimation of moments creates a problem due to the presence of heteroskedasticity. Estimation of the coefficients of moment functions generates consistent estimators of the coefficients (Antle, 1987). However, the variance of the variance function is not constant (Antle, 1987 and Chavas, 2009). Hence, Chavas (2004) suggests the weighted least square methods to estimate the moment functions.

2.4. Conclusion

This review focused on two major areas. First is the farmer’s crop adoption decision. In the economics literature, farmer’s decision making is influenced by the mean return to the investment. NPV of producer theory provides an approach to evaluate the decision of adoption. However, economics literature has highlighted the importance of risk and uncertainty of the returns on crop adoption. In the context of energy crop adoption, the studies are based on mostly NPV and the farmers risk exposure is neglected. Hence, it was important to review the existing knowledge on the measurement of risk in order to test relevant hypotheses. For the risk measurement, the adequate theoretical model is the expected utility maximization model. This provides a framework for the measurement of risk preferences. Another necessity was to find an econometric method to model output data and estimate risk premium which is the cost of private risk.

Flexible moments based approach provides the framework to estimate and summarize the probability distribution functions under uncertainty. Further, this model allows estimating Arrow-Pratt risk coefficients and downside risk aversion coefficients. However, Chavas (2009) and Kim and Chavas (2003) proposed a convenient method to estimate the risk premium under the assumption of Constant Relative Risk Aversion (CRRA). Hence this method is more appropriate given the data availability for the current study. In the next chapter the theoretical frame work, empirical methods and the econometric models used are detailed.

3. METHODOLOGY

In this chapter the conceptual framework, empirical implementation, econometric specifications and the data sources are discussed. The analysis has two major steps. As the first step moments of the profit distribution of corn, energy beet, soybean and wheat are estimates as a function of irrigation type, station, planting date and trend. Then the cost of private risk bearing was calculated and was tested to see whether there are differences of the cost of private risk bearing between locations and between different crops. The analysis is based on the utility maximizing framework and the empirical and econometric framework suggested by Kim and Chavas (2003) was used. The organization of the chapter as follows. First the conceptual framework is given which is followed by the empirical implementation. Then the econometric specifications are discussed which is followed by the data sources are discussed.

3.1. Conceptual framework

This study is based on the expected utility maximizing framework in the risk literature. Hence in this section the conceptualization of the probability distribution of profits which are summarized by their moments as a function of independent variables and translation of that estimated moments to the cost of private risk bearing which is measured by risk premium (R) following Pratt (1964) is discussed.

Assume that the farmer is producing a vector of output $Y= (Y_1, Y_2, Y_{3 \ldots} Y_n)$, subjected to a risk. When the i^{th}output is considered, the farm production $Y_i$under the technology of t is given by $Y_i = A_{i.}\, y_i(x_i,t,e)$ stochastic function where A_i is the acreage allocation for the ith crop and $y_i(x_i,t,e)$ is the yield per acre. The vector of input used to produce $y_i$is given by x_i and e is a vector of stochastic factor and it represents unpredictable weather effects and the effects of pests and diseases on the farm production. As $y_i$is a function of random variables $y_i$itself is a random variable. Following the same way we can define the farm production cost under the technology of t in producing the i^{th}crop by the stochastic function $C_i = A_i.\ c_i\ (x_i,t,e)$ where $c_i\ (x_i,t,e)$ is the cost per acre as a function of the input choices x_i, technology t and production uncertainty e. If p_i is the price of output y_i then total profits associated with farm activities Y can be given by equation 1.

$$\text{л} = \sum_{i=1}^{n}\{A_i.\ [p_i.y_i(x_i,t,e) - c_i\ (x_i,t,e)]\} \tag{1}$$

Subjected to

$$\sum_{i=1}^{n} A_i = \text{A}$$

where A is the total availability of acres for the farm production.

Then assume a representative utility maximizing farmer whose utility can be depicted by the von Neumann-Morgenstern utility function. If the inputs are chosen to maximize the expected utility of profit $EU(\text{л})$ and as von Neumann-Morgenstern utility function $U(\text{л})$ represents the risk preferences of the decision maker with $\vartheta U/\vartheta \text{л}>0$, farmers optimization problem in decision making can be characterized by Max{ $EU(\text{л})$}. The cost of private cost of private risk bearing can be measured by the sure amount of R satisfying

$$EU(\text{л}) = U[\ E(\text{л})-R] \tag{2}$$

In equation 2 $[\ E(\text{л})-R]$ is the certainty equivalent of profits (Pratt, 1964) and the R is the risk premium measuring highest value a farmer is willing to pay to replace the random variable л by its expected value $EU(\text{л})$. This R is a monetary value of implicit cost bearing (Kim and Chavas, 2003) and under the risk aversion, R>0. Then concavity of the utility function is given by $\vartheta^2 U/\vartheta \text{л}^2<0$ (Pratt, 1964). Maximizing expected utility is equivalent to maximizing certainty equivalent $E[\text{л}(x,t,.)]-R(x,t)$ and this depends on input use x and technology t. With this information at hand following Kim and Chavas (2003) we can define input/technology as risk increasing or risk decreasing. A risk increasing (decreasing) input and technology can be defined through the effects on the relative risk premium $R(x,t) / [E(л(x,t,.))-R(x,t)]$. Under the risk aversion (R>0) an input/technology is risk increasing (decreasing) if

$$\frac{R(x,t)\ /\ [E(л(x,t,.))-R(x,t)]}{\Delta x}>0(<0) \text{ and } \frac{R(x,t)\ /\ [E(л(x,t,.))-R(x,t)]}{\Delta t}>0(<) \text{ respectively.}$$

Following this conceptual framework we need to explore two things. First is to derive a formula for the risk premium under the expected utility model that can be approximated based on our knowledge on the moments of profit distribution. Second thing is to estimate the moments econometrically and to translate moments into the risk premium. The relevant empirical and econometric specifications are discussed in the following sections.

3.2. Empirical approximation of cost of private risk bearing (R)

As noted by Kim and Chavas (2003) obtaining an implicit solution for R from equation 2 is restrictive as it requires both the utility function U(л) and the probability distribution of л. An alternative for this is to estimate the moments of the random variableл. As shown by Antle (1983 and 1987) and Antle and Goodger (1984) and applied by Chavas et.al.,(2009) and Kim and Chavas (2003) all the relevant central moments (mean, variance and skewness) can be estimated consistently. As this approach allows the analysis of mean, variance and skewness we use this approach here. We have a particular interest on the skewness as it helps to analyze the exposure to downside risk. The estimation procedure is given in the econometric specification section.

The next step is obtaining an approximation for risk premium R in term of the moments of random variable л .For this purpose the equation 2 is differentiated taking the first order Taylor series expansion as shown by Antle (1987) which gives the following approximation for R.

$$R = \frac{1}{U^1}.[-\sum_{j=2}^{m}\frac{U^j}{j!}.\, E[л-E(л)]^j] \qquad (3)$$

Where $U^{j} = (\vartheta^{i}U/\vartheta \text{л})$ (E(л), J= 1,…..,m, m>= 2 and $E[\text{л}-E(\text{л})]^{j}$ is the jth central moment ofл. As risk aversion means $\vartheta^{2}U/\vartheta \text{л}^{2}<0$ (Pratt, 1964) equation 3 implies that when the variance of profit increases risk premium is also increasing. When m is 3 then we can get the skewness. We use skewness to measure the downside exposure following Kim and Chavas (2003). Then we define the following series of equations generalizing the above model (i=1). Let

$$\text{л} = \sum_{i=1}^{n}[A_{i}.\text{л}_{i}]$$

Where $\text{л}_{i} = p_{i}.y_{i}(x_{i},t,e) - c_{i}(x_{i},t,e)$ denotes profit per acre of the i^{th} commodity. Then

$$(\sum_{i=1}^{n}\varepsilon_{i})^{j} = \sum \frac{j!}{j_{1}!j_{2}!....j_{n}!}\varepsilon_{1}^{j_{1}}.\varepsilon_{2}^{j_{2}}\dots\varepsilon_{n}^{j_{n}}$$

Where $j_{1}, j_{2},\dots,j_{n}$ are non-negative integers satisfying

$$\sum_{i=1}^{n} j_{i} = j$$

Note that $\varepsilon_{i} = [Ai.(\text{л}_{i}-E(\text{л}_{i}))]$

Hence the risk premium can be approximated as

$$R = \frac{1}{U^{1}}.[-\sum_{j=2}^{m}\frac{U^{j}}{j!}.[A_{1}^{j}.\mu_{j\text{л}} + \delta_{j}]]$$

Where $\mu_{j\text{л}} = E[\text{л}_{1}-E(\text{л}_{1})]^{j}$ is the jth central moment of profit per acre of the first commodity, j>= 2, and

$$\delta_{j} = \sum \frac{j!}{j_{1}!j_{2}!....j_{n}!}E[\varepsilon_{1}^{j_{1}}.\varepsilon_{2}^{j_{2}}\dots\varepsilon_{n}^{j_{n}}] \tag{4}$$

Where δ_{j} accounts for the effects of risky returns of other production activities and j=2,….,m

Expression 4 relates the risk premium with the m moments of л_{1}. Then the certainty equivalent of profit can be approximated by the following given equation 5.

$$E(\text{л})-R = \sum_{i=1}^{n}[A_{i}.E(\text{л}_{i})] - \frac{1}{U^{1}}.[-\sum_{j=2}^{m}\frac{U^{j}}{j!}.[A_{1}^{j}.\mu_{j\text{л}} + \delta_{j}]] \tag{5}$$

For the first commodity (energy beet in this study)

$$A_1 . \mu_{1\text{л}} - \frac{1}{U^1}.[-\sum_{j=2}^{m} \frac{U^j}{j!}.[A_1^j . \mu_{j\text{л}}]] \qquad (6)$$

Where $\mu_{1\text{л}} = E(\text{л}_1)$. Now we have an expression showing the direct effect of the first m moments of the distribution of profit л_1 on the certainty equivalent. Kim and Chavas (2003) provide the following expression to approximate the risk premium.

$$R = -\frac{1}{A_i U^1}.[-\sum_{j=2}^{m} \frac{U^j}{j!}.[A_1^j . \mu_{j\text{л}}]] \qquad (7)$$

Following Antle (1987) and Chavas et al(2009) above can be reduced to the following equation.

$$R = 1/2 r_2 V + 1/6\ r_3 S \qquad (8)$$

In equation r_2 and r_3 are parameters reflecting the nature of risk preferences. Based on the expected utility theory risk preferences are represented by a utility function U(л) satisfying the following conditions (Pratt,1964).

$$\delta U/\delta \text{л} > 0 \text{ and } \delta^2 U/\delta \text{л}^2 \quad \begin{matrix} > \\ = \\ < \end{matrix} \quad 0 \text{ under} \quad \begin{matrix} \text{Risk aversion} \\ \text{Risk neutrality} \\ \text{Risk Loving} \end{matrix}$$

Based on above conditions r_2 is the Arrow-Pratt absolute risk aversion parameter satisfying $r_2 = -(\delta^2 U/\delta \text{л}^2)/(\delta U/\delta \text{л})$. Following Antle (1987) r_3 in the equation 3 is the downside risk aversion parameter satisfying $r_3 = -(\delta^3 U/\delta \text{л}^3)/ -(\delta U/\delta \text{л})$. Under risk aversion $-(\delta^2 U/\delta \text{л}^2) < 0$ r_2 is positive. Similarly under downside risk aversion $\delta^3 U/\delta \text{л}^3 > 0$ r3is negative.

Empirical estimates of the above theoretically formulated R was done following Kim and Chavas (2003) and Chavas et al (2009) in the following way. The logarithmic utility function was considered as U(л) =ln(л) where $r_2 = 1/\text{л}$ and $r_3 = 1/\text{л}^2$ .This particular utility function belongs to the class of risk preferences exhibiting constant relative risk aversion with an Arrow-Pratt relative risk aversion parameter equal to 1.

$$-\{(\delta^2 U/\delta л^2)/(\delta U/\delta л)\}\ л=1 \text{ (Pratt, 1964)}$$

Based on this and evaluated at mean return M>0 this implies that $r_2 = 1/M > 0$ and $r_3 = -2/M^2 < 0$. The next task is the estimating of moments using the moments based approach econometrically. The next section provides the details of the econometric implementation.

3.3. Econometric specification and empirical model

Profit is the interested variable in the study. Profit is a random variable and it is stochastic as it is a function of stochastic yield and unpredicted whether effects. In this study we did not consider output price as stochastic due to the data restriction. Further we consider the location as an input. Hence the return $\pi = (x, y, \varepsilon)$ depends on the production systems (x,y) as well as $\varepsilon = (v)$ uncertain variable. With this conditions the cost of private risk bearing can be calculated by evaluating the moments of profit $\pi = (x,y,\varepsilon)$ distribution. Three central moments; mean, variance and skewness are considered here.

$$M(x,y) = E[\pi(x,y,\varepsilon)] \tag{9}$$

Here M(x,y) is the mean return. As most farmers worry about the risk exposure it should be incorporated into an economic analysis. Hence second and third moment also can be measured.

$$V(x.y) = E\{[\pi(x,y,\varepsilon) - M(x,y)]^2\} \tag{10}$$

$$S(x.y) = E\{[\pi(x,y,\varepsilon) - M(x,y)]^3\} \tag{11}$$

V(x.y) and S(x.y) are variance and the skewness of return respectively.

In order to obtain the information about first three central moments equations 9 to 11 should be estimated. Following Antle (1987) the estimation procedure is given below. Consider that the mean function in equation has the parametric form of $M(x,y,\beta_1)$. The regression model can be given as

$$\pi = M(x,y,\beta_1) + u_1 \tag{12}$$

where u_1 is the error term with mean zero.

Estimating equation 12 yields a consistent $\beta_{1(estimated)}$ and the associated error term $u_{1(estimated)}$. As the next step variance and skewness can be estimated. Consider that variance and skewness functions take the parametric form $V(x,y,\beta_2)$ and $S(x,y,\beta_3)$ respectively. Equation 13 and 14 give the regression models.

$$(u_{1(\mathrm{estimated})}))^2 = V(x,y,\beta_2) + u_2 \tag{13}$$

$$(u_{1(\mathrm{estimated})}))^3 = S(x,y,\beta_3) + u_3 \tag{14}$$

Estimating the regression equations 13 and 14 gives consistent estimators (Antle, 1987). As variance of error u_1 in equation 12 is $V(x,y,\beta_2)$ and variance $u_2$and u_3 are not constant, weighted regression is used to increase efficiency (Chavas, 2004 and Chvaset al, 2009).Following Chavas (2004) weighted least square (WLS), a better estimator to estimate these moment functions under the presence of heteroscedasticity, is used. WLS estimator is used to estimate the models using the wls command in STATA statistical software.

3.4. Data

Energy beet variety trails data are available for 2009-2014. Corn, Wheat and Soybean data are available from 2008-2014. Data was collected from Carrington REC, Oakes irrigated research site of the Carrington REC and Langdon dry land REC. Fin Bin farm budgets were used to calculate the profit for wheat, corn and soybean. As mentioned earlier commodity prices were not taken as stochastic. This is mainly due to the fact that the crop of interest i.e., energy beet is not grown in North Dakota and hence a market price can’t be found. Hence the average of production cost was added a 15% of that and it was taken as the commodity price. This is done for all the other crops too.

Estimation of the models was done using STATA statistical software. SATA -13 has the required command (wls) to estimate the regression equations using the weighted least square estimator. Further all the descriptive statistics estimation and data procession were also done using STATA.

4. RESULTS AND DISCUSSION

This chapter presents the results and discusses the economic implications of the results obtained from hypotheses testing. The organization of the chapter is as follows. First the descriptive statistics of the variables are presented. In the second section the results of the moment estimates of the energy beet root yield, sugar yield and the profit are presented. In the third section the results of the moment estimates of the yield and profit of corn, soybean and wheat are presented. Hence second and third sections are devoted to the results obtained in achieving the first specific objective of the study i.e. to model the mean, variance and skewness of the profit and yield distributions of energy beet, corn, soybean and wheat. Fourth section is devoted to results of risk premium and certainty equivalent. Hence this section provides results to the second and third specific objectives i.e. to measure the cost of private risk bearing in cultivation of energy beet, corn, soybean and wheat and to compare the riskiness of the cultivation of energy beet, corn, soybean and wheat. The fifth section is devoted to a comprehensive discussion of the results with special focus on the testing of hypotheses i.e. irrigation and technology are risk decreasing input, planting date is a risk increasing input, there is a significant difference in risk premium in different farming systems and the adoption of energy beet is less risky than other conventional crops.

4.1. Descriptive statistics of the variables

The dependents variables are the profit of crops and their variance and skewness and crop yields. In energy beet sugar yield (ton/acre) and root yield (ton/acre) were both reported. The descriptive statistics of yieldare given in table 1.Oakes irrigated research site has the highest mean root (33.062 ton/acre) yield and the sugar yield (5.586 ton/acre). The lowest mean yields in both sugar yield (4.974 on/acre) and the root yield (27.114) are reported in Carrington REC.

Oakes irrigated research site has the highest mean yield for corn (5.551 ton/acre). Lowest mean yield of corn is reported in Langdon dry land REC (2.621 ton/acre). Langdon dry land REC has the highest mean yield for both soybean (1.856 ton/acre) and wheat (2.207 ton/acre). Lowest mean yield of soybean (1.382 ton/acre) is from Carrington REC and Oakes irrigated research site has the lowest mean yield for wheat (1.859 ton/acre). Lowest standard deviation of sugar yield of energy beet, root yield of energy beet, and soy bean yield (Carrington has the same value) is from Langdon dry land REC. Carrington has the lowest standard deviation for corn while Oakes has the lowest standard deviation for wheat.

Table 1. Descriptive statistics of yield (ton/acre)

Station	**Mean crop yield (ton/acre)***				
	Corn	**Energy Beet**		**Soy bean**	**Wheat**
		Sugar yield	**Root yield**		
Carrington	3.902	4.974	27.114	1.382	1.954
	(0.778)	(1.237)	(6.271)	(0.300)	(0.429)
Oakes	5.551	5.586	33.062	1.795	1.859
	(0.778)	(1.147)	(5.978)	(0.181)	(0.301)
Langdon	2.621	5.399	29.583	1.856	2.207
	(1.085)	(0.551)	(4.153)	(0.300)	(0.279)

*Standard deviations are in parenthesis

In the analysis cost of production and crop price were taken as non-stochastic. Price was determined adding 15% to the average direct cost of production (Appendix table 1). Hence profit is a non-negative variable. Further profit is a function of yield which is stochastic. Hence the stochastic nature of profit comes from the yield stochasticity. It is clear that as the crop prices are fixed the profit variability is not affected by the fluctuation of prices.

Table 2. Descriptive statistics of profit (USD/acre)

Station	**Profit (USD/acre)***			
	Corn	**Energy Beet**	**Soy bean**	**Wheat**
Carrington	73.270 (14.604)	121.179 (28.028)	53.350 (11.566)	51.367 (11.268)
Oakes	104.247 (14.594)	147.763 (26.717)	69.306 (6.970)	48.871 (7.910)
Langdon	49.214 (20.384)	132.215 (18.560)	71.659 (11.598)	58.005 (7.330)

*Standard deviations are in parenthesis

The effect of the planting date on the sugar beet yield and quality in terms of sugar content are addressed in the agronomical research based on experiments (Scott *et al*, 1973;Garcia and Bellido,1985; Smit, 1993 ; Lauer,1997 and Rykbost*et.al* (1997). Most of these researches have mentioned the importance of the plating date on root yield and the sugar content. In North America sugar beets are planted as early as possible in the spring (Lauer, 1997). Experimental evidences suggest that planting date is of a significant economic importance as it affects both production and the quality of sugar beet.

Delay in crop emergence causes significant loss of yield and sugar content (Smit, 1993 & Lauer, 1997). Garcia and Bellido (1985) have reported the same result in the context of autumn sugar beet production. Lauer, (1997) noted that a delay in emergence of the crop by 46d decreased root yield by 38%, sugar content by 4% and the recoverable sucrose by 42%. When the economics of planting date is considered the relationship between the planting date and economic returns has implications on the replanting decision. Replanting decision has to be made by the farmers as replanting is necessary due to the poor emergence of the crop due to various environmental, mechanical and pathological reasons (Lauer, 1997). Hence the economic tradeoff between the planting date and the sugar beet root yield and sugar yield is worthwhile to be addressed in the current study. The descriptive statistics of planting dates are given in table 3. Energy beet planting date varies from 15th of April to 17th of June in all research stations. Carrington REC has a prolonged planting period. When the mean planting date is considered Carrington REC has the earliest planting date (14th May) and Langdon REC has the most delayed mean planting date (27th May).

In the considered period of the study (2009-2014 for energy beet and 2008-2014 for all the other conventional crops) the weather changes were significant. For example the 2009 growing season was cooler and dryer than the1971 to 2000 average. The precipitation in 2011 was much higher than the actual trend (Bora et al., 2014). Further in 2011, Carrington REC had a hail severe enough to abandon irrigated and dry land wheat and dry land corn trials. 2012 had a dry and warm season and late planting. The 2014 growing season was wet and cold. State average precipitation during the 2014 growing season was 16.33 inches, the 18th wettest growing season since 1895.

Table 3. Descriptive statistics of planting date (Julian dates).

Station	**Planting date**											
	Corn			**Energy Beet**			**Soy bean**			**Wheat**		
	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
Carrington	131	117	136	134	105	168	140	135	150	121	105	142
	(11th May)	(27th April)	(17th May)	(14th May)	(15th April)	(17th June)	(20th May)	(17th May)	(30th May)	(1st May)	(15th April)	(22nd May)
Oakes	126	113	134	133	110	147	141	131	148	109	96	118
	(6th May)	(23rd April)	(15th May)	(13th May)	(20th April)	(27th May)	(21st May)	(11th May)	(28th May)	(19th April)	(16th April)	(28th April)
Langdon	135	127	141	147	135	161	108	98	118	128	112	139
	(16th May)	(7th May)	(21st May)	(27th May)	(16th May)	(10th June)	(18th April)	(8th April)	(28th April)	(8th May)	(22rd April)	(19th May)

The next section presents the results of the modeling three central moments of root yield, sugar yield and profit of energy beet. The importance of these results is twofold. First they give information about the influencing factors on expected yield and profit. Secondly they show a path in yield and profit risk of energy beet which is quite important in the policy realm.

4.2. Moments of root yield, sugar yield, profit of energy beet

The results of modeling the root yield of energy beet is given in table 4. All the models have a significant F-statistics. The R^2 are fairly satisfactory. The expected yield model explains 39% of the variance, variance model explains 26.2% of the variance and skewness model explains 13.4% of variance. In the expected root yield model all the independent variables and the intercept are significant at 0.01 probability level. As expected time trend has a significant positive effect (0.685) on the expected root yield. Time trend captures two effects. One is the technological improvement like improved varieties or other inputs. The other is the climate change. However we do not have necessary variables to decompose these two effects. As reported by experimental research mentioned earlier planting date has a negative significant effect on the root yield. This implies that with a delay of one day the yield decreases by 0.136 ton/acre. The planting season in most research stations started 15th April in the considered time span of the study. Irrigation has a significant positive effect (3.270) on energy beet root yield. This implies that comparing to the dry lands; irrigated lands have a higher yield of the magnitude of 3.270 ton/acre. Further the expected yield in Oakes irrigated research station and Langdon REC are significantly higher (by 4.892 ton/acre and 6.267 ton/acre respectively) comparing to Carrington REC.

The effect of time trend, planting date and irrigation on the variance and skewness of yield is important in risk management decisions. Although technology is viewed as a risk reducing input conventionally the obtained results shows that the time trend increases the variance of yield. This is a fairly consistent result except for corn in the obtained results of the study. It can be assumed that as time trend captures both technology and weather changes this outcome is a result of the interactive effect of climate change. Variance is a traditional measure of risk. However time trend has positive significant effect on the skewness (64.060) at 10% probability level. Skewness is a measure of the “down-side risk”. Higher the skewness is lesser the “down-side risk”. In contrast planting date has a significant negative effect on the variance and negative but not significant effect on skewness. Irrigation’s effect on both variance and the skewness are not significant. Hence the overall conclusion is technology and irrigation increase the energy beet root yield while planting date reduces it. However usage of these inputs in risk management should be done considering the direction of the effect on the expected yield and variance and skewness.

Table 4. Moments of root yield (tons/acre).

Variable	Mean Function		Variance Function		Skewness Function	
	Parameter estimate	SD	Parameter estimate	SD	Parameter estimate	SD
Intercept	41.341***	2.668	70.788**	33.415	28.571	566.417
Year	0.685***	0.147	6.372***	1.613	64.060*	34.813
Planting Date	-0.136***	0.018	-0.478**	0.224	-0.954	3.851
Station 2	4.892***	0.678	16.955***	1.994	372.410***	70.018
Station 3	6.267***	0.826	-7.303	9.218	-95.939	369.306
Irrigation (0=Dry;1=irrigated)	3.270***	0.619	0.003	2.033	-4.161	104.869
Fit Statistics						
R^2	0.390		0.262		0.134	
Adjusted R^2	0.381		0.251		0.121	
F statistics (5,338)	43.23***		24.03***		10.45***	

*** Significant at 0.01 level, ** Significant at 0.05 level and * Significant at 0.10 level

The results of modelling sugar yield of energy beet is given in table 5. All the models have a significant F-statistics. The expected sugar yield model explains 33.7% of the variance, variance model explains 55.3% of the variance and skewness model explains 28.7% of variance. In the expected sugar yield model all the independent variables and the intercept are significant at 0.01 probability level. As expected time trend has a significant positive effect (0.270) on the expected sugar yield. Planting date has a negative significant effect on the sugar yield. This result is consistent with previous studies related to sugar beet. This implies that with a delay of one day the sugar yield decreases by 0.019 ton/acre. The planting season in most research stations started 15th April in the considered time span of the study. Irrigation has a significant positive effect (0.645) on energy beet sugar yield. This implies that comparing to the dry lands;

irrigated lands have a higher yield of the magnitude of 0.645 ton/acre. Further the expected sugar yield in Oakes irrigation research site and Langdon REC are significantly higher (by 0.777 ton/acre and 1.069 ton/acre respectively) comparing to Carrington REC.

In the context of sugar yield also the effect of time trend, planting date and irrigation on the variance and skewness of yield is important in risk management decisions in energy beet cultivation. The obtained results show that the time trend increases the variance of sugar yield. However the time trend has positive significant effect on the skewness (1.436) at 1% probability level. In contrast planting date has a significant negative effect of risk (variance) and positive but not significant effect on skewness. Interestingly irrigation increases the skewness. Hence in “down-side” risk management of sugar yield irrigation can be effectively used. The effect of irrigation on variance is not significant. The overall conclusion is technology and irrigation increase the expected sugar yield of energy beet while planting date reduces it. Further irrigation and technology are significantly affecting the skewness of sugar yield.

Table 5. Moments of sugar yield (tons/acre).

Variable	**Mean Function**		**Variance Function**		**Skewness Function**	
	Parameter estimate	**SD**	**Parameter estimate**	**SD**	**Parameter estimate**	**SD**
Intercept	6.215***	0.511	5.596***	1.811	-16.165*	8.574
Year	0.270***	0.030	0.177***	0.065	1.436***	0.125
Planting Date	-0.019***	0.003	-0.039***	0.012	0.060	0.063
Station 2	0.777***	0.146	1.288***	0.172	2.096	2.030
Station 3	1.069***	0.166	0.311	0.225	-1.654	1.201
Irrigation (0=Dry;1=irrigated)	0.645***	0.128	0.352	0.232	2.798***	0.628
			Fit Statistics			
R^2	0.337		0.553		0.287	
Adjusted R^2	0.327		0.546		0.277	
F statistics (5,338)	34.360***		83.49***		27.22***	

*** Significant at 0.01 level, ** Significant at 0.05 level and * Significant at 0.10 level

Moments of profit are reported in table 6. All the models have significant F-statistics implying that models are significant. The expected profit model explains 39.0% of the variance, variance model explains 26.2% of the variance and skewness model explains 13.4% of variance. As mentioned earlier profit is a function of yield and output price is not stochastic. Hence the signs and the significance of the parameter estimates of the profit moments are same as them in yield moments estimates. Hence the overall conclusion for the moments of energy beet profit is that the time trend and irrigation increase the energy beet profit while planting date reduces it. However usage of these inputs in management of risk of return should be done considering the tradeoff between expected profit and variance of profit and the skewness of profit.

Table 6. Moments of profit of energy beet (USD/acre).

Variable	Mean Function		Variance Function		Skewness Function	
	Parameter estimate	**SD**	**Parameter estimate**	**SD**	**Parameter estimate**	**SD**
Intercept	184.767***	11.925	1413.960**	667.462	2550.682	50565.68
Year	3.061***	0.658	127.285***	32.221	5718.865*	3107.85
Planting Date	-0.608***	0.080	-9.557***	4.468	-85.195	343.833
Station 2	21.865***	3.031	338.680***	39.837	33246.120 ***	6250.703
Station 3	28.0082***	3.691	-145.882	184.136	-8564.712	13138.46
Irrigation (0=Dry;1=irrigated)	14.615***	2.767	0.063	40.610	-371.468	9361.995
			Fit Statistics			
R^2	0.390		0.262		0.134	
Adjusted R^2	0.381		0.251		0.121	
F statistics (5,338)	43.23***		24.03***		10.45***	

*** Significant at 0.01 level, ** Significant at 0.05 level and * Significant at 0.10 level

Based on the results for energy beet it can be concluded that time trend and irrigation increase root yield, sugar yield and profit. Irrigation is a useful input in controlling the skewness of sugar yield. The time trend reduces the skewness of root yield, sugar yield and profit significantly. However it increases variance of all these outputs. Irrigation is not affecting root yield and profit of energy beet significantly hence the risk implications are insignificant. The next section presents the results of the moment estimates of yield and profit of corn, soybean and wheat.

4.3. Moments of yield and profit of corn, soy bean, and wheat

The results of modeling corn yield and profit are in table 7 and 8. All the models have a significant F-statistics. The expected sugar yield and profit models explain more than 60% of the variance but the explanatory power of the variance and skewness models are fairly low. The reason can be that the unexplained variance is attributed to the unexpected weather effects captured by the error terms. In the expected profit and yield models all the independent variables and the intercept are significant at 0.01 probability level. The time trend has a significant positive effect on both expected corn yield and expected corn profit (7.912 and 148.591 respectively). Planting date has a negative significant effect on the yield and profit of corn. This implies that with a delay of one day the corn yield decreases by 0.357 ton/acre while profit decreases by 0.671 USD/acre. The planting season for corn in most RECs started in later part of April in the considered time span of the study. Irrigation has a significant positive effect (0.164 and 3.076) on corn yield and profit respectively. This implies that comparing to the dry lands; irrigated lands have a higher corn yield of the magnitude of 0.164 ton/acre while profit is higher by 3.076 USD/acre. Further the expected corn yield in Oakes irrigated research station and Langdon REC are significantly different (by 1.039 ton/acre and -1.023 ton/acre respectively) comparing to Carrington REC while profit is different by 26.184 USD/acre and -19.225 USD/acre.

The time trend has a significant negative effect on both corn yield and profit variance (-0.078 and -20.565 respectively). Similarly irrigation reduces the variance of corn yield and profit (-0.084 and -26.397). However both coefficients are not significant. But the effect of irrigation and time trend is positive and significant in skewness models for corn yield and profit.

Table 7. Moments of corn yield (ton/acre).

Variable	Mean Function		Variance Function		Skewness Function	
	Parameter estimate	SD	Parameter estimate	SD	Parameter estimate	SD
Intercept	7.912***	0.323	-1.063***	0.637	2.169*	1.296
Year	0.155***	0.010	-0.078***	0.012	0.112**	0.031
Planting Date	-0.357***	0.003	0.013***	0.005	-0.023***	0.010
Station 2	1.039***	0.044	0.328***	0.072	-0.587**	0.142
Station 3	-1.023***	0.068	0.917*	0.076	0.227	0.186
Irrigation (0=Dry;1= irrigated)	0.164***	0.042	-0.084	0.064	0.364***	0.135
			Fit Statistics			
R^2	0.647		0.161		0.020	
Adjusted R^2	0.646		0.158		0.014	
F statistics (5,1630)	596.80***		62.46***		5.74***	

*** Significant at 0.01 level, ** Significant at 0.05 level and * Significant at 0.10 level

Table 8. Moments of corn profit (USD/acre).

Variable	Mean Function		Variance Function		Skewness Function	
	Parameter estimate	**SD**	**Parameter estimate**	**SD**	**Parameter estimate**	**SD**
Intercept	148.591***	6.078	199.521	190.019	14368.060*	8560.562
Year	2.917***	0.179	-20.565***	4.097	744.509***	203.208
Planting Date	-0.671***	0.048	3.223**	1.506	-151.160**	69.132
Station 2	26.184***	0.827	99.612***	23.075	-3890.981***	940.080
Station 3	-19.225***	1.280	187.337***	26.966	1504.896	1231.348
Irrigation (0=Dry;1= irrigated)	3.076***	0.780	-26.397	21.227	2411.858***	890.562
			Fit Statistics			
R^2	0.647		0.07		0.020	
Adjusted R^2	0.646		0.06		0.014	
F statistics (5,1630)	596.80***		23.61***		5.74***	

*** Significant at 0.01 level, ** Significant at 0.05 level and * Significant at 0.10 level

The results of modeling soybean yield and profit are in table 9 and 10. All the models have a significant F-statistics. The expected soybean yield and profit models explain more than 70% of the variance and the explanatory power of the variance and skewness models are fairly satisfactory having R^2 of 31% and 28% respectively. In the expected profit and yield models all the independent variables and the intercept are significant at 0.01 probability level except planting date which is significant at 5% level. As expected, time trend has a significant positive effect on both expected soybean yield and expected soybean profit (0.055 and 2.14 respectively). Planting date has a positive significant effect on the yield and profit of soybean. This implies that with a delay of one day the soybean yield increases by 0.004 ton/acre while profit increases by 0.161 USD/acre. The planting season for soybean in most research stations started in just after the mid of April and in May in the considered time span of the study. Irrigation has a significant positive effect (0.194 and 7.056) on soybean yield and profit respectively. This implies that comparing to the dry lands; irrigated lands have a higher soybean yield of the magnitude of 0.194 ton/acre while profit is higher by 7.056 USD/acre. Further the expected soybean yield in Oakes research station and Langdon REC are significantly higher (by 0.297 ton/acre and 1.032 ton/acre respectively) comparing to Carrington REC while profit is different by 11.458 USD/acre and 39.824 USD/acre.

The time trend coefficients have no significant effect on both variance and skewness of soybean yield and skewness of profit although the sign is positive. However the effect on the variance of soybean profit is positive and significant. The irrigation significantly reduces the variance of soybean yield and profit (-0.072 and -67.110 respectively). Interestingly irrigation increases skewness in both yield and profit of soybean. Hence irrigation is an important input of risk management in soybean. Further planting date significantly increases the variance of yield and profit of soybean (by 0.010 and 13.669 respectively). In contrast it decreases the skewness significantly (-0.009 and -446.121 respectively). Hence planting date also is an important input that can be used in risk management of soybean profit and yield.

Table 9. Moments of soy bean yield (ton/acre).

Variable	**Mean Function**		**Variance Function**		**Skewness Function**	
	Parameter estimate	**SD**	**Parameter estimate**	**SD**	**Parameter estimate**	**SD**
Intercept	0.492**	0.236	-1.341***	0.085	1.151***	0.067
Year	0.055***	0.004	0.001	0.002	0.002	0.001
Planting Date	0.004**	0.002	0.010***	0.001	-0.009***	0.001
Station 2	0.297***	0.018	-0.019**	0.008	0.001	0.006
Station 3	1.032***	0.055	0.417***	0.026	-0.355***	0.021
Irrigation (0=Dry;1= irrigated)	0.194***	0.015	-0.072***	0.007	0.047***	0.005
			Fit Statistics			
R^2	0.711		0.314		0.278	
Adjusted R^2	0.710		0.311		0.276	
F statistics (5,1438)	706.22***		131.42***		110.96***	

*** Significant at 0.01 level, ** Significant at 0.05 level and * Significant at 0.10 level

Table 10. Moments of soy bean profit (USD/acre).

Variable	Mean Function		Variance Function		Skewness Function	
	Parameter estimate	**SD**	**Parameter estimate**	**SD**	**Parameter estimate**	**SD**
Intercept	18.993**	9.114	-1806.055***	122.865	60549.550***	3661.872
Year	2.124***	0.153	7.454***	2.290	22.360	27.183
Planting Date	0.161**	0.067	13.668***	0.911	-446.121***	27.183
Station 2	11.458***	0.676	-46.698***	9.890	329.064***	304.633
Station 3	39.824***	2.132	578.952***	35.742	18869.140***	1052.106
Irrigation (0=Dry;1=irrigated)	7.506***	0.585	-67.110***	8.947	1780.075***	3661.871
			Fit Statistics			
R^2	0.711		0.311		0.267	
Adjusted R^2	0.710		0.309		0.265	
F statistics (5,1438)	706.220***		191.130***		20.660***	

*** Significant at 0.01 level, ** Significant at 0.05 level and * Significant at 0.10 level

Table 11 and 12 show the results of modeling wheat yield and profit. All the models have a significant F-statistics. The expected soybean yield and profit models explain more than 25% of the variance and the explanatory power of the variance models are fairly satisfactory having R^2 of 28%. However the skewness models explain just 6% of the variance. In the expected profit and yield models all the independent variables are significant at 0.01 probability level except planting date and intercept which is significant at 5% level. Contrary to the expectation, time trend has a significant negative effect on both expected wheat yield and expected wheat profit (-0.055 and -1.440 respectively). Planting date has a positive significant effect on the yield and profit of wheat. This implies that with a delay of one day the soybean yield increases by 0.007 ton/acre while profit increases by 0.172 USD/acre. The planting season for soybean in most RECs started in after the mid of April in the considered time span of the study. Irrigation has a significant positive effect (0.542 and 14.248) on wheat yield and profit respectively. This implies that comparing to the dry lands; irrigated lands have a higher what yield of the magnitude of 0.542 ton/acre while profit is higher by 14.248 USD/acre. Further the expected wheat yield in Oakes REC and Langdon REC are significantly different (by -0.297 ton/acre and 0.360 ton/acre respectively) comparing to Carrington REC while profit is different by -8.480 USD/acre and 9.471 USD/acre.

In the context of wheat time trend coefficients have a significant effect (at 1% probability level) on both variance and skewness of wheat yield and profit. The irrigation significantly reduces the variance of wheat yield and profit (-0.213 and -83.314 respectively) comparing to dry lands. Irrigation increases skewness in both yield and profit of soybean but parameter estimates are not significant. Hence irrigation is an important input of risk management in wheat but the effect in down side risk management is not significant. Further planting date significantly decreases the variance of yield and profit of wheat (by -0.003 and -0.001 respectively). Similarly it decreases the skewness significantly (-0.947 and -21.438 respectively). Hence planting date also is an important input that can be used in risk management of wheat profit and yield given the trade-off between risk and down-side risk.

Table 11. Moments of wheat yield (ton/acre).

Variable	Mean Function		Variance Function		Skewness Function	
	Parameter estimate	SD	Parameter estimate	SD	Parameter estimate	SD
Intercept	1.126**	9.114	0.327***	0.109	0.100**	0.045
Year	-0.055***	0.153	0.073***	0.006	0.019***	0.004
Planting Date	0.007**	0.067	-0.003***	0.001	-0.001***	0.001
Station 2	-0.323***	0.676	0.032	0.049	-0.012	0.009
Station 3	0.360***	2.132	-0.204***	0.027	-0.051***	0.012
Irrigation (0=Dry;1= irrigated)	0.542***	0.585	-0.213***	0.025	0.005	0.007
			Fit Statistics			
R^2	0.255		0.293		0.061	
Adjusted R^2	0.250		0.289		0.055	
F statistics (5,781)	53.450***		64.870***		10.060***	

*** Significant at 0.01 level, ** Significant at 0.05 level and * Significant at 0.10 level

Table 12. Moments of wheat profit (USD/acre).

Variable	Mean Function		Variance Function		Skewness Function	
	Parameter estimate	SD	Parameter estimate	SD	Parameter estimate	SD
Intercept	29.611**	3.948	127.453**	57.925	1823.731**	820.050
Year	-1.440***	0.346	37.355***	2.786	351.684***	68.315
Planting Date	0.172**	0.034	-0.947*	0.518	-21.438***	7.989
Station 2	-8.480***	2.683	11.519	24.134	-222.081	156.700
Station 3	9.471***	1.115	-71.350***	14.156	-928.914***	212.806
Irrigation (0=Dry;1= irrigated)	14.248***	1.158	-83.314***	13.337	97.4024	126.050
			Fit Statistics			
R^2	0.255		0.252		0.061	
Adjusted R^2	0.250		0.248		0.055	
F statistics (5,781)	53.450***		52.720***		10.060***	

*** Significant at 0.01 level, ** Significant at 0.05 level and * Significant at 0.10 level

4.4. Risk premium and certainty equivalent

In order to evaluate the economic implications of the profit distributions, after estimating the moments, the risk premiums were calculated. The purpose of this step was twofold. The first purpose was to get an understanding of the spatial distribution of risk premium among different research stations for energy beet. The second purpose was to map the risk premium of energy beet comparing to other conventional crops in each site. It should be noted that statistical mean comparisons are not possible as risk premium value is a one point value and it is not a sample parameter. The year 2012 was selected as data were available for a comparison in this year. The calculated risk premiums are given in table 13.

Before explaining the evolution of risk premium across crops and research stations one important thing should be noted on profit variability. The profit variable is stochastic because yield is stochastic. Hence, the stochasticity of profit is underestimated. As variance and skewness directly determine the risk premium, it can be argued that risk premiums for the openly traded conventional crops: corn, soybean, and wheat are underestimates. It is expected that energy beets will be mostly cultivated under long-term contracts keeping the non-stochastic price for energy beet realistic. For other conventional crops, the obtained price by adding 15 percent to the cost of production is arbitrary. It is noteworthy to look whether this pricing mechanism will have an effect on the overall conclusions of the study. It can be assumed that if the price stochasticity is considered the variability of the conventional crops and their risk premium will be higher, while that for energy beets will be the same. Hence, even though the price stochasticity is not considered the conclusions will be the same.

The risk premium, R, is defined as the sure amount of money a decision maker would be willing to receive to become indifferent between receiving the risky return ‘‘a’’ (a monetary return) versus receiving the sure amount [E(a)-R], where E(a) is the expected value of ‘‘a.’’ (Chavas,2004). Hence intuitively risk premium is the cost of private risk bearing. This definition is more useful in evaluating the farmers’ decision on the crop adoption as it can be hypothesized that a risk averse farmer will go for the least risk option. Across the research stations there is a considerable variation of the risk premium in energy beet. The lowest is reported for Langdon. Interestingly Langdon is a dry land research station. Further in descriptive statistics Langdon has the least standard deviation in root yield, sugar yield and profit distributions. The possible explanation is that unobserved characteristics like soil conditions cause less variation of yield in Langdon. The highest risk premium is reported for Carrington dry research station. There the cost of private risk bearing for energy beet is 2.727 USD/Acre. Carrington irrigated and Oakes irrigated research site has lower risk premiums than Carrington dry research station but higher than Langdon dry REC.

It is important to compare the risk premium across crops. In Carrington dry research station corn has the lowest risk premium while wheat has the highest. Although the risk premium for the energy beet (2.727 USD/acre) is not the highest it is quietly similar to the wheat (2.841 USD/acre). In Carrington irrigated research station energy beet has the highest risk premium. This is similar in the case of Oakes irrigated research site. However in Langdon energy beet has the lowest risk premium (0.733). Hence it can be concluded that a risk averse farmer can opt for energy beet in Langdon.

Table 13. Risk premium (2012).

Station	**Risk Premium (USD/Acre) for each crop**			
	Corn	**Energy Beet**	**Soybean**	**Wheat**
Carrington (Dry)	0.562	2.727	0.866	2.841
Carrington (Irrigated)	0.279	2.324	0.669	1.210
Oakes (Irrigated)	0.724	2.581	-0.078	1.109
Langdon (Dry)	2.318	0.733	1.287	1.232

The risk adjusted expected return or the certainty equivalent (CE) of crops for each site is given in table 14. We estimated the profit as a function of yield and the profits are not a function of their price. Each crop has its own price and some crops can be higher priced irrespective of the cost of production. Hence certainty equivalent should be compared across the sites for each crop and not across crops for each site. For energy beet the highest certainty equivalent is reported for Oakes irrigated research site. However in the risk premium ranking Oakes irrigated research site has the highest risk premium. Risk theory provides a framework to make inferences in this condition. Under risk aversion the decision maker always choose to obtain the highest possible expected profit for a given variance or the least possible variance for a given expected profit (Anderson et al., 1977). Risk premium illustrates the variability of return based on Antle (1987). Hence risk adjusted mean return or CE can be used to evaluate the farmers' crop adoption decision in energy beet across sites. After bearing the cost of risk, the sure amount of return is the highest in Oakes irrigated research site. The second highest is at Carrington irrigated research site. Hence in irrigated RECs energy beet can be an appealing crop for farmers.

Table 14. Certainty equivalent (Expected return-risk premium) (2012).

Station	**Certainty Equivalent (USD/Acre) for each crop**			
	Corn	**Energy Beet**	**Soybean**	**Wheat**
Carrington (Dry)	86.534	137.236	52.731	29.822
Carrington (Irrigated)	98.007	159.469	61.820	43.243
Oakes (Irrigated)	122.182	198.761	75.598	56.268
Langdon (Dry)	65.381	139.155	82.815	51.883

4.5. Summary

Time trend and irrigation have a significant positive effect on the expected sugar yield, expected root yield and expected profit. In their risk implications time trend increase both variance and skewness of root yield, sugar yield and profit of energy beet. Hence there is an obvious trade-off between risk and down side risk in using technology as a risk management tool. Irrigation significantly increases the skewness of sugar yield. However it has no significant effect to the risk of root yield, sugar yield and profit and to the down side risk of root yield and profit. Planting date reduces root yield, sugar yield and profit significantly. In risk management planting date significantly reduces the risk of root yield, sugar yield and profit. Hence planting date creates a tradeoff between expected yield/profit and the risk of yield/profit. Table 15 summarizes the effect of independent variables on the moments of each variable.

Table 15. Effect of variables on sugar yield, root yield, and profit of energy beet.

Variable	**Root Yield (ton/acre)**			**Sugar yield (ton/acre)**			**Profit (USD/acre)**		
	M	**V**	**S**	**M**	**V**	**S**	**M**	**V**	**S**
Time	(+)***	(+)***	(+)*	(+)***	(+)***	(+)***	(+)***	(+)***	(+)***
Planting date	(-)***	(-)**	(-)	(-)***	(-)***	(+)	(-)***	(-)**	(-)
Irrigation (1=irr;0= dry)	(+)***	(+)	(-)	(+)***	(+)	(+)***	(+)***	(+)	(-)
Oakes research site	(+)***	(+)***	(+)***	(+)***	(+)***	(+)	(+)***	(+)***	(-)
Langdon REC	(+)***	(-)	(-)	(+)***	(+)	(-)	(+)***	(-)***	(+)***

*** Significant at 0.01 level, ** Significant at 0.05 level and * Significant at 0.10 level

For corn the time trend increases expected yield and skewness while reduces the variance favorably. Irrigation behaves in a similar way. In contrast, planting date reduces corn expected yield and skewness while increases variances. The behavior of these inputs in the context of profit (table 17) are same. Hence for yield and profit risk management in corn these inputs can be effectively used.

Table 16. Effect of variables on the yield of corn, soy bean, and wheat.

Variable	**Corn (ton/acre)**			**Soybean (ton/acre)**			**Wheat (ton/acre)**		
	M	**V**	**S**	**M**	**V**	**S**	**M**	**V**	**S**
Time	**(+)*****	**(-)*****	**(+)*****	**(+)*****	(+)	(+)	**(-)*****	**(+)*****	**(+)*****
Planting date	**(-)*****	**(+)*****	**(-)*****	**(+)*****	**(+)*****	**(-)*****	**(+)*****	**(-)*****	**(-)**
Irrigation (1=irr;0= dry)	**(+)*****	**(-)**	**(+)*****	**(+)*****	**(-)*****	**(+)*****	**(+)*****	**(-)*****	**(+)**
Oakes research site	**(+)*****	**(+)*****	**(-)*****	**(+)*****	**(-)****	**(+)**	**(-)*****	**(+)**	**(-)**
Langdon REC	**(-)*****	**(+)***	**(+)**	**(+)*****	**(+)*****	**(-)*****	**(+)*****	**(-)*****	**(-)*****

*** Significant at 0.01 level, ** Significant at 0.05 level and * Significant at 0.10 level

In the context of soy bean time trend significantly increases mean yield and profit but does not affect variance or skewness of soy bean yield. However it increases the variance of soybean profit. Irrigation increases the mean yield and profit and skewness of yield and profit. It decreases the variance of yield and profit. Although planting date increases the mean yield and profit it decreases the skewness of profit and yield while increases the variance of profit and yield. For wheat irrigation is important in risk management. It increases the expected yield and decreases the variance significantly. Although it is not significant irrigation has a positive coefficient in skewness models.

Table 17. Effect of variables on the profit of corn, soy bean, and wheat.

Variable	**Corn (ton/acre)**			**Soybean (ton/acre)**			**Wheat (ton/acre)**		
	M	**V**	**S**	**M**	**V**	**S**	**M**	**V**	**S**
Time	**(+)*****	**(-)*****	**(+)*****	**(+)*****	**(+)*****	**(+)**	**(-)*****	**(+)*****	**(+)*****
Planting date	**(-)*****	**(+)*****	**(-)*****	**(+)*****	**(+)*****	**(-)*****	**(+)*****	**(-)***	**(-)*****
Irrigation (1=irr;0=dry)	**(+)*****	**(-)**	**(+)*****	**(+)*****	**(-)*****	**(+)****	**(+)*****	**(-)*****	**(+)**
Oakes research site	**(+)*****	**(+)*****	**(-)*****	**(+)*****	**(-)****	**(+)**	**(-)*****	**(+)**	**(-)**
Langdon REC	**(-)*****	**(+)***	**(+)**	**(+)*****	**(+)*****	**(-)****	**(+)*****	**(-)*****	**(-)*****

*** Significant at 0.01 level, ** Significant at 0.05 level and * Significant at 0.10 level

The time trend variable has a positive effect on the variance in all the crops except corn. As the crop requirements and physiological properties the differences in the direction of effects can be expected. It should be noted that time trend captures both technology and climate change. Hence in the effect of time trend the effect of climate change is also included. The sign is a manifestation of the both. The possible explanation for this positive effect is that the combined effects of technology and climate change are increasing the variance. As noted earlier the decomposition of the effects is not possible due to the lack of data for required variables.

5. CONCLUSION

This study investigated the cost of private risk bearing of a representative risk averse energy beet farmer comparing the risk of return with the other conventional crops such as corn, soy bean and wheat. The moment-based approach proposed by Antle (1987) was used following Chavas et al. (2009) and Kim and Chavas (2003). The obtained results provide a guideline to assess the risk of energy beet cultivation in different agricultural systems in North Dakota represented by different research stations comparing to the conventional crops.

Time trend and irrigation have a significant positive effect on the expected sugar yield, expected root yield and expected profit. In their risk implications time trend increase both variance and skewness of root yield, sugar yield and profit of energy beet. The trade-off between risk and down side risk in using technology as a risk management tool is important. Irrigation significantly increases the skewness of sugar yield. However it has no significant effect to the variance of root yield, sugar yield and profit and to the skewness of root yield and profit. Planting date reduces root yield, sugar yield and profit significantly. In risk management planting date significantly reduces the risk of root yield, sugar yield and profit. Hence planting date creates a tradeoff between expected yield/profit and the risk of yield/profit.

The time trend increases expected yield and skewness of corn while reduces the variance favorably. Irrigation behaves in a similar way. In contrast planting date reduces corn expected yield and skewness while increases variances. Hence for yield and profit risk management in corn these inputs can be effectively used. In the context of soy bean time trend significantly increases mean yield and profit but does not affect variance or skewness of soy bean yield. However it increases the variance of soybean profit. Irrigation increases the mean yield and profit and skewness of yield and profit. It decreases the variance of yield and profit .Although planting date increases the mean yield and profit it decreases the skewness of profit and yield while increases the variance of profit and yield. For wheat irrigation is important in risk management. It increases the expected yield and decreases the variance significantly. Although it is not significant irrigation has a positive coefficient in skewness models.

Across the research stations there is a considerable variation of the risk premium in energy beet. The lowest is reported for Langdon. Interestingly Langdon is a dry land research station. The highest risk premium is reported for Carrington dry RECs. There the cost of private risk bearing for energy beet is 2.727 USD/Acre. Carrington irrigated and Oakes irrigated have lower risk premiums than Carrington dry research stations but higher than Langdon dry REC. When compared across crops Carrington dry research stations' corn has the lowest risk premium while wheat has the highest. Although the risk premium for the energy beet (2.727 USD/acre) is not the highest it is quietly similar to the wheat (2.841 USD/acre). In Carrington irrigated research stations energy beet has the highest risk premium. This is similar in the case of Oakes irrigated research stations. However in Langdon energy beet has the lowest risk premium (0.733). Hence it can be concluded that a risk averse farmer can opt for energy beet in Langdon. After bearing the cost of risk the sure amount of return is the highest in Oakes irrigated research site. The second highest is at Carrington irrigated REC. Hence in irrigated RECs energy beet can be an appealing crop for farmers.

It should be noted that the degree of risk premium is not consistent across the research stations. As an example although we can expect that research stations with irrigation can have the lowest risk premium in each crop. But results show that risk premiums are not behaving that way. This is mainly due to the differences of the crops. Further even within dry or irrigated research stations the risk premiums have a considerable difference. The possible explanation is that the crop yield variability and skewness are determined by the factors captured by the location dummy. These factors can be soil properties, location specific precipitation levels, evapotranspiration etc.

In this study the stochasticity of the return came from yield stochasticity. The price stochasticity was not considered. Hence considering the price stochasticity will be a good future research area.

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APPENDIX

Table A1. Budgets of conventional crops.

Crops	Costs									
	2008	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**Average COP**	**15% of average**	**Mean+15%**
Wheat	180.779	129.705	142.198	263.453	183.719	168.654	158.366	175.268	26.290	201.558
Soybean	259.752	231.462	205.009	282.531	246.525	293.553	279.959	256.970	38.546	295.516
Corn	111.417	124.803	98.819	139.370	124.409	148.031	129.528	125.197	18.780	143.976

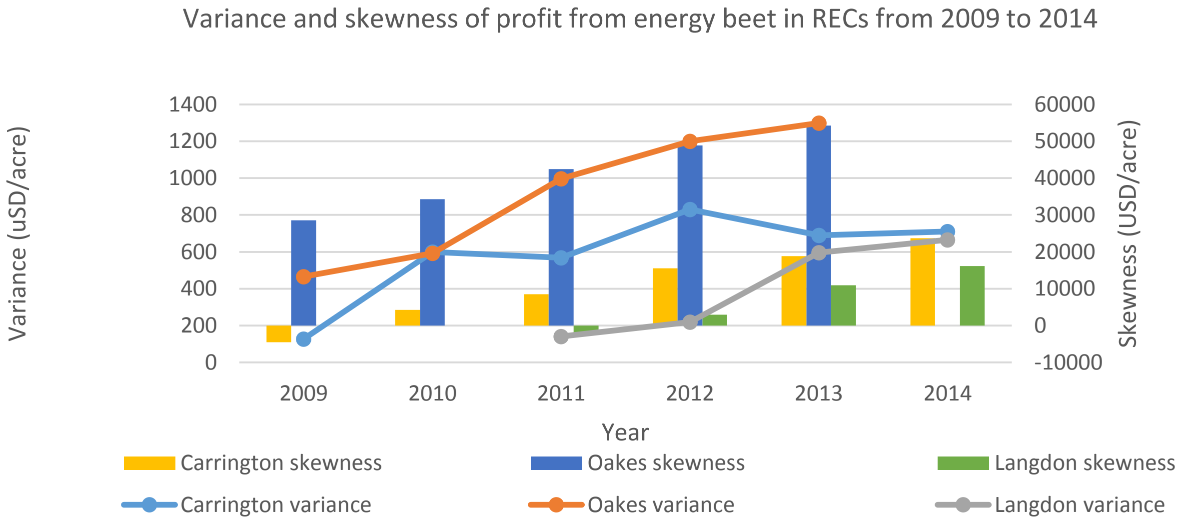

Figure A1. The evolution of variance and skewness of the profit of energy beet.

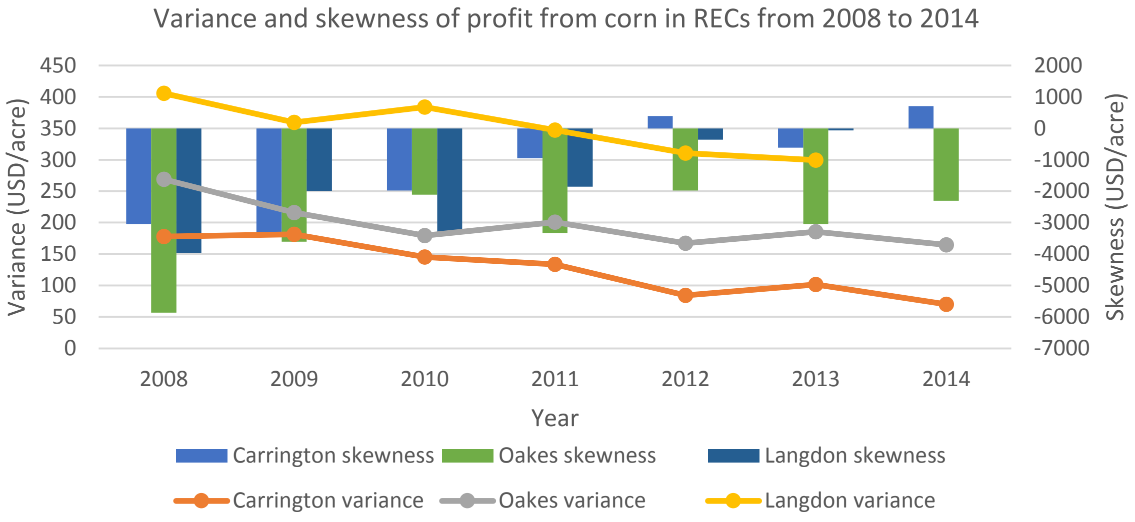

Figure A2. The evolution of variance and skewness of the profit of corn.

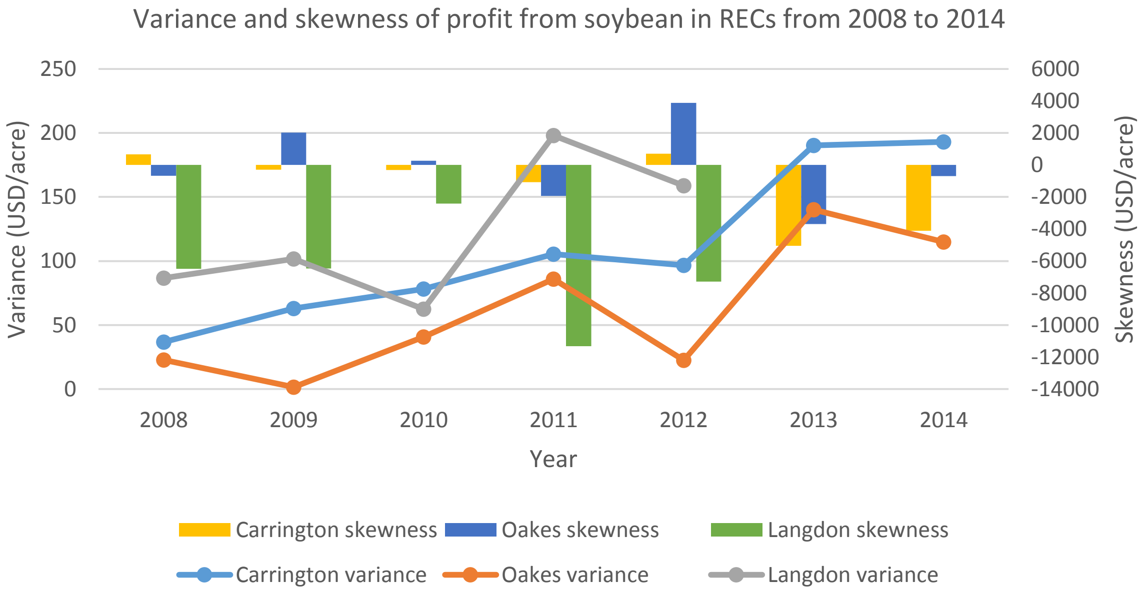

Figure A3. The evolution of variance and skewness of the profit of soybean.

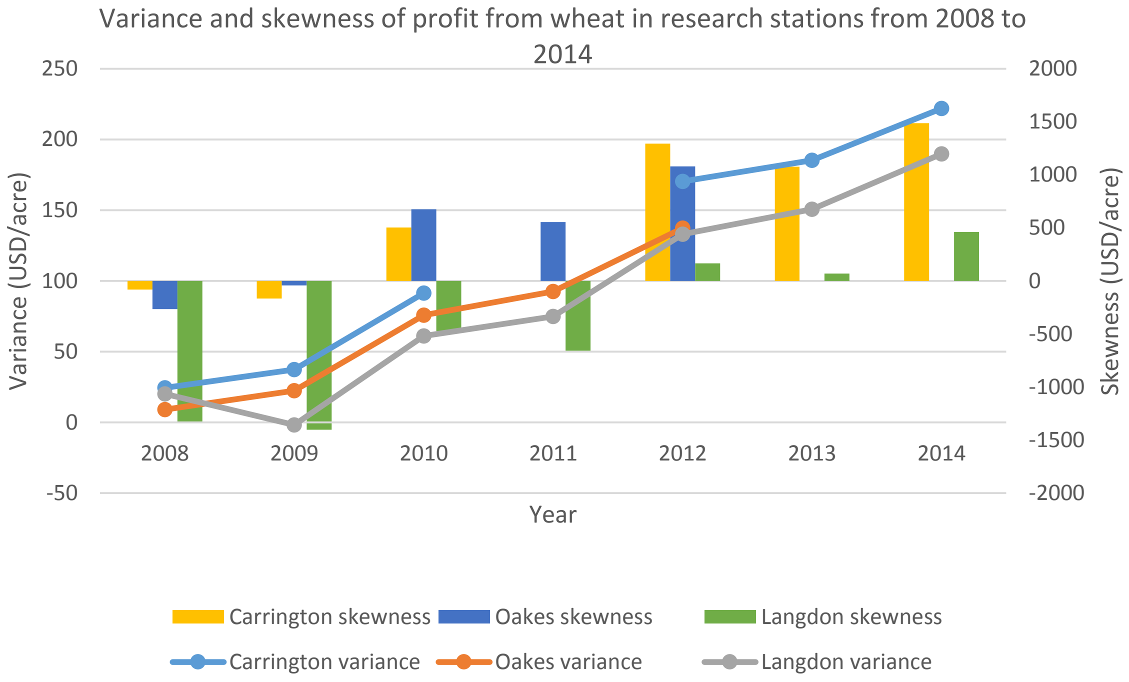

Figure A4. The evolution of variance and skewness of the profit of wheat.