國立屏東科技大學熱帶農業暨國際合作系
Department of Tropical Agriculture and International Cooperation
National Pingtung University of Science and Technology

博士學位論文
Ph.D. Dissertation

尼泊爾稻米、玉米、小麥之區域單位產量保險之研究—母數與無母數方法之應用

Area Yield Insurance of Rice, Maize, and Wheat in Nepal: Parametric and Non-Parametric Approaches

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中華民國 102 年 8 月 25 日
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This is to certify that Mr. Mahadeb Prasad Poudel has successfully passed the oral examination.

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摘要

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論文摘要內容:

因為道德風險和逆向選擇問題的弱點，使多風險作物保險商品因效率低而績效不彰；因此，選擇區域單位產量保險被建議可以用來減少多風險作物保險的這些弱點。過高或過低的保險費率也會影響作物保險的績，然而過去並沒有研究尼泊爾農業保險費率的研究。本研究目的即要精準地評估尼泊爾稻米、玉米、小麥之區域單位產量保險之保險費率及其績效。

本研究利用三種作物1990-91到2010-2011年各20個行政區的單位產量資料，進行實證分析。各20個行政區域的選擇條件，是該作物種植面積超過4,000公頃的行政區中，其單位產量的變異係數(coefficient of variance) 前20名者。本研究採用最小平方法(ordinary least square; OLS)和分量迴歸(quantile regression; QR)來預測單位產量，利用最大概似法(maximum likelihood estimation; MLE)來評估各模型參數。

本研究Anderson-Darling檢定結果顯示，OLS玉米、QR玉米、QR小麥的單位產量對Beta分配的配適度較佳，OLS稻米、QR稻米、OLS小麥對常態分配的配適度較佳，Lognormal分配則對三種作物的單位產量在

五個有母數分配中，配適度最低。除了在Banke區的稻米保險與Mugu區的小麥保險外，本研究評估的保險費率皆低於總責任的1%，這比過去相關研究的保險費率都低。以Beta分配評估的保險費率顯著地低於 Lognormal分配評估的保險費率，這表示不同的機率分配會導出顯著不同的保險費率評估。本研究結果無法分辨Kernel無母數分配所評估之保險費率與其他有母數分配所評估之保險費率之高低優劣。在玉米與小麥評估中，以QR預測單位產量評估之保險費率顯著地比以OLS預測單位產量評估之保險費率高。對配適度佳之非常態分配而言，以QR預測單位產量評估之保險費率皆比以OLS預測單位產量評估之保險費率高。

本研究結果發現在尼泊爾稻米、玉米、小麥之區域單位產量能保險成功地降低風險。另外，具有區域單位產量保險契約比沒有保險契約能獲得比較高的收益等值(certainty equivalent of the revenues; CER)，擁有保險契約可以使尼泊爾的農民獲得比較高的福利。

關鍵字：區域單位產量保險、保險費率、最小平方法、分量迴歸、母數方法、無母數方法、尼泊爾因

Abstract

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Name of Student: Mahadeb Prasad Poudel Adviser: Shwu-En Chen, Ph.D.

The contents of abstract in this dissertation:

Multiple peril crop insurance (MPCI) products seemed inefficient for actuarial performance because of vulnerability to moral hazard and adverse selection. Thus, the area yield insurance product is suggested as an alternative to MPCI as it is reported to be less vulnerable to those problems. Under and over rating of premium always remained a problem for the lower performance of crop insurance. There was none of research of insurance premium of agricultural production in Nepal. The objective of this study was to accurately estimate the pure premium rate for the area yield insurance of rice, maize, and wheat in Nepal and to evaluate its performance.

For this, this study applied yields data from 1990-91 to 2010-11 at twenty districts for each crop. The districts were selected if the cropped area was more than 4000 hectares for each crop in 2010-11 and the highest coefficient of variance (CV) of yields were the top twenty high. Ordinary least square (OLS) and quantile regression (QR) approaches were applied for yield prediction. The maximum likelihood estimation (MLE) method was used to estimate the parameters.

As a result, Anderson Darling (AD) test statistics showed the Beta distribution fitted well to OLS maize, QR maize, and QR wheat and Normal fitted well to OLS rice, QR rice, and OLS wheat yield series; Lognormal showed considerably least fitted among the five examined parametric distributions. The study observed smaller premium rates compared to the previous studies, i.e., mostly less than 1% of liability except in rice at Banke and wheat at Mugu district. The results showed that the probability distribution function plays a significant role in generating premium rate difference as the Beta distribution was observed to be significantly smaller premium rates among fitted distributions in contrast to those in Lognormal distribution. Our study could not observe any illustratable premium rate results of non-parametric Kernel distribution in comparison to other distributions. The significantly larger premium rates were observed with QR yield series as compared to OLS yield series in maize and wheat. Based on results, QR yield prediction approach may generate a larger premium rate than the OLS approach if the yield series is fitted well with non-normal distribution.

The area yield insurance contract was found successful in reducing the yield risk rice, maize, and wheat in Nepal. In addition, it also generated higher certainty equivalent of the revenues (CER) with area yield insurance contract indicated that area yield insurance can generate better welfare of the farmer in Nepal.

Keywords: area yield insurance, premium rate, quantile regression, OLS regression, parametric distribution, non-parametric distribution, Nepal

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1. Introduction

1.1 Statement of the Problem

Risk issues in agriculture have been discussed for years. Yield fluctuation is severe in agriculture since farming is exposed to the less controllable external environment. Variations in climate, disease and pest make agricultural production uncertain. The influences of such external factors can hardly be avoided; therefore, there are concerns on how to minimize the effect of production fluctuation. Among the risk management tools, crop insurance is considered one of the best tools to minimize the effect from farm income fluctuations. Many developed and a few developing countries have been offered crop insurance contracts for their farmers. However, crop insurance contracts are yet to develop in many developing countries.

Many problems are explained for the non-emergence of the crop insurance market in developing countries. Firstly, the crop insurance industry is difficult to sustain economically. Past experiences of practicing countries reveled collected premium in majority cases were lesser than the indemnity payments and the administrative costs (Hazell, 1992; Sigurdson and Sin, 1994). Therefore, governments need to invest huge amounts of money to cover losses for crop insurance agencies, which is an economic burden to taxpayers in a country. The main reason for this is that there is always a high probability of crop loss at large areas. Private entrepreneurs do not motivate to the crop insurance market. As it needs huge government support, the developing countries are far from the reach of the crop insurance.

Secondly, adverse selection and moral hazard are indicated as major problems in the crop insurance that may cause failure of crop insurance (Skees and Reed, 1986; Chambers, 1989; Quiggin *et al.*, 1994; Smith and

Goodwin, 1996; Coble *et al.*, 1997). The problem of moral hazard arises when the farmer modifies the crop management practices after buying the crop insurance. An insured farmer applies fewer inputs to get indemnity from the insurer. The moral hazard problem will be greater if monitoring of crop management practices is lesser. Likewise, adverse selection arises if higher risk farmers are highly motivated to buy the crop insurance in the same premium rate than the less risk farmers. These both problems arise because of asymmetric information, i.e., insurers will have less information and the insured will have more information on the risk situation. Both problems are naturally significant in the developing countries because of the existence of small scale as well as scattered farms. Monitoring of small scale and scattered farms is difficult, thus insurers will get less information about risk existence.

Thirdly, lack of proper yield data is another problem in designing a crop insurance product in the developing countries. The longer the data period, the higher will be the accuracy of actuarial estimation. Mostly, farm level yield data are said to be more precise for risk analysis and insurance rate making; however, they are lacking in the developing countries. Fortunately, area (counties, district) yield records are available even though it is for a shorter period.

Additionally, absence of precise premium rate estimation methods is indicated as another major problem of the non-emergence of the crop insurance market in developing countries (Ozaki *et al.*, 2008).

Group Risk Plan (GRP) or area yield insurance can be a better option to handle above the problems (Miranda, 1991; Skee *et al.,* 1997; Goodwin and Mahul, 2004; Ozaki *et al.*, 2008). GRP was introduced by Risk Management Agency (RMA) in 1994, but the approach was first suggested by Halcrow (1949). The main feature of this contract is indemnity payment that is made based on the realized area yields rather than farm yields. Since the change in crop management practice by an individual farmer does not influence the area yields, this insurance product can solve problem of moral hazard and adverse selection (Skees *et al.*, 19971; Miranda, 1991; Goodwin and Mahul, 2004). Besides, no monitoring is required for individual farmer's crop management and input use practices in the area yield insurance contract. This minimizes the administrative costs. In addition, this insurance product is helpful to minimize the problems of farm data requirement since it applies the area level yield data for actuarial estimation.

Importantly, a precise and accurate risk analysis has always remained an important issue while designing the crop insurance contracts (Botts and Boles, 1958; Yeh and Wu, 1966; Nelson, 1990; Goodwin, 1994; Field *et al.*, 2003; Lu *et al.*, 2008). The inaccurate risk assessment may cause under or over rating of insurance premium. In both cases, it can lead to the failure of crop insurance programs. Among many factors that generate biasness in the actuarial results, two issues are considered important. Firstly, inaccurate estimation expected yields will generate the bias in the premium rate (Zhu *et al.*, 2011; Adhikari *et al.*, 2012). Secondly, the shape of distribution plays important role to calculate the probability of yield loss and expected yield loss. Thus, fitting of the yield series to a proper probability distribution always remained the most important issue (Sherrick *et al.*, 2004). Failing to fit the proper distribution will generate an inaccurate premium rate.

Crop yields show an upward movement due to the technological evolution over the years. Therefore, the major issue is the proper prediction of the expected yield in crop area yield insurance. Application of different prediction methods will generate the different predicted yield. Most previous studies applied deterministic regression models (Goodwin and Mahul, 2004; Ozaki *et al*., 2008; Zhu *et al*., 2011), whereas other applied stochastic autoregressive integrated moving average (ARIMA) (Ker and Goodwin, 2000). Some other scholars applied spline and knot model (Harri *et al.*, 2011; Adhikari *et al.*, 2012). Although quantile regression is recommended for the yield prediction in the area yield insurance, it is hardly applied in past studies.

However, the debate is ongoing in the literature regarding which probability distribution does fit well to the crop yields. Some researchers are in support of Normality of yield distribution (Just and Weninger, 1999), and others are against the Normality of the yield distribution (Day, 1965; Ramirez, 1997; Ramirez *et al.*, 2003). Moreover, some applied parametric distributions and other applied non-parametric distributions in the actuarial estimation.

Both parametric and nonparametric distributions have been assumed in yield modeling as well as rate making in the crop yield insurance contracts. In the parametric group, the Normal and Beta distributions are frequently considered in designing the crop insurance (Ozaki *et al.*, 2008; Zhu *et al.*, 2011), whereas in the non-parametric group, Kernel distribution is frequently considered the best suitable one (Goodwin and Ker, 1998; Ker and Goodwin, 2000; Ozaki *et al.*, 2008). Sherrick et al. (2004) fitted Beta, Normal, Lognormal, Weibull, and Logistic distributions. Ramirez et al. (2010) applied Johnson unbounded, Johnson bounded, Beta, and Normal distributions. However, Gamma distribution has been rarely applied in the actuarial estimation.

Despite the interest for crop insurance programs in low and middle-income countries, there are few report on how to apply actuarial techniques outside high-income countries. Ozaki et al. (2008) reported to yield risk modeling and rate making by considering corn, wheat, and soybean yields in Brazil. Governments in many developing countries' have raised the interest to develop crop insurance in recent years. The Government of Nepal has raised the interest and approved the policy towards crop insurance in Agricultural Policy-2004 (GoN, 2004). A crop insurance feasibility study recommended the suitability of area yield and weather index insurance contract in Nepal (The World Bank, 2009). Further, Agriculture Development Strategy-2012 prioritized the crop insurance under the government program (GoN, 2012). Therefore, this study could be helpful in designing an appropriate insurance products and premium rate making in case of major cereals in Nepal.

1.2 Objectives of the Study

The objective of this study was to accurately estimate the pure premium rate of the area yield insurance of rice, maize, and wheat in Nepal and to evaluate its performance. In order to achieve the overall objective, this study applied the following approaches:

1. To estimate area yields of rice, maize, and wheat in Nepal;
2. To model parametric and non-parametric probability distribution functions of area yields;
3. To estimate the pure premium rates of area yield insurance;
4. To examine the difference of pure premium rates between different probability distributions and yield estimation approaches; and
5. To evaluate the performance of area yield insurance.

As a typical example of developing countries with high yield risk and absence of yield insurance, Nepal was selected to investigate the crop production insurance in this study. The crops of area yield insurance in this study were rice, maize, and wheat, which are major staple crops in Nepal.

The yield prediction is the first step in the process of pure premium estimation. In order to predict the yields of rice, maize, wheat in different districts in Nepal accurately, ordinary least square (OLS) and quantile regressions (QR), two linear yield prediction approaches were followed and applied the normalization. The OLS estimator is widely recognized that sum of square squared errors estimator remains unbiased and has minimum variance. However, OLS estimators may not be robust in case of data deviate from normality. Alternatively, quantile regression (QR) may be more robust. QR may offer advantages over OLS estimators in case of data are distributed non-normally. Consequently, OLS and QR estimation approach were adopted in the yield prediction.

To design a successful crop insurance, accurate estimation of distribution is important. To model the distribution of yield series, the normalized yields and goodness-of-fit tests were used. For crop yield distribution modeling, both parametric and non-parametric approaches were adopted in this study. The parametric approaches in this study applied Normal, Lognormal, Beta, Weibull, and Gamma distributions. Kernel distribution was selected for a non-parametric approach.

After the estimation of the pure premium rates of area yield insurance, the difference of pure premium rates due to different probability distributions and different yield prediction approaches was examined. Finally, whether the area yield insurance is effective in reducing yield risk and increasing the probability of getting higher income was evaluated in terms of risk reduction and certainty equivalent of the revenues.

1.3 Outline of the Study

The study consists of six chapters. Following the introduction in chapter one, chapter two gives a brief description of the cereal industry in Nepal. Chapter three is about literature review. Chapter four is about methodology applied during this research. This follows the results and discussion in Chapter five. The final chapter summarizes the results, outline the contributions, and suggest the further research.

2. Staple Crops in Nepal

2.1 Area, Production, and Productivity

Agriculture is the base of Nepal's economy that contributed about 33% of the gross domestic product (GDP) in 2010-11 (MoF, 2010-11). Cereal is the key supplier to the AGDP (agricultural gross domestic product) among sub-sectors. The major cereals in Nepal are rice, maize, wheat, millet, and barley, which collectively shared 36.36% to the total AGDP in 2006-07. As the cereals play a major role in the country's food security, the Nepalese Government has planned to increase the share of cereal in AGDP. Accordingly, the target was set to increase the share of cereals to 38.6% by the end of 2010-11 (NPC, 2008-09). Among different cereals, rice shares about 55.57%, maize 22.15%, wheat 17.99%, millet 3.87%, and barley 0.40% (nine years average of 2000-01 to 2009-10) (MoAD, 2010-11).

Rice, maize, and wheat are considered major staple crops in Nepal. Rice is the first staple food in ranking, which is grown in 73 districts out of 75 (except Manang and Mustang) districts. Area under rice was about 1.54 million hectares in 2004-05, which accounts for 46% of total cultivated agricultural lands in Nepal (AICC, 2004-05). The recorded national average rice yield was 2.98 metric ton per hectare and total national production was 4.46 million metric tons in 2010-11 (MoAD, 2010-11).

Maize is the second staple food in ranking. This crop is grown in all districts covering 0.91 million hectares that accounts for about 27% of the total cultivated agricultural lands in Nepal (AICC, 2004-05). The national average yields and production of maize in 2010-11 were 2.28 metric ton per hectare and 2.07 million metric tons, respectively.

Wheat is considered the third major staple food in Nepal. It is grown mostly in all districts covering about 0.77 million hectares representing about 22% of the total cultivated agricultural lands (AICC, 2004-05). About10.75 million metric tons production were recorded in 2010-11 with an average annual yield of 2.28 metric ton per hectare (MoAD, 2010-11).

The average annual growth rates of area, production, and yields for rice, maize, and wheat were observed in various magnitudes at national level during the last 5 decades (1960-61 to 2010-11). The areas of rice and maize grew modestly by 0.74%, and 2.08% per annum, whereas wheat areas grew drastically by 11.72% per annum (Figure 2.1). Similarly, the yields of rice grew by 1.05% per annum, maize by 0.38%, and wheat by 1.67% during the last five decades (Figure 2.2). Production of these cereals showed similar growth trends to the areas and yields as illustrated in Figure 2.3. Rice production grew by 2.19%, maize by 2.87%, and wheat by 23.4%. The tremendous wheat production growth observed during the periods was mainly due to area expansion.

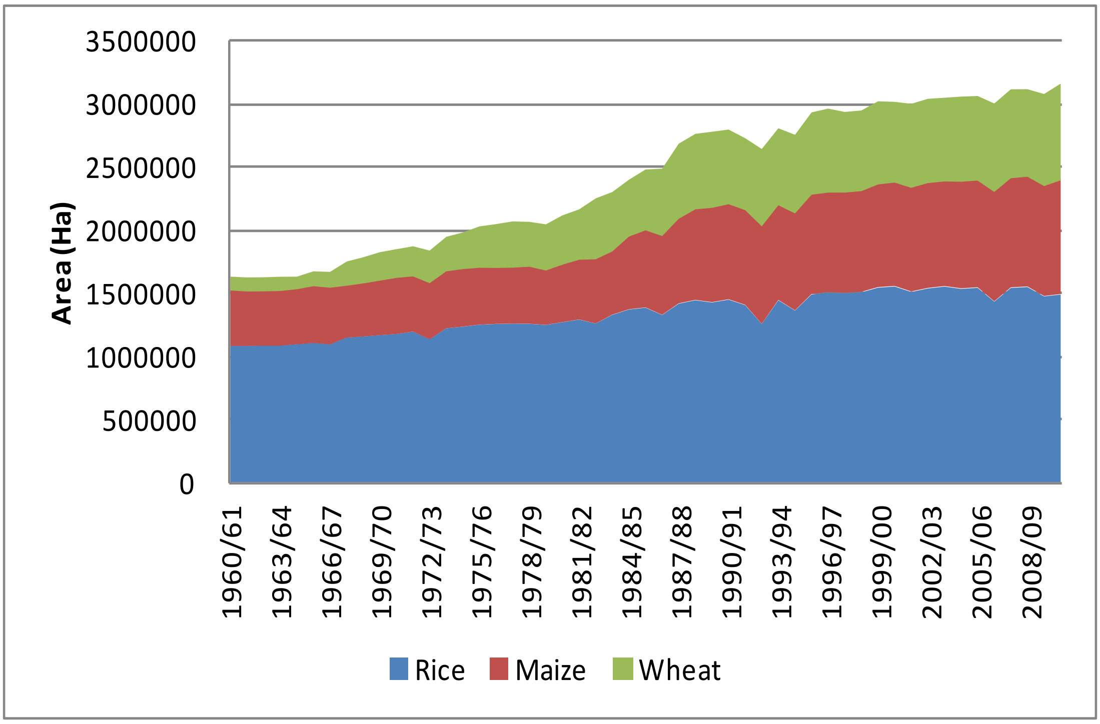

Figure 2.1 Trends of Rice, Maize, and Wheat Area in Nepal (1960-61 to 2010-11).

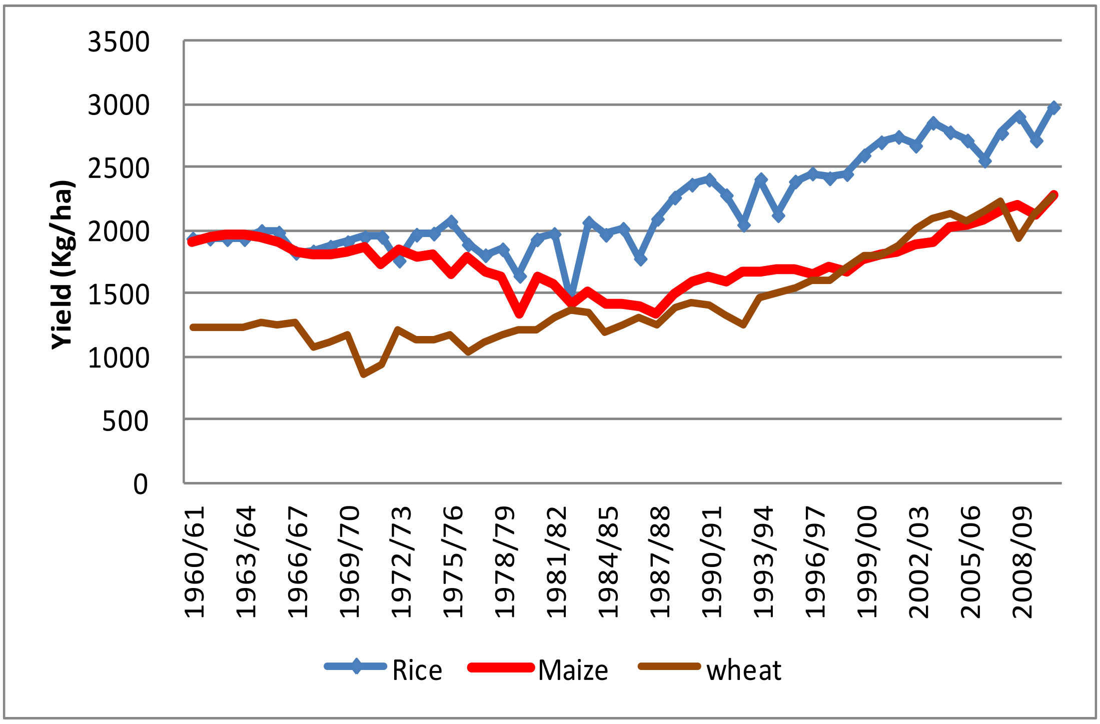

Figure 2.2 Trends of Rice, Maize, and Wheat Yields in Nepal (1960-61 to 2010-11).

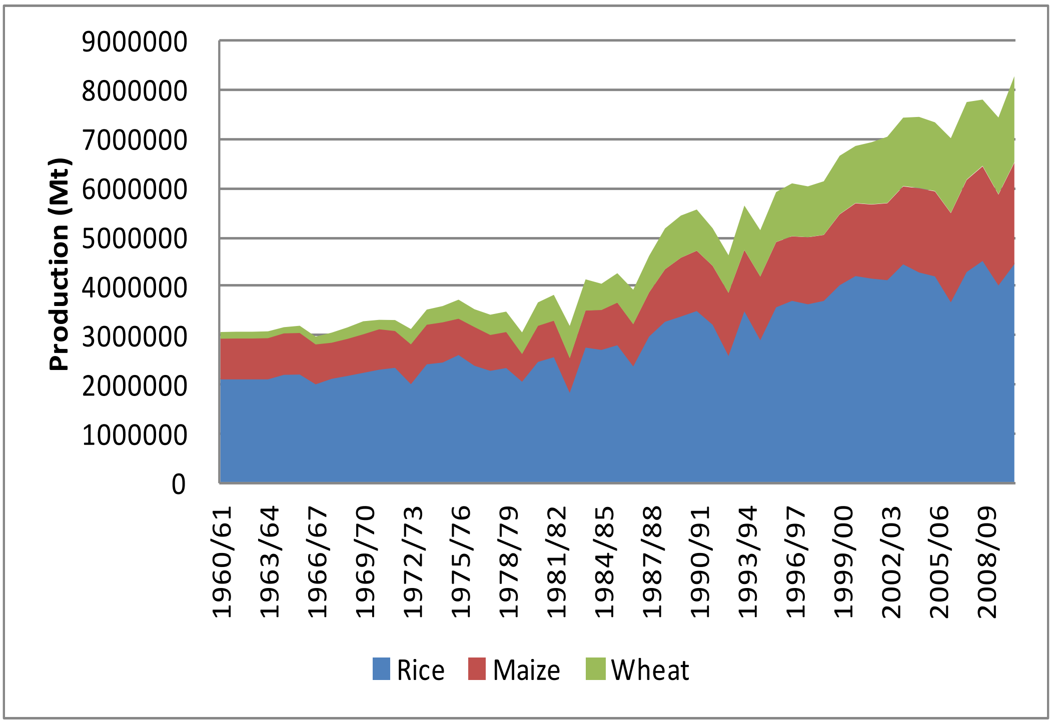

Figure 2.3 Trends of Rice, Maize, and Wheat Production in Nepal (1960-61 to 2010-11).

2.2 Yield Variation

The coefficients of variation in the national average yields of rice, maize, and wheat were observed at 17.16%, 12.67%, and 25.76% during 1960-61 to 2010-11. The coefficients of variation in rice and maize were seen modest, whereas in wheat, it was substantial. On the other hand, inter annual yield fluctuations were observed relatively higher in rice (Figure 2.2).

Previous studies in different countries indicated that climate change plays a role in cereal yield fluctuations. Poudel and Kotani (2012) reported that variation in climatic variables adversely affected rice and wheat yields in Nepal. They also indicated climate change heterogeneously influenced rice and wheat yield variabilities in Nepal.

We illustrated the coefficients of variation of rice, maize, and wheat yields to reveal situation of yield variations at districts level (Table 2.1).

Moreover, we also presented coefficient of variation (CV) of rice, maize, and wheat for individual districts in Figure 2.4, 2.5, and 2.6, respectively.

Table 2.1 Categories of Districts Based on Coefficient of Variation (CV) of Rice, Maize, and Wheat Yields in Nepal (1990-91 to 2010-11)

S.N.	CV (%)	Number of districts		
		Rice	maize	Wheat
1	Under10	10	7	0
2	10 to 15	40	30	7
3	15 to 20	17	27	38
4	20 to 25	5	7	24
5	25 to 30	1	1	3
6	30 and over	0	3	3
	Total	73	75	75

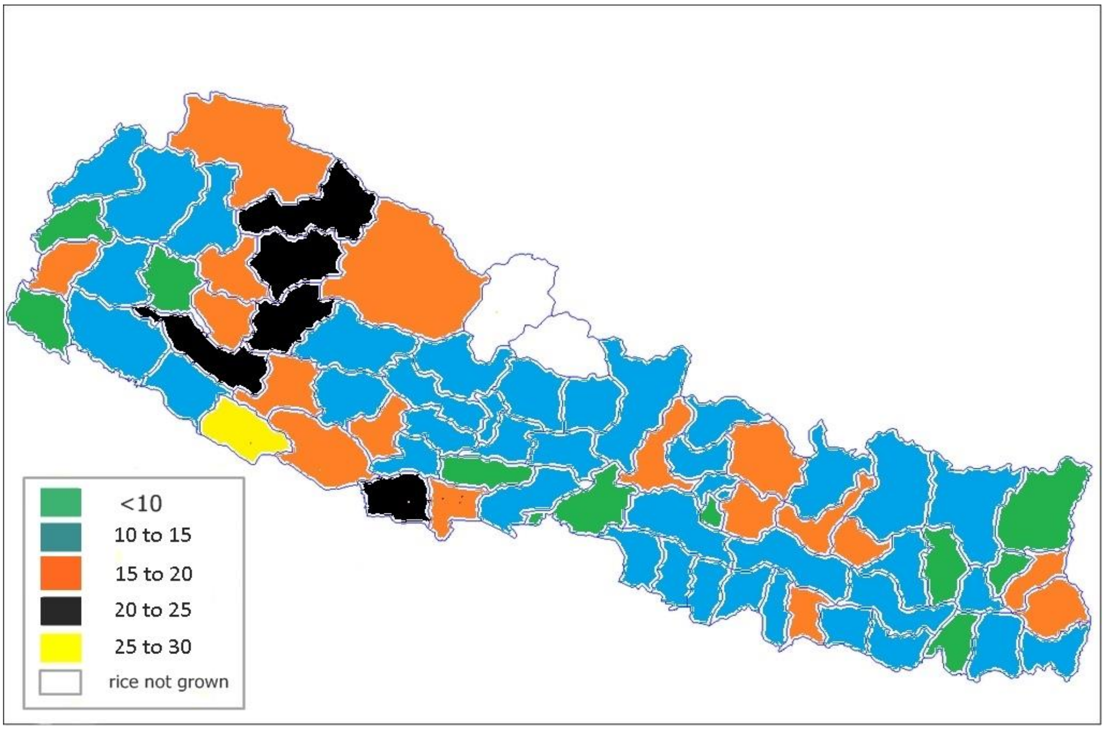

Figure 2.4 Coefficient of Variation of Rice Yields in Different Districts in Nepal (1990-91 to 2010-11).

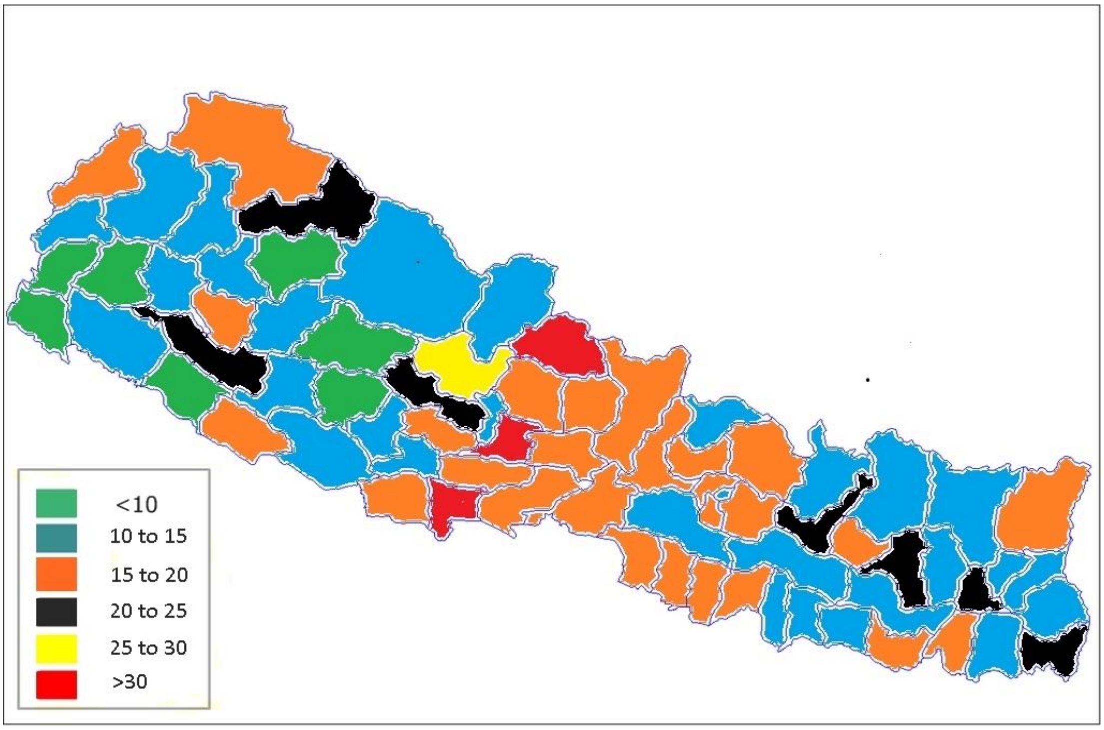

Figure 2.5 Coefficient of Variation of Maize Yields in Different Districts in Nepal (1990-91 to 2010-11).

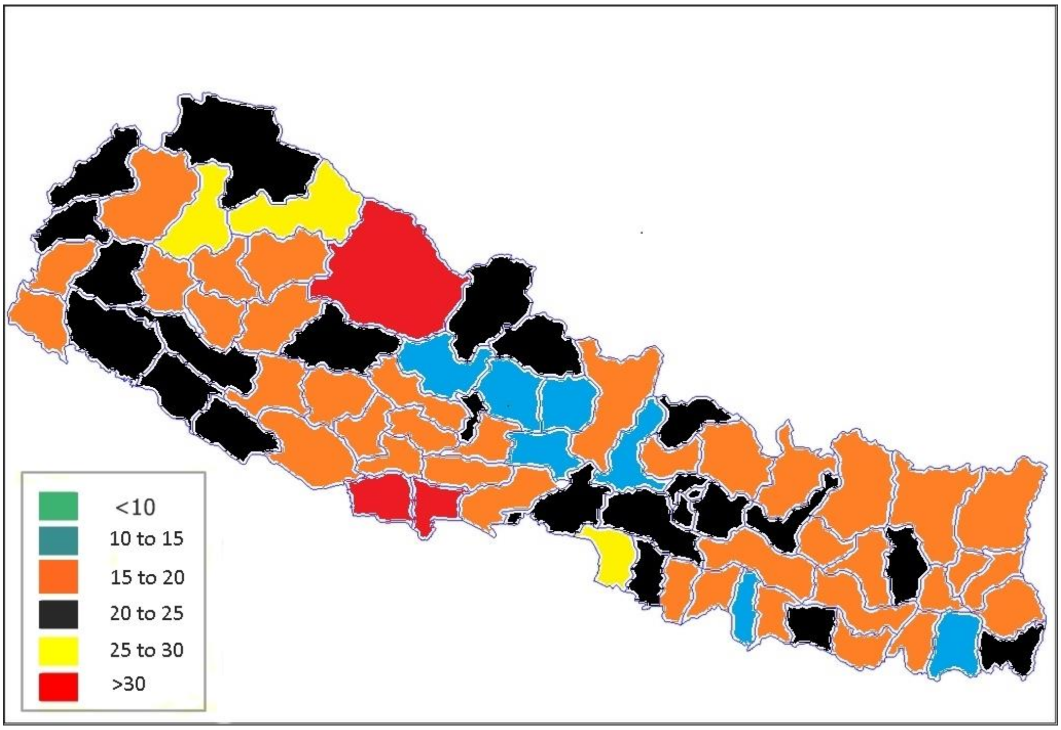

Figure 2.6 Coefficient of Variation of Wheat Yields in Different Districts in Nepal (1990-91 to 2010-11).

3. Literature Review

3.1 Risk and Uncertainty

There is no common definition of “risk” in the literature. Different scholars have defined “risk” differently. Thus, the opinion and perception for “risk” differs among people. The term risk mostly mixed with uncertainty because it is difficult to separate risk and uncertainty in a clear sense. Therefore, both terms are used interchangeably. Knight (1921) differentiated the risk and uncertainty as measurable uncertainty and immeasurable uncertainty. He explained risk as a measurable uncertain event. In the same way, Chavas (2004) defined risk as any situation where some events are known with certainty. Likewise, Seog (2010) explained risk in terms of probability of loss of a random variable. Besides, other scholars have used probability theory to differentiate risk with uncertainty. In probability theory, the risk is stated when the probability of outcomes is determined objectively but it cannot be determined objectively in the uncertainty.

The risk has a comprehensive meaning in a wide range of issues, such as, financial, economical, societal, and technological. Meaning of risk differs based on contexts and situations. In general, the meaning of risk is taken as negative connotation, such as, loss, harm, destruction or an undesirable event (Victor, 2004). Chavas (2004) emphasized the significance of risk due to three reasons. Firstly, risk is important because its precise measurement is difficult. Secondly, present knowledge of information processing is limited. Thirdly, obtaining and processing the information is costly. As a result, risk is the major factor to be considered before the final decision to be made in any economic activity.

3.2 Risk in Agriculture

By nature, the risk in agriculture is more important as compared to other enterprise because farming is often exposed to uncontrollable weather. In addition, its production process is long and exposed to biotic (disease, pests, weeds, and wildlife) and abiotic (weather, fire, earthquake, volcanoes, and others) factors. On the other hand, it is also affected by the volatile prices on inputs and outputs.

The sources of risk in farming are categorized in different groups. Some scholars have made five groups and other made for six or seven groups. The broad five categories of agricultural risk are: (1) production, (2) price or marketing, (3) financial, (4) legal, and (5) human resource or personal (USDA, 1997; Hardaker *et al.*, 2004; Kay *et al.*, 2008). Similarly, seven sources of risks in agriculture as: (1) production and yields, (2) market and prices, (3) severe casualties and disaster, (4) social and legal, (5) human management and labor, (6) technological changes and obsolescence, and (7) finance (Barry *et al.*, 1995). The risk categories presented by Barry et al. (2005) is more accurate because they included technological changes and obsolescence as an important category.

According to Hardaker et al. (2004), production risk mostly arises due to the unpredictability of weather and sudden outbreak of diseases and pests, whereas price risk arises because of unpredictable input and output price. Financial risk is associated with leverage that is related to the use of credit. Legal risk arises from the different obligations and income taxes placed by the government. In addition, human resource or personal risk arises due to the illness of manager and/or workers, strikes, and scarcity of labor at the time of working.

3.3 Effect of Risk in Agriculture

Risk plays a significant role in agricultural production and income of the farmer. Since the tolerability of risk is different among farmers, same risk may not have same level of shocks to the individual farmer. It affects more for low income farmers (Hazell, 1992). Risk shocks are disproportionate in low income countries than middle and higher income countries.

Risk plays a significant role in the decision behavior of the farmer. The farmer will modify his decision under risk condition compared to a normal situation. Studies have indicated that farmers will not be motivated to use marketed inputs in risky farming ventures. Dalal and Alghalith (2009) explained producers commit to decrease production in a production/price or both risk situations. Likewise, Pannell and Nordblom (1998) agreed that farmers reduce the volume of business to avoid the risk. They presented risk averse farmers substantially reduced the number of sheep in high risk conditions. However, they also indicated low risk averse farmer did not reduce the number of sheep at the same risk condition.

Batra and Ullah (1974) presented risk averse farmer utilized lesser amount of production inputs under price risk condition. Consequently, productions get lower compared to the farms operating in the price certainty condition. According to Krause et al. (1995), a positive response was observed to use inputs in the certainty condition of the expected price, whereas the opposite result was found in the case of the price risk. A firm maximizes the utility by minimizing the production cost in the price certainty case.

In general, the risk averse farmers reduce either the volume of input use or they cut the volume of production. Therefore, the optimal production capacity will be underutilized and the cost of risk goes to the farmer, consumers, and the nation as a whole.

3.4 Risk Management Tools in Agriculture

Hardaker et al. (2004) broadly categorized the risk management strategies in two categories for example, on-farm and risk sharing. Information collection, riskless technology selection, farm diversification, and flexibility are explained under on-farm strategies. Similarly, farm financing, insurance, share contracts, contract marketing, and trading in commodity derivatives are under risk sharing strategies. Harwood et al. (1999) explained farm risk management strategies as enterprise diversification, vertical integration, production contracts, hedging in futures, maintaining financial reserve, and leveraging liquidity, leasing inputs and hiring custom works, insuring crop yield and crop revenues, off- farm employment and other types of off-farm income, and others ways of managing risk.

Kay et al. (2008) presented risk management tools in separate headings, for instance management of production risk, market risk, financial risk, legal risk, and personal risk. They presented stable enterprise, diversification, insurance, extra production capacity, share leases, custom farming and feeding, and input procurement for production risk management. Likewise, spreading sales, contract sales, hedging, commodity options, flexibility are under price risk management tools. Similarly, fixed interest rates, Self-liquidating loans, liquid loans, credit reserve, owner equity are to financial risk management tools. Business organization, estate planning, and liability insurance are presented legal risk management tools. Finally, health insurance, life insurance, safety precautions, and backup management are placed for personal risk management tools.

3.5 Crop Insurance

Agriculture insurance was started in 1938 in the USA. At present, it has been offered in 86 countries (Mahul and Stutley, 2010). Farmers in higher and middle income countries are enjoying different kinds of agricultural insurance products. However, agriculture insurance in lower income countries has been either recently started in effect.

The demand of crop insurance has increased due to the increasing incidence of crop damaging weather events, introduction of exotic pests and diseases, commercialization in farming and others. However, farmers in many countries particularly in the developing countries are beyond the reach of the insurance contracts.

3.5.1 Types of Crop Insurance Products

Crop insurance products are broadly categorized in two kinds, i.e., yield protection and revenue protection. In the yield protection, crop insurance products are single peril, multiple perils, and all perils yield insurance. Among them multiple peril crop insurance (MPCI) is popular, which is also called actual production history (APH) product. Similarly, area yield insurance or group risk plan (GRP) is another category. MPCI product is based on individual farmer's yields but the area yield insurance is based on the yields of particular area.

Likewise, crop revenue coverage (CRC), revenue assurance (RA), and income protection (IP) are revenue insurance products. In addition, there is a new insurance product called weather index insurance, which is based on the weather events.

3.5.2 Problems of Multiple Peril Crop Insurance (MPCI)

MPCI is the most widely used crop insurance product. However, actuarial performance of multi-peril crop insurance product is poor. The poor actuarial performance is the main drawback for crop insurance market development. It is also considered that poor actuarial performance is the main limitation to develop insurance market in developing countries. Past experience showed a high loss ratio (indemnity payout divided by premiums collected) of multi perils crop insurance products (Hazell, 1992; Sigurdson and Sin, 1994; Skees and Professor, 2000). The indemnity payment plus administrative costs to premium ratio should be less than one for sound actuarial performance of the insurance program. However, Hazell (1992) presented this ratio 4.57 in Brazil (1975-81), 2.80 in Costa Rica (1970-89), 3.65 in Mexico (1980-89), 2.60 and 4.56 in Japan (1947-77 and 1985-89), and 2.42 in USA (1980-89). Likewise, Skees and Professor (2000) expected this ratio 3.68 in the US crop insurance program in 1999. From this ratio, we can estimate the insurance program in the US covers only 27% of its indemnity payment and administrative costs and the remaining costs (73%) need to be supported by the US government. The subsidy for federal crop insurance was 700-800 million USD per annum during 1980s (Smith et al., 1994). Similarly, the amount increased every year and rose to more than 5000 million USD in 2009 (Adhikari, 2011).

The poor actuarial performance of crop insurance was attributed by asymmetric information regarding risk situation. The asymmetric information regarding risk causes two problems-- adverse selection and moral hazard. In literature, the adverse selection and moral hazard are considered major problems for the poor performance of crop insurance programs (Skees and Reed, 1986; Chambers, 1989; Quiggin *et al.*, 1994; Smith and Goodwin, 1996; Coble *et al.*, 1997; Just *et al.*, 1999). When there is asymmetry in information between the insured and insurer, market failure condition arises. As a result, multiple risk crop insurance schemes are unable to collect enough premiums to cover the costs of indemnity and its administrative costs.

3.5.2.1 Moral Hazard

The moral hazard is characterized when the farmer modifies the crop management practices after buying the crop insurance products, such as, applying less fertilizer, pesticides, irrigation to increase the probability of collecting indemnity (Quiggin *et al.*, 1994).

3.5.2.2 Adverse Selection

Adverse selection is characterized when higher risk farmers buy the crop insurance, whereas lower risk farmer does not buy the crop insurance. Higher risk farmers are more motivated more to buy the crop insurance in the same premium rate than the less risk farmers (Quiggin *et al.*, 1994).

During 1980s and 1990s, a number of studies were conducted about the moral hazard and the adverse section problems. Quiggin et al. (1994) carried out studies to access the solution of adverse selection and moral hazard problems. Their findings could not present adequate support for the financial viability of multiple peril risk crop insurance.

Skees and Reed (1986) indicated the weakness of existing rate making procedure in the US federal crop insurance program that attributed to emerge the adverse selection in the Actual Production History (APH) crop insurance product. They mentioned two weaknesses in the existing rate making procedure. First, it considers the expected yield only and ignores the role of yield variance. This encourages buying insurance by higher yield variance farmer than the lower variance farmer. Secondly, it applies the trend unadjusted yields of the expected yield in the rate making procedure that encourages a farmer with the lower incremental yield trend to buy a contract than a farmer with the higher incremental yields.

The poor actuarial performance of the crop insurance program in the US received much attention and a debate begun in this issue in Congressional House and Senate Agricultural Committee and Administration. The committee suggested to review on existing crop insurance programs and also agreed to test the new crop insurance program. The federal crop insurance corporation (FCIC) introduced an area yield crop insurance product named as the Group Risk Plan (GRP) for crop year 1993-94. However, GRP was proposed by Halcrow (1949) as an alternative to individual yield crop insurance to solve the problem of adverse selection and moral hazard. The GRP is also called area yield crop insurance product.

3.6 Area Yield Insurance

The principle behind the area yield insurance product can solve the problem of moral hazard and adverse selection where the indemnity payment from area yield insurance is based on the realized area yields rather than farm yields. Individual farmer cannot influence the area yields. Thus, this insurance product can solve problem of moral hazard and adverse selection. Miranda (1991) agreed that area yield insurance at optimal coverage level can provide better yield loss coverage and could solve the problem of adverse selection and moral hazard problems.

3.6.1 Performance of Area Yield Insurance

Barry et al. (2005) examined 66,686 corn farms in 10 Corn Belt states and 3,152 sugar beet farms and revealed that the area yield insurance contract is comparable in the risk reduction to MPCI in some cases. Likewise, Smith et al. (1994) examined 123 dry land wheat producers in Montana and agreed that the area yield insurance can provide better risk reduction compared to the individual yield insurance contract. However, they presented higher premium rate in the area yield insurance. Deng et al. (2007) revealed area yield performs better than MPCI in the case of actual premium rate. MPCI preferred area yield insurance in case of actuarially fair premium rates. They concluded that area yield insurance may be a viable alternative to farm-level insurance when premium rates for farm contain large positive wedges.

It is free from moral hazard, adverse selection, and comparable in the risk reduction that provides enough support in favor of area yield insurance.

3.7 Yield Estimation Approaches

Crop yields show upward trends due to technological changes over the years, which exhibit non-constant data generating process. Thus, one cannot compare the yields observed in the 1990-91 with the yields in 2010-11. To make comparable the yields in 1990-91 with yields in 2010-11, different procedures are applied. According to Zhu et al. (2011), the commonly applied method is a conventional two-stage estimation framework.

In the two-stage framework, at first the yields are predicted by using different deterministic regression and stochastic models. In the second stage, detrending procedures are applied to make the yields comparable at different periods. In the deterministic procedure, different ordinary list squared regression, such as, linear (Goodwin and Mahul, 2004; Ozaki *et al.*, 2008; Adhikari *et al.*, 2012), quadratic (Lu *et al.*, 2010; Adhikari *et al.*, 2012), and polynomials (Ramirez *et al.*, 2003) has been applied. Deng et al. (2007) and Vedenov and Barnett (2004) applied log-linear model. Harri et al. (2011) and Adhikari et al. (2012) applied bilinear spline and knot method.

On the other hand, Ker (1996), Goodwin and Ker (1998), and Ker and Goodwin (2000) applied stochastic model, such as, autoregressive integrative moving average (ARIMA) for the yield prediction. Different model pose different in the predictability of yield, thereby generating difference in the expected yield.

Adhikari et al. (2012) noted that different yield prediction methods generate differences in the welfare effect due to crop insurance. OLS may not be robust for the yield prediction if yield series follow non-normality. Koenker and Bassett (1978) indicate that quantile regression may be more robust and offers better result over OLS if the yields follow non-normal distribution. Accordingly, Goodwin and Ker (1998) suggested quantile regression in the actuarial estimation purpose. However, no studies have applied quantile regression in the yield estimation for actuarial purpose.

The detrending of yield is carried out in the second step of two-stage estimation framework. This process is also called normalization. The normalization inflates yields at different periods. Two methods are applied for yield detrending. These two methods are based on the assumptions of constant (not affected by yield level) and non-constant errors (heteroscedasticity). If errors are assumed constant errors, one can add all the error to the reference yield (i.e., yield of last year of the data series) and generate the normalize yield series. However, if errors are assumed to affected by yield level, one can add the proportional errors (error divided by respective predicted yield) to the reference yield and generate the normalize yield series. This method can correct the heteroscedasticity problem.

3.8 Crop Yield Distribution Modeling

Rate making is a prime job in designing any successful crop insurance product. Proper modeling of yield series is important to accurately estimate the probability of yield loss, expected loss, and the rate making. Thus, it is necessary to understand the distribution of yield series.

There is a continuous debate in the present literature whether the crop yield series are distributed normally. The literature is divided into two groups, i.e., in favor of and against the normality. Just and Weninger (1999) support the normality of yield distribution. They argue non-normality results in past studies were due to three problems: (1) misspecification of nonrandom components of yield distributions, (2) misreporting of statistical significance, and (3) use of aggregate data. However, others strongly argue against the normality (Day, 1965; Taylor, 1990; Moss and Shonkwiler, 1993; Ramirez, 1997; Ramirez *et al.*, 2003). Ramirez et al. (2003) indicated yield series exhibit both negative and positive skewness.

The literature of the yield distribution modeling can be categorized in three broad categories parametric, semi-Parametric, and non-parametric.

3.8.1 Parametric Approach

This approach is based on the assumption that the stochastic behavior of the interest variables can be represented by the particular parametric distribution function. Parameters of specified distributions are estimated to describe the probability density or distribution function. The strength of this approach is that it can perform relatively well even in the small sample size. However, it contains the potential weakness of less flexibility to accurately model the crop yields. In the parametric modeling, the yield distribution is assumed to a particular distribution and the parameters of the candidate distribution area estimated. The maximum likelihood method has been commonly applied to estimate the parameters of the fitted parametric distribution.

The frequently applied parametric distributions for the yield distribution modeling are Normal (Goodwin and Mahul, 2004; Sherrick *et al.*, 2004; Ozaki *et al.*, 2008), Weibull (Sherrick *et al.*, 2004) Gamma (Gallagher, 1987), Beta (Nelson and Preckel, 1989; Goodwin and Mahul, 2004; Sherrick *et al.*, 2004; Ozaki *et al.*, 2008; Zhu *et al.*, 2011) , Lognormal (Day, 1965; Sherrick *et al.*, 2004), and logistic (Sherrick et al., 2004), Johnson family distributions (Lu *et al.*, 2008; Zhang and Wang, 2010).

3.8.2 Non-Parametric Approach

Another approach of crop yield distribution modeling is a non-parametric method. This method has opposite advantages and disadvantages of the parametric approach. It is free from functional form assumption. The non-parametric model is more flexible and exhibits lesser model specification error terms and has drawback of low performance in estimation at low sample size application. Moreover, the nonparametric approach cannot be applied for the prediction and simulation of yields beyond the sample framework.

The commonly applied non-parametric distribution for yield distribution modeling is a Kernel distribution (Goodwin and Ker, 1998; Ker and Goodwin, 2000; Goodwin and Mahul, 2004; Ozaki *et al.*, 2008).

3.8.3 Semi-Parametric Approach

Semi parametric models are considered more flexible than the parametric models and provide more precise estimation than the non-parametric methods in small sample application. However, the error risk persists in semi-parametric approach for small sample application.

Ker and Coble (2003) applied semi-parametric Beta distribution for yield distribution modeling and crop insurance rate making.

3.9 Weather Index Insurance

In the earlier section, we discussed MPCI has been suffered by poor actuarial performance. We also discussed area yield insurance has some advantages over MPCI. Similar to area yield insurance, weather index insurance products are less vulnerable to the problem of moral hazard and adverse selection. Therefore, weather index insurance is found self-sustaining. Some weather index insurance, particularly single peril insurance on hailstorm/hail is commercially feasible to offer by the private insurer. The literature indicates weather index insurance is well suited in the developing countries (Barnett and Mahul, 2007; Linnerooth-Bayer *et al.*, 2009). It is due to less vulnerability to moral hazard, adverse selection, and less costly to administer.

The weather index insurance contract is a new concept. There are only a few studies that have been conducted to design and rating premium. Martin et al. (2001) developed a rainfall derivative insurance of a cotton harvest in Mississippi by fitting rainfall for the Gamma distribution. The relationship between loss and amount of rainfall is presented and they estimated the premium rates and evaluated the weather derivatives based on the certainty equivalent of the revenues. Similarly, Vedenov and Barnett (2004) extended Martin et al. (2001) work and developed a weather derivative insurance of corn, cotton, and soybean. They fitted non-parametric Kernel distribution of weather index. They concluded that the weather index insurance is efficient based on the risk reduction, value at risk, and certainty equivalent of revenues.

The important challenge of developing a weather index product is to establish a relation between weather events and crop yields. It is more difficult in the case of developing countries because data on climatic factors, yields or both are not available for a longer time period.

3.10 Premium Rate in Area Yield Insurance

The premium rate is the amount of dollar paid for each dollar of liability for the insurance. In case of actuarially fair premium rate, the premium rate is equal to expected ensured loss (expected indemnities). Pure premium rate estimation methods differ in different insurance contracts. In area yield insurance contract, premium rate will be expressed as the ratio of expected loss to the total liability (Ker, 1996; Goodwin and Mahul, 2004).

For example, an insurance contract will pay indemnity when yields fall beneath the predefined guarantee level. The guarantee level of yields is a proportion (λ) of the expected yield μ. According to Goodwin and Mahul (2004), the expected insured loss is the product of the probability that a loss will be realized times the expected loss in a condition that loss occurs.

$$\text{Expected insured loss (y)} = Emax(\phi\text{y} - \text{y}_i, 0)$$

$$= \text{Prob}(\text{y}_i < \phi\text{y})(\phi\mu - \text{E}(\text{Y}|\text{y} < \phi\text{y}) \qquad (3.1)$$

$$\text{Pure premium rate} = \frac{\text{Expected insured loss}}{\text{Total Liability}} \qquad (3.2)$$

where E is expectation operator, ϕy is guarantee yield, and y_i is observed yield. $\text{Prob}(y_i < \phi y)$ is the probability of yield to be beneath the guarantee yield. This depends on the underlying yield distribution. Similarly, $(\phi y - y_i, 0)$ is the indemnity function.

The above equation is theoretical pure premium rate. Pure premium provides break-even condition for the insurer. This will not motivate private sector for the agriculture insurance market. Therefore, premium is composed of some other costs including pure premium rate (Goodwin and Mahul, 2004).

$$\text{Premium} = \text{pure premium} + \text{reserve load} + \text{administrative cost} + \text{return on equity} \quad (3.3)$$

where reserve load is a safety net for the insurer during the year of unexpected loss. This is mostly estimated as a % of pure premium, such as, 5% or 10%. Administrative costs and return on equity (profit) is added to constitute the premium so that insurance company will run without any financial problems.

4. Methodology

This study primarily focused on pure premium rate making based on area yield insurance for rice, maize, and wheat yields in Nepal. Moreover, this study utilizes the estimated pure premium rate to evaluate the effectiveness of area yield insurance based on yield risk reduction and utility maximization of the farmer.

The biasness in premium rate arises mainly due to the imprecise prediction of expected yields, i.e., under prediction or over prediction. Similarly, imprecise prediction of the probability of yield loss is another important factor to arise biasness. Thus, we applied the following procedures to estimate the precise pure premium rate of area yield insurance for rice, maize, and wheat yields in Nepal.

1. Two yield estimation approaches, i.e., ordinary least square and quantile regression were applied to rice, maize, and wheat in sample districts. The predicted yields were normalized to the yield of 2010-11 to make the yields of different years comparable.
2. Parametric and non-parametric probability distributions were fitted to the normalized yield series. Anderson Darling (AD) test was applied to examine the goodness of fit test for the parametric distributions.
3. We estimated the parameters of the each probability distribution. Maximum likelihood estimation (MLE) method was applied in the case of parametric distributions.
4. Parameter estimates of each distribution were applied to construct the shape of each probability distribution and to estimate the probability of yield loss at 90% coverage level of the expected yields of each crop in the sample district.

5. By multiplying the probability of yield loss and average yield loss, we estimated the expected yield loss. The expected yield loss is the pure premium in a physical unit, such as, kilogram per hectare.
6. The pure premium rate is estimated by dividing the expected yield loss with the liability (yield at 90% coverage level) and multiplying it by 100.
7. The study also examined the difference of the pure premium rates between probability distributions and yield estimation approaches by using Wilcoxon sign rank test.

In the next final step, the performance of area yield insurance was evaluated. Two approaches, such as risk, reduction and certainty equivalent of the revenues were applied to evaluate the performance of area yield insurance. The estimated premium rates were applied.

4.1 Yield Prediction

Crop yields show upward trend due to technological advancement over the years. Yields at different time periods are not comparable if the yields present an upward trend. Thus, fitting yields series in the proper data generating process is important.

In the present literature, deterministic regression methods, such as, linear, quadratic, and polynomial are frequently applied for yield detrending. Similarly, other applied methods are autoregressive moving average (ARIMA), spline, and nonparametric smoothing. We applied of two regression approaches, i.e., ordinary least square (OLS) and quantile regression (QR).

4.1.1 Ordinary Least Square (OLS)

The OLS estimator is selected because it is widely recognized that sum of square squared errors estimator remains unbiased and has minimum variance (Goodwin and Ker, 1998). Moreover, this estimator is simple and convenient to apply and provide the plausible results to capture the trends of yield growth. Many previous studies applied this approach. We applied this technique for yield prediction because it is already considered by previous studies (Goodwin and Mahul, 2004; Ozaki *et al.*, 2008) and the results from this technique can be taken as a reference value to compare the results from other yield estimation techniques.

4.1.2 Quantile Regression (QR)

Although least square techniques are convenient to apply for yield prediction, it may not be robust in case if yields deviate from normality. The quantile regression may offer advantages over least square estimators if yields follow a non-normal distribution (Koenker and Bassett, 1978; Sarker *et al.*, 2012). Accordingly, Goodwin and Ker (1998) suggested that quantile regression estimator can be applied for yield prediction for actuarial estimation. Thus, this study considered quantile regression for yield prediction.

We followed a linear approach rather than polynomial regression due to shortness of data set. Both linear OLS and linear quantile regressions follow the same specification. The model is

$$y_{ijt} = \alpha_{ij} + \beta_{ij}t + u_{ijt} \tag{4.1}$$

where y_{ijt} is the yield of crop i of district j at time t. Likewise, u_{ijt} represents the residual with mean 0 and variance σ_y^2.

Normalization of yield is the process of yield detrending in relation to the reference yield. It makes the yields of different years comparable. There are two types of normalization. The first one is the simple addition of error terms to the reference yield and the second is the addition of ratio of error term of its predicted yield to the reference yield. The first method is applied when the yield variance is assumed constant, while the second one is used when the yield variance is non-constant (heteroscedasticity). The second one is helpful to correct the potential problem of non-constant yield variation (Goodwin and Ker, 1998; Ozaki *et al.*, 2008). In this study, we found non-constant variance of yields in some yield series as presented in Table 5.1, Table 5.2, and Table 5.3; we; therefore, applied the second method for yield normalization. Moreover, we normalized the yields to a 2010-11 level. By normalizing yields to the yield of 2010-11, all the yields are become comparable to the yield of 2010-11. The yield normalization model is

$$\tilde{y}_{ijt} = y_{ij2010-11} + \left(\frac{\hat{u}_{ijt}}{\hat{y}_{ijt}}\right) * y_{ij2010-11} \quad (4.2)$$

where $\tilde{y}_{ijt}$ is the normalized yield of crop i of district j at time t and $y_{ij2010-11}$ is the yield of crop i of district j in 2010-11; $\hat{y}_{ijt}$ is the predicted yield and $\hat{u}_{ijt}$ is the error, the difference between actual yield and predicted yield.

In the next step, the normalized yield series were fitted to the parametric and non-parametric distributions.

4.2 Yield Distributions

The assessment of probability of yield loss is a primary step in actuarial estimation irrespective of insurance product. The shape of the distribution plays a significant role to determine the probability of yield loss. Past studies indicated the significance of different distributions in the pure premium rate. Sherrick et al. (2004) compared premium rates based on five parametric distributions and showed the different results between distributions. Likewise, Ozaki et al. (2008) and Goodwin and Mahul (2004) compared the premium rates based on parametric and non-parametric distribution. They concluded that premium rates may vary because of differences in the fitted distributions.

Modeling of yield series to a particular probability distribution is based on the assumption that the yield distribution is fitted well to that distribution.

In the case of parametric distribution, specific assumptions are made for the shape and scale parameters of the parametric distribution while in case of non-parametric distribution no such specific assumptions are made. The problem in fitting parametric distribution is that whether the yield series is fitted well to the distribution and the parameters can truly represent the shape yield series.

This study applied five parametric distributions and one non-parametric distribution for yield distribution modeling. Normal, Lognormal, Beta, Gamma, and Weibull are the parametric distributions and Gaussian Kernel is the non-parametric. The applied distributions are explained in section 4.2.1.

4.2.1 Parametric and Non-Parametric Distributions

4.2.1.1 Normal Distribution

The Normal distribution is the most widely applied distribution in the statistics. It is a bell shaped and symmetrical distribution. This distribution is inflexible in nature because of its constant skewness (0) and kurtosis (3) values. There are ongoing debates in literature whether the crop yields are distributed normally. Some authors believe yield series follow a normal distribution while others are against this opinion. Previous studies have widely applied this distribution in crop insurance rate making (Botts and Boles, 1958; Just and Waninger, 1999; Sherrick *et al.*, 2004; Ozaki *et al.*, 2008). We applied this distribution in this study for two reasons. Firstly, some authors believe that yield series follow the normal distribution and successfully applied in the crop insurance rate making. Secondly, this distribution is efficient in the condition of data shortness. This distribution is a probability distribution of a random variable whose logarithm is normally distributed.

4.2.1.2 Lognormal Distribution

We applied Lognormal distribution to evaluate the fitness to the yield series for rice, maize, and wheat in Nepal and premium rate estimation. It is a distribution of a random variable whose logarithm is normally distributed. Lognormal distribution is a positively skewed distribution. The distribution is fitted to the exponentially distributed variables. Stokes (2000) and Sherrick et al. (2004) applied this distribution in yield distribution modeling and premium rate making. Sherrick et al. (2004) revealed lognormal distribution was the least fitted distribution among the five fitted distributions of corn and soybean yields in the USA.

4.2.1.3 Beta Distribution

The Beta distribution has a wide range of skewness and kurtosis. This distribution is both positively and negatively skewed. The highly flexible characteristic of skewness and kurtosis make this distribution empirically appealing. Many studies have applied beta distribution in yield distribution modeling and premium rate making (Nelson and Preckel, 1989; Babcock and Hennessy, 1996; Sherrick *et al.*, 2004; Ozaki *et al.*, 2008; Lu *et al.*, 2008). Sherrick et al. (2004) revealed that the Beta distribution performed highest in rank for goodness of fitness in both corn and soybean.

4.2.1.4 Weibull Distribution

This distribution is also a relatively flexible distribution and permits positive or negative skewness values. Because of its flexible nature, the Weibull distribution is one of the frequently applied distributions for crop yield modeling. Sherrick et al. (2004) revealed that Weibull distribution performed the best fittings among five distributions to the corn and soybean yield in the USA.

4.2.1.5 Gamma Distribution

This distribution is a positively skewed distribution (Ramirez *et al.*, 2010) and poses a better flexibility than the Normal distribution (Martin *et al.*, 2001). The Gamma distribution is less frequently applied in the crop yield distribution modeling. Gallagher (1987) applied the Gamma distribution for U.S. soybean yields estimation and forecasting. However, no studies have applied this distribution for premium rate making.

4.2.1.6 Gaussian Kernel Distribution

This study applied non-parametric distributions because they are superior to the parametric distribution in some aspects. Non-parametric distributions are more flexible because unlike parametric distribution they have no any defined shape. Thus, the shape of the distribution is defined by the data itself. Non- parametric distributions can capture the distribution of bimodality and multimodality, which is not possible in case of parametric distribution. Non-parametric distributions are sensitive in the case of data shortness. Therefore, both parametric and non-parametric distributions were applied in this study.

Among the different Kernel distributions, Gaussian Kernel is the simplest in estimation. It is the most widely applied distribution for premium rate making (Goodwin and Ker, 1998; Ker and Goodwin, 2000; Ozaki *et al.*, 2008).

4.2.2 Goodness-of-fit Test

Goodness-of-fit test is applied to examine the fitness of yield series to the particular distribution. Recent literature of crop insurance has been applied in different goodness of fit tests. The most commonly applied goodness of fit tests are Shapiro-Wilk statistics, Anderson Darling test, Kolmogorov Smirnov Test, and Chi-Squared test.

We applied Anderson Darling test (1952) to examine the goodness-of- fit for parametric distributions. The reason behind this is this study is more concerned on the tail part of the distribution and while comparing the distance between sample points and ECDF in the AD test it assigns weights more heavily to the tail region of the distribution (D' Agostino and Stephens, 1986; Corder and Foreman, 2009). This test measures the distance between each sample point in the empirical cumulative distribution function (ECDF) and fitted probability density function at that point and to examine whether the yield distribution fits closely with theoretical probability distribution (Sherrick *et al.*, 2004; Fischer *et al.*, 2012).

The test statistics (A^2) measures how well the data follow the candidate distribution. The smaller test statistics will be the better fits for the data to the candidate distribution. The AD test model explained by Sherrick et al. (2004) and Law and Kelton (2000) is

$$A_n^2 = n\int_{-\infty}^{\infty}\left[F_n(x) - \hat{F}(x)\right]^2 \psi(x)\hat{f}(x)d(x) \tag{4.3}$$

where the weight function $\psi(x) = 1/[F_n\,(x)(1 - \hat{F}(x))]$, $F(.)$ is fitted cumulative distribution function, $f(.)$ is fitted probability density function, n is the sample size. Therefore, A_n^2 is a weighted average of $[F_n\,(x)(1 - \hat{F}(x))]^2$. The applied model for the AD test is

$$A_n^2 = \left(-\left\{\sum_{i=1}^{n}(2i-1)\left[\ln(\hat{F}(x_i) + \ln\left(1 - \hat{F}(x_{n+1-i})\right)\right]\right\}/n\right) - n \tag{4.4}$$

4.2.3 Parameters Estimation

We estimated the parameters of shape and scale parameters of the parametric distributions and bandwidth of non-parametric distribution. Mean and standard deviations of Normal distribution and bandwidth of kernel distribution were estimated by using an ordinary estimation technique, whereas shape and scale parameters of Lognormal, Beta, Weibull, and Gamma distributions were estimated by using the maximum likelihood estimation (MLE).

There are two approaches in the literature to estimate the parameters of parametric distributions, i.e., maximum likelihood and method of moment estimation methods. The maximum likelihood estimation (MLE) method provides better outcomes even in shorter data length. Thus, we applied MLE in this study.

Log likelihood approaches are used to estimate the parameters because the log likelihood approaches are convenient to apply in the MLE. The log likelihood models for Lognormal, Beta, Weibull, and Gamma distribution are

4.2.3.1 Lognormal

$$LL_{LN} = -n\,ln\left(\tilde{y}_{ijt} - \theta\right) - \frac{n}{2}ln(2\pi) - \mathrm{n}\,ln(\sigma) - \frac{1}{2\sigma^2}\sum_{i=1}^{n}\left(ln\left(\tilde{y}_{ijt} - \theta\right) - \boldsymbol{\zeta}\right)^2 \quad (4.5)$$

where $\tilde{y}_{ijt}$ is the normalized yield, n is the number of observations, θ is the threshold parameter ($\theta = 0$), σ is the shape parameter ($\sigma > 0$), $\boldsymbol{\zeta}$ is the scale parameter ($-\infty < \boldsymbol{\zeta} < \infty$).

4.2.3.2 Beta

$$LL_B = \sum_{i=1}^{n}\left((\alpha - 1)\,ln\left(\tilde{y}_{ijt} - \theta\right)^+\right) + \sum_{i=1}^{n}\left((\beta - 1)\,ln\left(\delta + \theta - \tilde{y}_{ijt}\right)^+\right) + \sum_{i=1}^{n}\left(\ln\left(B(\alpha,\beta)\right)\right) + \sum_{i=1}^{n}(\alpha + \beta - 1)\ln(\delta) \quad (4.6)$$

where $\ln\big(B(\alpha,\beta)\big) = \ln\big(\Gamma(\alpha)\big) + \ln\big(\Gamma(\beta)\big) - \ln\big(\Gamma(\alpha+\beta)\big)$ and $ln(\alpha)^{+} = ln(\alpha)$ if $\alpha > 0$, $ln(\alpha)^{+} = 0$ otherwise, which ensure $\theta \leq \tilde{y} \leq \theta + \delta\ \forall t$, for any θ, δ>0, $\tilde{y}_{ijt}$ the normalized yield, n is the number of observations, θ ($\theta \geq 0$) is the location parameter, α, β are shape parameters , and $\delta(\delta \geq 0)$ scale parameters and Γ is the gamma function.

The upper limit of the beta distribution was set at 20% above the maximum yield recorded. Ker and Coble (1998) suggest that further sensitivity analysis should be considered when upper limits on the beta distribution are defined arbitrarily. The importance of imposing an upper yield on the beta distributions can be assessed by comparing the probability mass above the maximum yields. Sherrick et al. (2004) applied at 10% above the maximum yield recorded. In this study, we set at 20% above the maximum yield recorded because the yield series showed the positive skewness in majority of the cases.

4.2.3.3 Weibull

$$LL_W = n\ln(c) + (c-1)\sum_{i=1}^{n}(\ln\big(\tilde{y}_{ijt} - \theta\big) - nc\ln(\sigma) - \sum_{i=1}^{n}\left(\frac{\tilde{y}_{ijt-}\theta}{\sigma}\right)^{c} \quad (4.7)$$

where $\tilde{y}_{ijt}$ is the normalized yield, n is the number of observations, θ is the threshold parameter ($\theta = 0$), σ is the scale parameter ($\sigma > 0$), and c is the shape parameter ($c > 0$).

4.2.3.4 Gamma

$$LL_G = (\alpha - 1)\sum_{i=1}^{n}(\ln(\tilde{y}_{ijt} - \theta) - nln\Gamma(\alpha) - n\alpha\ln(\sigma) -$$

$$\frac{1}{\sigma}\sum_{i=1}^{n}\big(\tilde{y}_{ijt} - \theta\big) \quad (4.8)$$

where $\tilde{y}_{ijt}$ is the normalized yield, n is the number of observations, θ is the threshold parameter ($\theta = 0$), σ is the scale parameter ($\sigma > 0$), α is the shape parameter ($\alpha > 0$), and Γ is the gamma function.

4.2.3.5 Gaussian Kernel

Non-parametric distributions do not need prior assumptions of shape and scale parameters to define the shape of the distribution. The Gaussian Kernel distribution model explained by Goodwin and Ker (1998); Ozaki et al. (2008) is

$$\hat{f}_{\lambda}(y) = \frac{1}{n(\lambda)} \sum_{i=1}^{n} \mathrm{K}_0 \left(\frac{y - \tilde{y}_{ijt}}{\lambda} \right) \tag{4.9}$$

where $\mathrm{K}_0(.)$ is the kernel function, n is the sample size, $\tilde{y}_{ijt}$ is the normalized yield at time t, and λ is a bandwidth. Here $\lambda = cQn^{-\frac{1}{5}}$, c is a standardized bandwidth and Q is interquartile range. Thus, $c = \lambda / Qn^{-\frac{1}{5}}$.

The smoothness of the kernel density depends on the bandwidth parameter. If the bandwidth is larger (smaller), the shape of the density is smoother (rough). Silverman (1986) adopted mean integrated squared error (MISE) to measure the discrepancy of $\hat{\mathrm{f}}_{\lambda}(.)$ in relation to the true density. Silverman (1986) explained the choice of optimum smoothing parameter for the Gaussian Kernel distribution, $1.06 * \sigma n^{-1/5}$. Ozaki et al. (2008) explained that the smoothing parameter factor reduced from 1.06 to 0.90 showed better results. In this study, we let the optimum value to be chosen based on data series.

4.3 Premium Rate

Insurance ratemaking is the most important part in any crop insurance product. The success of crop insurance product depends on the accuracy of premium rate. It is based on two factors-- average yield loss of yield and probability of yield loss. Probability of yield loss of guarantee yield is estimated based on the area under a curve. The estimated parameters were applied to construct the parametric and non-parametric distributions and estimated the probability of yield loss. The area under the curve is estimated following trapezoidal rule.

The pure premium rate was estimated in this study because it is based on the risk situations of the area yield and does not include the administrative costs to administer the insurance. The study followed pure premium rate estimation model that was applied in the previous studies (Goodwin and Ker, 1998; Ker and Goodwin, 2000; Ozaki *et al.*, 2008). The fair premium rate estimation model is

$$Pure\ Premium\ rate\ (\pi) = \frac{F_Y(\phi y^e) E_Y[\phi y^e - (Y|y < \phi y^e)]}{\phi y^e} \qquad (4.10)$$

where E_Y is expectation operator, y^e expected yield, Y is observed yield, ϕ is coverage level ($0 < \phi < 1$), and $F_Y(.)$ is the probability of loss based on respective applied density functions.

The estimated pure premium rate is applied to evaluate the effectiveness of the area yield insurance.

4.4 Effectiveness of Area Yield Insurance

In this study we evaluated the effectiveness of area yield insurance in two approaches. The first approach measures the risk reduction while the second approach measures the income change of the farmer due to area yield insurance.

4.4.1 Risk Reduction

Since the motivation of crop insurance is to reduce the yield risk, the effectiveness of area yield insurance is to reduce the yield variance of individual insured farmer. However, yield risk reduction of a farmer depends on the correlation of farmer's yields to the area yields. If the farm yield is highly correlated, risk reduction will be higher and vice versa. Miranda (1991) suggests the relationship of farm to area yields. Later, other studies (Mahul, 1999; Carriquiry *et al.*, 2008; Adhikari *et al.*, 2012) also applied this model to estimate farm to area yield relations. The model by Miranda is

$$Y_{Ft} = \mu_F + \beta_F(Y_{At} - \mu_A) + \epsilon_{Ft} \tag{4.11}$$

where Y_{Ft} represents farm yield, μ_F is farm mean yield, μ_A is area mean yield Y_{At} is area yield, ϵ_{Ft} is error term, and t is the time index. The random term ϵ_{Ft} is assumed to be $E(\epsilon_{Ft}) = 0$, and $Var(\epsilon_{Ft}) = \sigma^2_{\epsilon_{Ft}}$. Similarly, it is also assumed that Cov $(Y_{Ft}, \epsilon_{Ft}) = 0$, $EY_{Ft} = \mu_F$, $Var(Y_{Ft}) = \sigma^2_{Y_F}$, $EY_{At} = \mu_A$, and $Var(Y_{At}) = \sigma^2_{Y_A}$.

Similarly,

$$\beta_F = Cov(Y_{Ft,}Y_{At})/\sigma^2_F \tag{4.12}$$

We assumed in area yield insurance that the premium and indemnity are paid in production unit, i.e., kilogram per hectare. The farmer buys insurance for certain coverage at a premium rate of π kilogram per hectare as estimated by equation (4.10). If the area yield $\mathrm{Y_A}$ falls below the guarantee yield($\phi \mathrm{y^e}$), the insurer receives an indemnity, I in kilogram per hectare. The indemnity equation applied by Miranda (1991) is

$$I = \max(\phi y^e - Y_A, 0) \tag{4.13}$$

Producer's net yield equals

$$Y_F^{net} = Y_A + I - \pi \tag{4.14}$$

where Y_F^{net} net yield of a producer in a unit area, Y_A is realized yield, I, indemnity received (if realized yield falls below guarantee yield level), and π is the premium paid for the area yield insurance to the guarantee yield at certain levels.

We then need to measure the yield risk of the net yield as a variance of the net yield. The variance of net yield equals

$$Var(Y_F^{net}) = \sigma_F^2 + \sigma_I^2 + 2.Cov(Y_F, I) \tag{4.15}$$

With area yield insurance, the yield risk reduction of the insured farmer will be as

$$\Delta_F = Var(Y_F) - Var(Y_F^{net}) = -\sigma_I^2 - 2.Cov(Y_F, I) \tag{4.16}$$

4.4.2 Certainty Equivalent of Revenues

Risk-averse farmer will be motivated to buy an area insurance contract with indemnity I(.) and premium π (.) schedules if he is convinced his utility will be higher with the insurance, i.e., Max $\mathrm{EU}(\mathrm{X_i}/\mathrm{I}, \pi) \geq$ Max $\mathrm{EU}(\mathrm{X_i})$. Thus, a successful crop insurance product should maximize the farmer's expected utility.

The farmer's utility function over wealth is characterized by a utility function. The utility function explained by Martin et al. (2001) for the constant relative risk aversion is

$$E(U_r) = \sum_{t=1}^{T} \frac{W_t^{1-r}}{T(1-r)}, \quad r \neq 1 \tag{4.17}$$

$$E(U_r) = \sum_{t=1}^{T} \frac{1}{T} \ln(W_t), \quad r = 1 \tag{4.18}$$

where U is a utility, W_t is annual ending wealth at t time, r is the coefficient of constant relative risk aversion (CRRA). The models used for the certainty equivalent of Revenues (CERs) estimation are

$$CE_r = (1-r)E(U_r)^{1/(1-r)}, \quad r \neq 1 \tag{4.19}$$

$$CE_r = e^{E(U_r)}, \quad r = 1 \tag{4.20}$$

We applied the constant relative risk aversion r =1, 2 in this study.

4.5 Data

Since this study focuses on the area yield insurance, selection of a unit area is very important. The unit area for an area yield insurance should be a homogeneous production environment so that the fluctuation of yields within selected area will be more or less uniform within the unit area. Considering this issue, we selected 'crop reporting district', as a unit area of the area yield insurance. The crop reporting districts are administrative districts. Whole country is divided into 75 administrative districts and on an average the area of a district is about 1962 square kilometers in Nepal. Moreover, every district is located in a single agro-ecological zone, which meant a higher possibility to be a uniform climate within a district. Another important reason is that time series yields data are available at district level.

We considered rice, maize, and wheat in this study because they are staple food crops in Nepal. These three cereals are grown throughout Nepal, i.e., maize and wheat are grown in all districts, whereas rice is grown in 73 districts out of 75 districts in Nepal. Twenty districts (27% of the population district) were selected for each crop to estimate the insurance premium rates. The top twenty high coefficient-of-variation (CV) districts were selected from the districts where each crop, i.e., rice, maize, and wheat were planted more than 4,000 hectares in 2010-11. The farmer living at the districts with higher CV suffered from higher yield risk and might benefit by the yield insurance more.

The study applied neighbouring districts' yields information to the yield observation. This was done to improve the data shortness situation (21 observations) in this study and its impact on yield distribution modeling.

Non-parametric modeling is sensitive to the shortness of the data in the estimation. Consequently, considering a central district *i* observations of the *j*th neighbour districts in relation to *i* were incorporated in order to increase the number of observations used, to estimate the conditional yield density and reduce the spatial dependence between counties. Goodwin and Ker (1998) and Ozaki et al. (2008) suggested the incorporation of neighbouring districts' yield information may improve the information situation and can provide better results.

Additionally, the incorporation of neighbouring districts' yield information also improves the problem of premium rate difference between two neighbouring districts. The existence of higher premium rate difference between two neighbouring district attracts border farmers of the lower premium district. Therefore, the process of correcting yields by incorporating yields of the neighbouring district helps to minimize the gap on the premium rates between two districts.

The central districts and districts that are taken for yield correction (neighbouring) are presented in Table 4.1; 4.2, and 4.3 for rice, for maize, and wheat, respectively.

Annual crop yield data were obtained from Ministry of Agricultural development (MoAD), Nepal from 1990-91 to 2010-11. MOAD publishes agricultural statistics annually in the book 'Statistical Information on Nepalese Agriculture.' MoAD collects data from all districts. The area, production, and productivity of major crops are collected at the district offices based on the crop cutting survey done by the agriculture technicians. Thus, the data are reliable and representative of the production situation in Nepal.

Table 4.1 Districts of Data Used in Rice Yields Model

S.N.	Central Districts	Neigbouring Districts
1	Banke	Bardiya, Dang, Salyan
2	Kapilbastu	Arghakhanchi, Rupandehi, Dang
3	Surkhet	Bardiya, Dailekh, Salyan
4	Rupandehi	Nawalparasi, Palpa, Kapilbastu
5	Dhanusha	Mahottari, Sindhuli, Siraha
6	Kavre	Lalitpur, Sindhuli, Sidhu
7	Dhading	Nuwakot, Gorkha, Makawanpur
8	Dang	Kapilbastu, Salyan, Banke
9	Salyan	Rukum, Rolpa, Surkhet
10	Ramechhap	Kavre, Sindhuli, Okhaldhunga
11	Dailekh	Surkhet, Jajarkot, Achham
12	Ilam	Jhapa, Morang, Panchthar
13	Pyuthan	Rolpa, Dang, Arghakhanchi
14	Sindhupalchok	Kavre, Rasuwa, Dolakha
15	Okhaldhunga	Khotang, Ramechhap, Solukhumbu
16	Dadeldhura	Kanchanpur, Baitadi, Doti
17	Gulmi	Arghakhanchi, Syanja, Baglung
18	Udayepur	Khotang, Saptari, Sindhuli
19	Doti	Dadeldhura, Achham, Kailali
20	Syanja	Kaski, Tanahun, Palpa

Table 4.2 Districts of Data Used in Maize Yields Model

S.N.	Central Districts	Neigbouring Districts
1	Syangja	Kaski, Tanahun, Palpa
2	Myagdi	Baglung, Kaski, Mustang
3	Dhankuta	Bhojpur, Terhathum, Morang
4	Jhapa	Dhankuta, Ilam, Morang
5	Baglung	Myagdi, Gulmi, Rukum
6	Ramechhap	Kavre, Sindhuli, Okhaldhunga
7	Surkhet	Dailekh, Bardiya, Salyan
8	Khotang	Bhojpur, Okhaldhunga, Udayepur
9	Solukhumbu	Ramechhap, Okhal, Sankhuwasabha
10	Bara	Parsa, Rautahat, Makawanpur
11	Nawalparasi	Chitwan, Rupandehi, Syanja
12	Lamjung	Gorkha, Kaski, Tanahun
13	Tanahun	Syanja, Nawalparsi, Gorkha
14	Taplejung	Sankhuwasabha, Terhathum, Panchthar
15	Kaski	Lamjung, Syanja, Myagdi
16	Nuwakot	Rasuwa, Sindhupalchok, Dhading
17	Dailekh	Surkhet, Jajarkot, Achham
18	Sindhupalchok	Dolakha, Rasuwa, Kavre
19	Gulmi	Baglung, Arghakhanchi, Syanja
20	Okhaldhunga	Khotang, Ramechhap, Solukhumbu

Table 4.3 Districts of Data Used in Wheat Yields Model

S.N.	Central Districts	Neibouring Districts
1	Rupandehi	Nawalparasi, Palpa, Kapilbastu
2	Kapilbastu	Arghakhanchi, Rupandehi, Dang
3	Bajura	Kalikot, Achham, Bajhang
4	Parsa	Chitwan, Bara, Makawanpur
5	Mugu	Jumla, Humla, Dolpa
6	Bara	Parsa, Rautahat, Makawanpur
7	Bardiya	Surkhet, Banke, Kailali
8	Rukum	Dolpa, Jajarkot, Rolpa
9	Darchula	Humla, Bajhang, Baitadi
10	Surkhet	Bardiya, Salyan, Dailekh
11	Jhapa	Dhankuta, Ilam, Morang
12	Doti	Dadeldhura, Achham, Kailali
13	Kavre	Lalitpur, Sindhuli, Sindhupalchok
14	Ramechhap	Kavre, Sindhuli, Okhaldhunga
15	Baitadi	Dadeldhura, Bajhang, Darchula
16	Banke	Bardiya, Salyan, Dang
17	Chitwan	Nawalparasi, Makawapur, Parsa
18	Kailali	Bardiya, Kanchanpur, Doti
19	Makawanpur	Chitwan, Parsa, Dading
20	Siraha	Saptari, Dhanusha, Udayepur

Different weights are assigned to the central and neighbouring districts while incorporating the data information. We applied the weights suggested by Goodwin and Ker (1998) and Ozaki et al. (2008), which are

$$W_c = \frac{(m+1)}{(2m+1)} \tag{4.21}$$

$$W_N = \frac{1}{(2m+1)} \tag{4.22}$$

where W_c, W_N, and m represent weight for center district, weight for neighbouring district, and a number of neighbouring districts incorporated, respectively. We applied 3 nighbouring districts for yield adjustment for each center district.

The descriptive statistics of corrected yields for rice is presented in Table 4.4. The average of rice yields in 20 districts was ranged as low as 2104.98 to as high as 2342.48 kilogram per hectare. The skewness statics of rice yields showed negative skewness in 13 districts and positive skewness in the remaining 7 districts with a range of -1.03 to 0.93. This indicates the distributions of rice yield in 13 districts contained a long tail to the left hand, whereas in 7 districts it contained a long tail to the right hand side. Moreover, yield distribution in 13 districts showed a positive kurtosis and negative kurtosis in the remaining districts. The kurtosis values of rice yield were distributed from -1.75 to 1.41. The positive kurtosis value indicates the probability density function has a higher peak and a flatter tail than the Normal distribution, whereas a negative kurtosis value indicates a lower peak and a thinner tail than the Normal distribution. In the majority of cases (13 out of 20) of yield series showed a negative skewness reveals the yield distributions may fit well to the non-normal distribution with longer tail to the left hand side.

Similarly, the descriptive statistics of corrected yields for maize is presented in Table 4.5. The average of maize yields in 20 districts was ranged as low as 1624.10 to as high as 2288.21 kilogram per hectare. The skewness statics of maize yields showed a range of -0.5 to 1.06 having positive skewness in 17 districts and negative skewness in the remaining districts. This indicates the distributions of rice yield in 17 districts contained a long tail to the right hand side, whereas opposite in 3 districts.

Moreover, yield distribution in 15 districts showed a negative kurtosis and in 5 districts positive kurtosis. The kurtosis values of rice yields were distributed from -1.63 to 0.50. In the majority of cases (17 out of 20) of yield series showed a positive skewness reveals the yield distributions may fit well to the non-normal distribution with longer tail to the right hand side.

Likewise, the descriptive statistics of corrected yields of wheat is presented in Table 4.6. The average of wheat yields in 20 districts was ranged as low as 1150.89 to as high as 2257.95 kilogram per hectare. The skewness statics of wheat yields showed positive skewness in 12 districts and negative skewness in the remaining 8 districts with a range of -0.41 to 0.8. This indicates the distributions of rice yield in 12 districts contained a long tail to the right hand, whereas in 8 districts it contained a long tail to the left hand side. Moreover, yield distribution in 16 districts showed a negative kurtosis and positive kurtosis in the remaining 4 districts. The kurtosis value of rice yields were distributed from -1.59 to 1.17. In the majority of cases (16 out of 20) of yield series showed a positive skewness reveals the yield distributions may fit well to the non-normal distribution with longer tail to the right hand side.

Table 4.4 Descriptive Statistics of Rice Yields at Sample Districts (1990-91 to 2010-2011)

Districts	Min	Max	Mean	Std. Dev.	Skew	Kurtosis
Banke	1281.71	3251.00	2474.18	526.91	-1.00	0.35
Kapilbastu	1548.29	3144.57	2276.64	398.01	-0.11	0.24
Surkhet	1718.43	3347.86	2449.66	448.64	0.34	-0.67
Rupandehi	1714.29	3603.57	2589.22	429.49	0.17	1.11
Dhanusha	1606.42	2761.49	2355.94	284.02	-0.96	1.19
Kavre	2229.14	3771.43	2908.97	384.82	0.03	-0.01
Dhading	1670.00	2953.43	2443.01	362.50	-0.17	-0.84
Dang	1517.29	3082.57	2511.63	432.67	-1.03	0.96
Salyan	1730.57	3097.14	2238.45	324.14	0.73	0.95
Ramechhap	1577.29	2535.71	2182.85	232.84	-0.65	1.05
Dailekh	1648.43	3095.00	2158.89	340.24	0.93	1.37
Ilam	1879.86	3004.00	2340.62	284.06	0.55	0.01
Pyuthan	1524.16	2680.29	2104.98	245.91	-0.10	1.41
Sindhupalchok	1607.00	2558.57	2234.66	291.48	-0.74	-0.47
Okhaldhunga	1530.71	2444.86	2110.89	274.61	-0.65	-0.53
Dadeldhura	1590.43	2690.29	2178.49	267.25	-0.34	0.23
Gulmi	1663.43	2564.29	2241.71	253.31	-0.74	0.17
Udayepur	1747.57	2775.52	2343.75	270.10	-0.17	-0.31
Doti	1606.29	2689.01	2217.46	270.34	-0.78	0.17
Syanja	2135.71	2924.91	2487.66	302.51	0.25	-1.75

Table 4.5 Descriptive Statistics of Maize Yields at Sample Districts (1990-91 to 2010-11)

Districts	Min	Max	Mean	Std. Dev.	Skew	Kurtosis
Syanja	1465.43	2808.00	1984.83	500.70	0.42	-1.57
Myagdi	1255.38	2687.86	1768.53	370.86	1.00	0.31
Dhankuta	1428.57	2511.33	1790.13	300.46	1.03	0.17
Jhapa	1449.00	2565.12	1919.64	353.31	0.81	-0.60
Baglung	1375.57	2482.86	1756.81	323.32	0.85	-0.39
Ramechhap	1241.29	2211.01	1802.27	297.36	-0.50	-0.94
Surkhet	1519.71	2445.15	1907.46	308.94	0.40	-1.39
Khotang	1284.29	2222.92	1741.58	285.87	0.23	-1.13
Solukhumbu	1351.86	2321.00	1718.23	283.50	0.94	0.21
Bara	1926.57	2866.00	2288.21	258.97	0.31	-0.47
Nawalparasi	1592.76	3015.29	2052.53	433.57	0.78	-0.71
Lamjung	1535.43	2486.20	1950.00	351.83	0.51	-1.53
Tanahun	1622.86	2719.86	2075.22	414.59	0.42	-1.63
Taplejung	1407.71	2093.29	1624.10	201.34	1.06	0.08
Kaski	1499.00	2663.71	1919.39	390.02	0.65	-1.08
Nuwakot	1422.46	2475.71	1766.05	271.41	0.82	0.50
Dailekh	1225.14	1990.30	1673.84	230.59	-0.19	-1.26
Sindhupalchok	1419.43	2234.81	1847.23	271.75	0.13	-1.61
Gulmi	1380.00	2159.67	1689.99	289.19	0.67	-1.49
Okhaldhunga	1251.71	2067.57	1660.59	264.65	-0.01	-0.83

Table 4.6 Descriptive Statistics of Wheat Yields at Sample Districts (1990-91 to 2010-11)

District	Min	Max	Mean	Std. Dev.	Skew	Kurtosis
Rupandehi	1137.43	3103.43	2037.99	545.96	0.42	-0.60
Kapilbastu	1035.14	2868.00	1791.99	480.89	0.80	0.24
Bajura	766.12	1783.00	1281.45	229.37	-0.41	0.66
Parsa	1405.14	3144.71	2225.03	530.03	0.33	-1.36
Mugu	683.97	1618.86	1150.89	246.14	0.18	0.30
Bara	1533.14	3113.14	2257.95	504.78	0.33	-1.29
Bardiya	1324.71	2582.57	1966.63	431.51	-0.17	-1.59
Rukum	907.89	2013.57	1325.70	257.67	0.68	1.17
Darchula	742.18	1503.25	1151.20	206.79	0.29	-0.43
Surkhet	1107.14	2431.43	1669.91	339.22	0.22	-0.34
Jhapa	1473.14	2599.19	1957.94	361.10	0.26	-1.20
Doti	1002.86	1861.29	1459.91	285.66	-0.30	-1.33
Kavre	1322.71	2369.94	1757.82	327.93	0.52	-0.93
Ramechhap	964.43	2093.89	1610.09	295.21	-0.36	-0.18
Baitadi	1088.78	1913.62	1531.62	253.43	-0.28	-0.88
Banke	1310.29	2394.01	1876.21	369.74	-0.26	-1.49
Chitwan	1537.57	2945.43	2099.23	435.20	0.43	-1.37
Kailali	1263.43	2446.37	1875.38	380.10	-0.32	-1.48
Makawanpur	1575.71	2734.14	2019.10	400.42	0.68	-1.17
Siraha	1253.57	2328.93	1843.31	335.94	-0.07	-1.43

5. Results and Discussion

Based on the methodology, the results are presented in a sequence of the approaches of the study objective in this section. The yield prediction is the first step in the process of pure premium estimation. To predict the yields of rice, maize, wheat in different districts in Nepal accurately, ordinary least square (OLS) and quantile regressions (QR) were adopted for normalization followed by heteroscedasticity test and correction measurement in section 5.1. In section 5.2, the normalized yields and goodness-of-fit tests were implemented to model the parametric distribution of yield series for successful crop insurance. The pure premium rates of different districts were resulted from the parametric and non-parametric distributions of yield series in section 5.3. The parametric approaches applied in this study are Normal, Lognormal, Beta, and Weibull distributions, whereas Gamma distribution was selected as a non-parametric approach. In section 5.4, the pure premium rates between different distributions and different yield estimation approaches are compared. Finally, the area yield insurance is evaluated in terms of variance reduction and higher certainty equivalent of the revenues of the area yield insurance in section 5.5.

5.1 Yield Prediction

After the prediction, a process of yield normalization was done to remove the trends and make the yields of different years comparable. Additionally, this technique was applied to correct the potential heteroscedasticity of problem that was found in some yield series. The equation (4.2) was applied for normalization of yield series by considering yield of 2010-11 as a reference yield for normalization. The study selected the yield in 2010-11 for normalization because it is the last yield of sample, which represents the technology of 2010-11. Thus, we deflated the yields based on the technology of 2010-11.

This study applied two techniques OLS (ordinary least square) and QR (quantile regression) approaches to estimate the yields of rice, maize, and wheat in Nepal. The assumption of normality and non-normality distribution of data behind this is that these two techniques may generate different yield series and lead to difference pure premium rate. This study applied equation (4.1) for both techniques for the prediction of district yield by time trend.

In this study, we used OLS rice, OLS maize, and OLS wheat represent for yield series of rice, maize, and wheat estimated and normalized by using ordinary least square approach and normalized and QR rice, QR maize, and QR wheat for rice, maize, and wheat by quantile regression approach. The descriptive statistics of normalized yield series of OLS rice, QR rice, OLS maize, QR maize, OLS wheat, and QR wheat are presented in the appendix B, Tables A4, A5, A6, A7, A8, and A9, respectively.

5.1.1 Comparison of Different Yield Series

To illustrate how yield pattern changes after normalization, we illustrated it in Figures 5.1, 5.2, and 5.3. We took Kapilbastu district as an example for rice yield in Figure 5.1, Nawalparasi district for maize yield in Figure 5.2, and Mugu district for wheat yields in Figure 5.3, respectively.

The normalized yields based on quantile regression showed lower yields compared to the normalized yields based on OLS regression at the beginning of the sample period and higher in the latter period. Therefore, we assumed that two yield prediction approaches may generate differences in the premium rate.

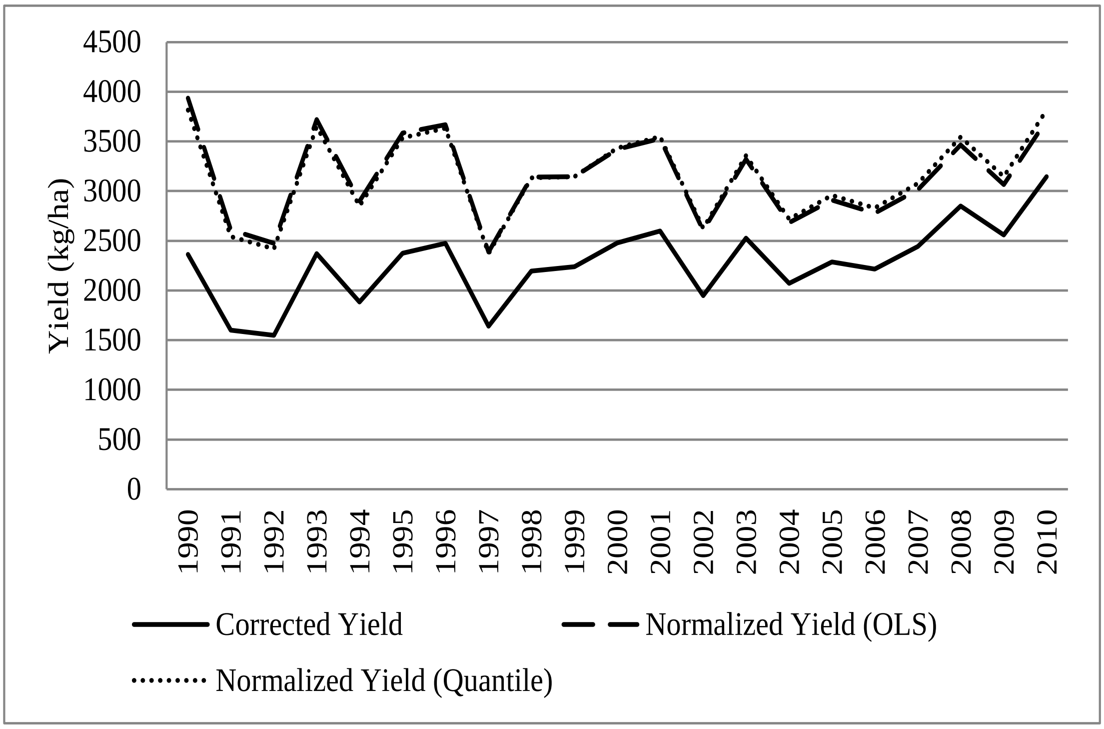

Figure 5.1 Trends of Corrected and Normalized Rice Yield Series at Kapilbastu District.

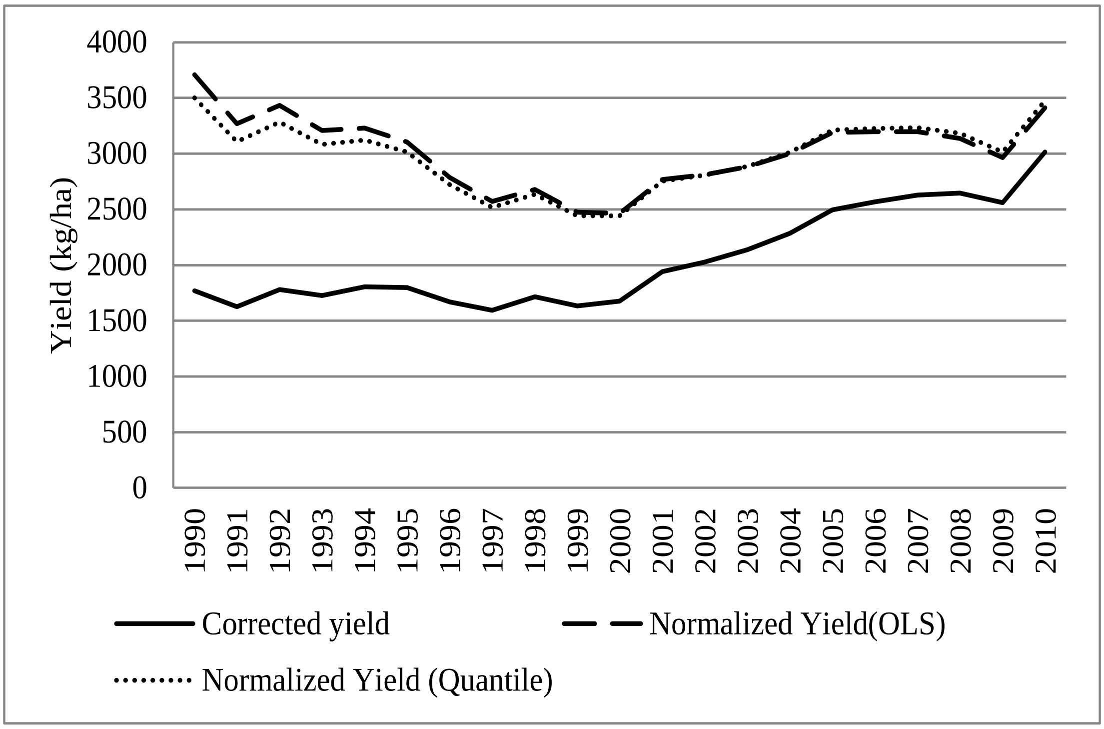

Figure 5.2 Trends of Corrected and Normalized Maize Yield Series at Nawalparasi District.

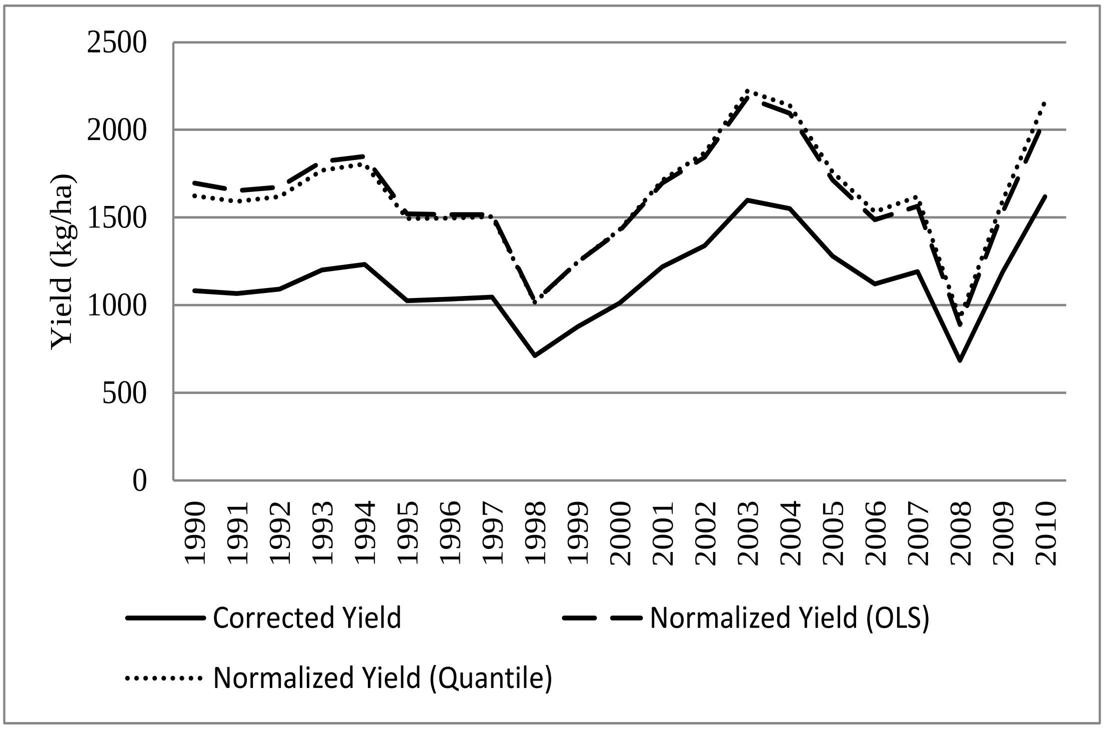

Figure 5.3 Trends of Corrected and Normalized Wheat Yield Series at Mugu District.

The average coefficient of variance (CV) of different yields series are shown in Table 5.1. The results showed CV in original yields was reduced gradually during the different steps of yield series processing. For example, we observed about 18 % average CV in original rice yield series, it decreased to about 14% in the corrected yield series and further it decreased to about 10% in the normalized yield series. Similar trends were observed in maize and wheat. This indicates that CV was reduced in every step of yield processing.

Table 5. 1 Coefficient of Variation (CV) in Different Yield Series (%)

Crop	Original Yield	Corrected Yield	Normalized Yield	
			OLS	QR
Rice	18.05	14.06	10.32	10.18
Maize	20.50	17.27	8.11	8.22
Wheat	23.56	20.59	11.32	11.40

5.2 Distribution of Yield Series

5.2.1 Goodness-of-fit Test

The normalized yields of rice, maize, and wheat were fitted to five parametric--Normal, Lognormal, Beta, Weibull, and gamma distributions to examine goodness-of-fit yield series to each distribution. The Anderson Darling (AD) test was applied to evaluate the goodness- of-fit of yield series to those distributions individulally. The AD test was based on equation (4.4). The lower the AD test statistics indicate the higher goodness of fit of yield series to the particular distribution among the fitted distributions (Fisher *et al.*, 2012; Sherrick *et al.*, 2004). Sherrick et al. (2004) ranked the different fitted distributions from the highest to the lowest in order based on the highest to lowest test statistics. This study ranked the different distributions in order based on the AD test statistics.

To evaluate the fitness of the yield series, every distribution was assigned 1, 2, 3, 4, and 5 weights based on the AD test statistics. The yield distribution with the lowest test statistics were ranked 1, the second lowest 2, the third lowest given 3, the fourth lowest 4, the fifth lowest 5. We summed up all the rank orders for each candidate distribution and divided by 20. The final outcome was taken as the weighted average of the distribution. We categorized the final rank of distribution based on the lowest to highest weighted average assigned to the particular distribution for each yield series separately.

The ranks of parametric distributions based on goodness-of-test are explained in section 5.2.1.1, 5.2.1.2, and 5.2.1.3 for series of rice, maize, and wheat yield series, respectively.

5.2.1.1 Rice

The rank orders of distributions of OLS rice yield series is presented in Table 5.2. The results indicated Normal distribution was the best fitted distribution and followed by Gamma, Beta, Lognormal and Weibull distributions in order.

Similarly, the rank orders of distributions of QR rice yield series is presented in Table 5.3. The results revealed Normal distribution was the best fitted distribution and followed by Beta, Gamma, Lognormal, and Weibull distributions in order.

We considered Kapilbastu district as an example to illustrate the probability of density function of rice yield series. The histogram and the probability of density function of Normal, Lognormal, Beta, Weibull, Gamma, and Kernel of OLS and QR rice yield series are presented in Figures 5.4 and 5.5, respectively.

Table 5.2 Anderson Darling Goodness-of-Fit Test Statistics of OLS Rice Yields Series

Districts	Normal	Lognormal	Beta	Weibull	Gamma
Banke	0.98	1.27	0.84	0.78	1.22
Kapilbastu	0.28	0.30	0.30	0.32	0.32
Surkhet	0.96	1.21	0.74	0.47	1.11
Rupandehi	0.40	0.50	0.33	0.28	0.49
Dhanusha	0.99	1.30	0.75	0.51	1.18
Kavre	0.63	0.42	0.83	1.31	0.46
Dhading	0.95	0.86	1.09	1.19	0.91
Dang	0.44	0.64	0.37	0.30	0.57
Salyan	0.56	0.44	0.75	0.91	0.50
Ramechhap	0.19	0.26	0.17	0.18	0.24
Dailekh	0.68	0.62	0.78	1.26	0.62
Ilam	0.32	0.27	0.42	0.60	0.26
Pyuthan	0.58	0.79	0.45	0.34	0.69
Sindhupalchok	0.72	0.66	0.85	1.32	0.65
Okhaldhunga	0.25	0.32	0.58	0.24	0.31
Dadeldhura	0.34	0.34	0.37	0.45	0.35
Gulmi	0.53	0.57	0.51	0.61	0.55
Udayepur	0.26	0.29	0.28	0.34	0.29
Doti	0.18	0.17	0.23	0.39	0.17
Syanja	0.30	0.24	0.41	0.67	0.27
Rank total	51	64	59	68	58
Weighted average	2.55	3.20	2.95	3.40	2.90
Rank of average	1	4	3	5	2

Table 5.3 Anderson Darling Goodness-of-Fit Test Statistics of QR Rice Yields Series

District	Normal	Log-normal	Beta	Weibull	Gamma
Banke	2.13	2.38	1.94	2.13	2.36
Kapilbastu	0.35	0.41	0.34	0.37	0.42
Surkhet	1.49	1.91	1.19	0.80	1.75
Rupandehi	0.64	0.79	0.56	0.46	0.75
Dhanusha	0.98	1.31	0.74	0.48	1.19
Kavre	1.28	0.82	1.60	2.16	0.93
Dhading	0.96	0.87	1.12	1.22	0.92
Dang	1.16	1.47	0.96	0.72	1.38
Salyan	0.96	0.81	1.14	1.28	0.88
Dailekh	0.77	0.71	0.89	1.52	0.70
Ramechhap	0.48	0.59	0.46	0.50	0.54
Ilam	0.60	0.60	0.64	0.86	0.60
Pyuthan	0.54	0.76	0.42	0.30	0.66
Sindhupalchok	1.39	1.08	1.67	2.28	1.13
Okhaldhunga	0.25	0.32	0.23	0.24	0.31
Dadeldhura	0.21	0.24	0.24	0.36	0.22
Gulmi	0.71	0.82	0.63	0.67	0.76
Udayepur	0.26	0.29	0.28	0.34	0.29
Doti	0.16	0.18	0.18	0.33	0.16
Syanja	0.33	0.25	0.45	0.72	0.29
Rank total	50	69	51	68	62
Weighted average	2.50	3.45	2.55	3.80	3.10
Rank of average	1	4	2	5	3

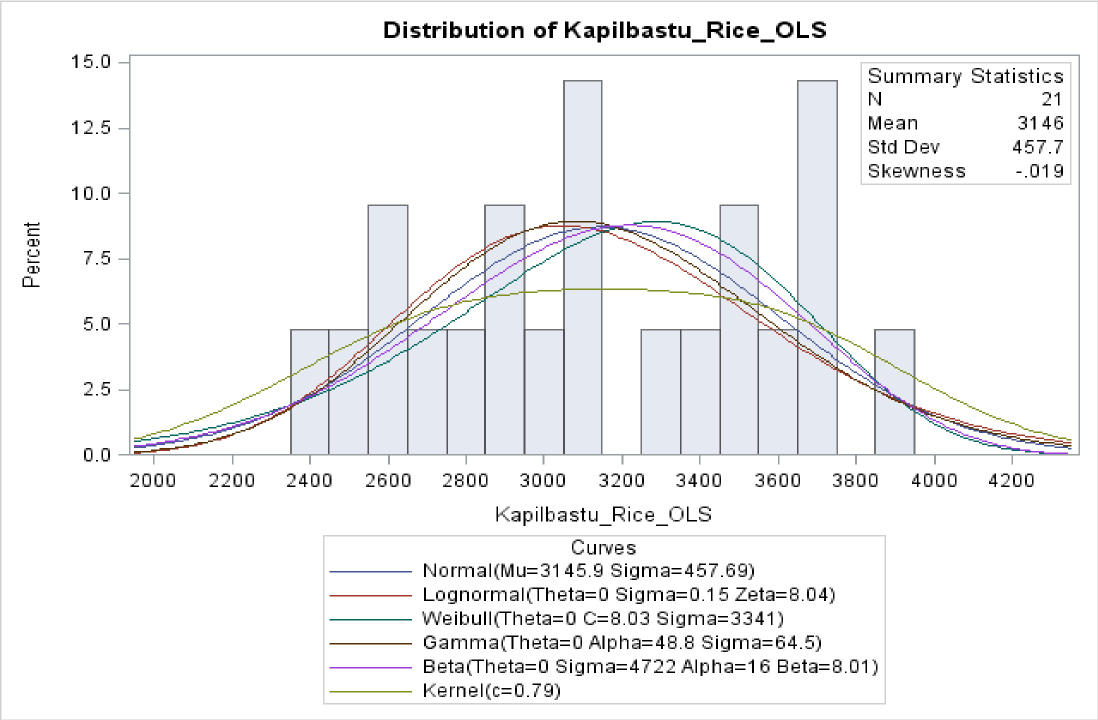

Figure 5.4 Probability Density Functions of Six Probability Distributions of OLS Rice Yield Series at Kapilbastu District

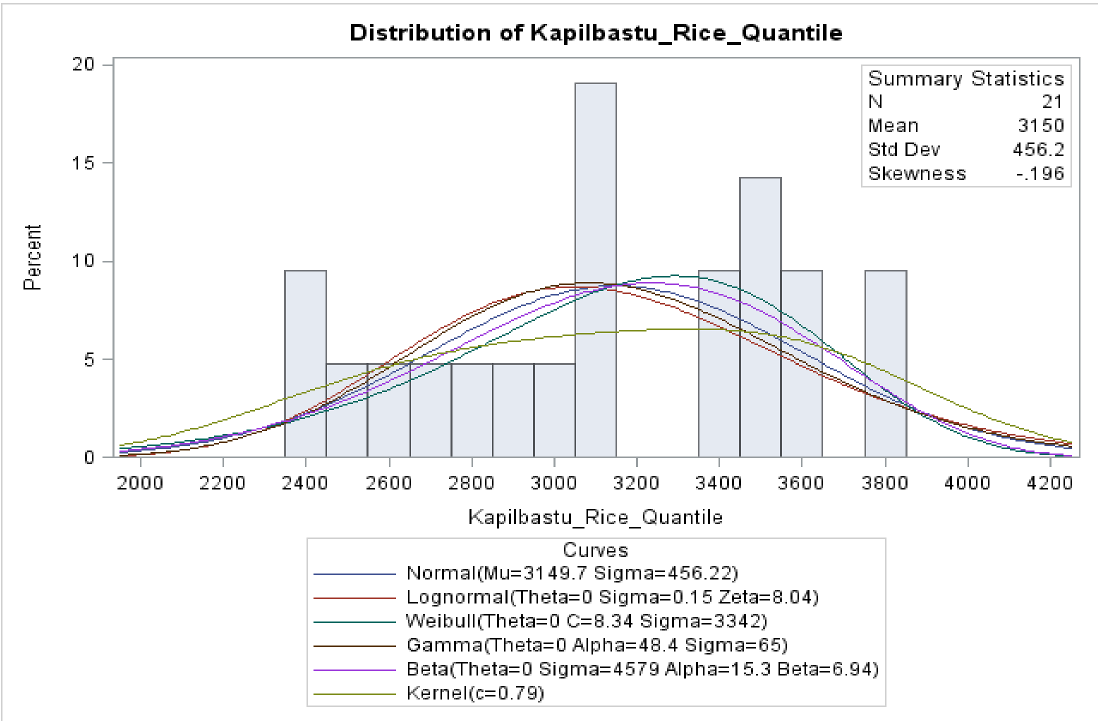

Figure 5.5 Probability Density Functions of Six Probability Distributions of QR Rice Yield Series at Kapilbastu District.

5.2.1.2 Maize

In the case of maize, the rank order results of OLS maize yield series are presented in Table 5.3. The results revealed Beta distribution was the best fitted distribution and followed by Normal, Lognormal, Weibull, and Gamma distributions in order.

Similarly, the rank orders of QR yield series is presented in Table 5.5. The results revealed Beta distribution was the best fitted distribution and followed by Normal, Weibull, Lognormal, and Gamma distributions in order.

We considered Nawalparasi district as an example to illustrate the probability density function for maize yield series. The histogram and the probability of density function of Normal, Lognormal, Beta, Weibull, Gamma, and Kernel of OLS and QR maize yield series at Nawalparasi district are presented in Figures 5.6 and 5.7, respectively.

Table 5.4 Anderson Darling Goodness-of-Fit Test Statistics of OLS Maize Yields Series.

District	Normal	Lognormal	Beta	Weibull	Gamma
Syanja	0.26	0.31	0.26	0.35	0.29
Myagdi	0.53	0.80	0.41	0.33	0.67
Dhankuta	0.47	0.68	0.36	0.26	0.62
Jhapa	0.68	0.71	0.68	0.68	0.75
Baglung	0.38	0.48	0.30	0.24	0.46
Ramechhap	0.18	0.18	0.21	0.32	0.19
Surkhet	0.36	0.32	0.45	0.63	0.35
Khotang	0.20	0.22	0.20	0.28	0.22
Solukhumbu	0.49	0.48	0.53	0.55	0.53
Bara	0.62	0.59	0.72	1.02	0.60
Nawalparasi	0.29	0.35	0.28	0.29	0.34
Lamjung	0.35	0.34	0.40	0.42	0.38
Tanahun	0.41	0.46	0.38	0.33	0.47
Taplejung	0.29	0.29	0.31	0.35	0.32
Kaski	0.15	0.18	0.14	0.21	0.18
Nuwakot	0.21	0.22	0.22	0.28	0.23
Dailekh	0.79	1.00	0.58	0.32	0.90
Sindhupalchok	0.51	0.46	0.61	1.18	0.45
Gulmi	0.18	0.25	0.15	0.15	0.23
Okhaldhunga	0.87	1.17	0.64	0.39	1.03
Rank total	48	65	47	69	71
Weighted Average	2.40	3.25	2.35	3.45	3.55
Rank of average	2	3	1	4	5

Table 5.5 Anderson Darling Goodness-of-Fit Test Statistics of QR Maize Yields Series

District	Normal	Log-normal	Beta	Weibull	Gamma
Syanja	0.31	0.38	0.29	0.34	0.36
Myagdi	0.54	0.82	0.42	0.33	0.69
Dhankuta	0.48	0.70	0.41	0.26	0.63
Jhapa	0.31	0.33	0.34	0.36	0.36
Baglung	0.30	0.38	0.25	0.25	0.36
Ramechhap	0.28	0.32	0.28	0.35	0.31
Surkhet	0.29	0.26	0.36	0.57	0.27
Khotang	0.19	0.21	0.18	0.26	0.21
Solukhumbu	0.39	0.43	0.38	0.35	0.45
Bara	0.76	0.60	0.97	1.47	0.62
Nawalparasi	0.34	0.43	0.29	0.25	0.42
Lamjung	0.35	0.31	0.45	0.54	0.35
Tanahun	0.55	0.61	0.51	0.43	0.62
Taplejung	0.38	0.36	0.45	0.69	0.38
Kaski	0.14	0.16	0.21	0.24	0.16
Nuwakot	0.33	0.32	0.39	0.69	0.31
Dailekh	1.15	1.39	0.88	0.40	1.28
Sindhupalchok	0.58	0.50	0.71	1.34	0.50
Gulmi	0.25	0.31	0.23	0.30	0.29
Olhadhunga	0.90	1.12	0.68	0.49	1.05
Rank total	51	67	50	65	67
Weighted average	2.55	3.35	2.50	3.25	3.35
Rank of average	2	4	1	3	5

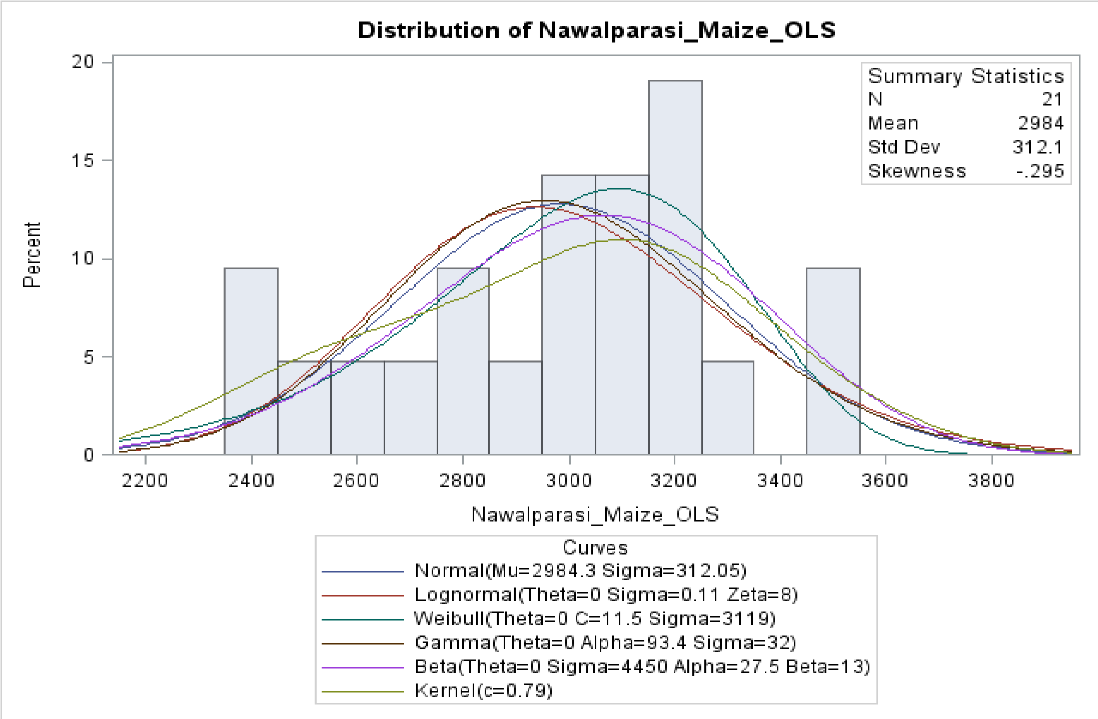

Figure 5.6 Probability Density Functions of Six Probability Distributions of OLS Maize Yield Series at Nawalparasi District.

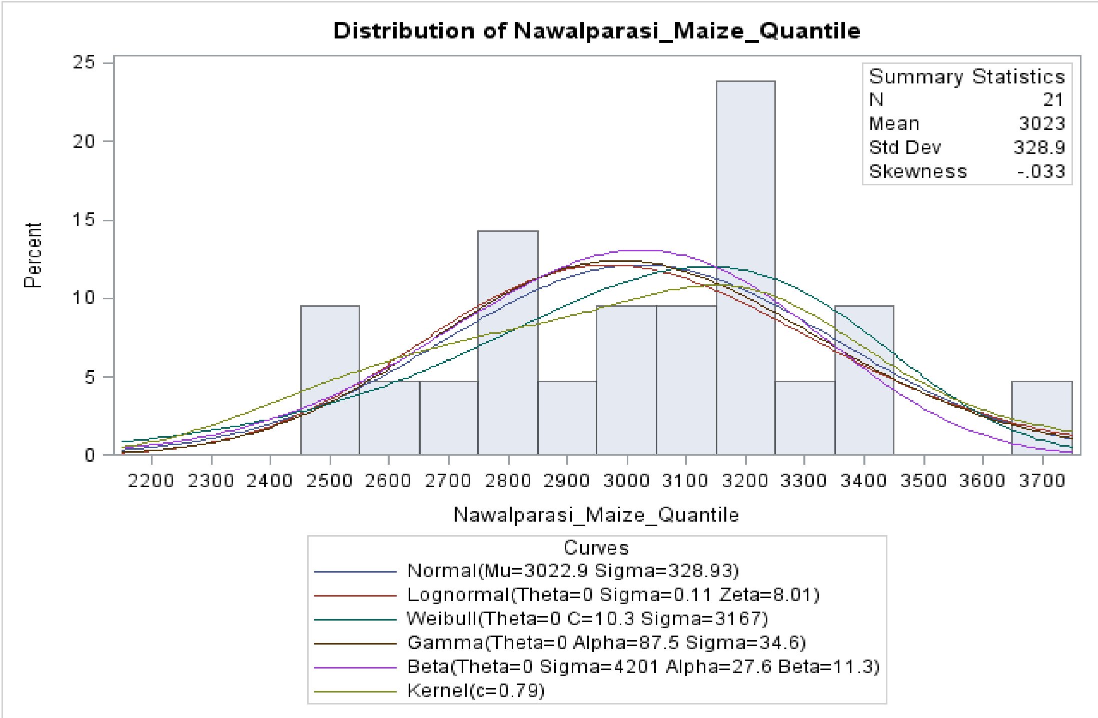

Figure 5.7 Probability Density Functions of Six Probability Distributions of QR Maize Yield Series at Nawalparasi District.

5.2.1.3 Wheat

Similarly, the rank results different distributions of OLS wheat yield series are presented in Table 5.6. The results revealed Normal distribution was the best fitted distribution and followed by Beta, Weibull, Gamma, and Lognormal distributions in order.

Likewise, the rank orders of different distributions of QR wheat yield series is presented in Table 5.7. The results revealed that Beta distribution was the best fitted distribution and followed by Normal, Weibull, Gamma, and Lognormal distributions in order.

We considered Mugu district as an example to illustrate probability density functions for wheat yield series and presented the histogram and the probability of density function of Normal, Lognormal, Beta, Weibull, Gamma, and Kernel of OLS and QR wheat yield series in Figures 5.8 and 5.9, respectively.

Table 5.6 Anderson Darling Goodness-of-Fit Test Statistics of OLS Wheat Yields Series

District	Normal	Lognormal	Beta	Weibull	Gamma
Rupandehi	0.57	0.52	0.69	1.17	0.51
Kapilbastu	0.23	0.21	0.30	0.49	0.22
Bajura	1.37	1.82	1.21	0.94	1.66
Parsa	0.26	0.23	0.33	0.60	0.23
Mugu	0.41	0.73	0.41	0.39	0.59
Bara	0.50	0.39	0.65	1.10	0.41
Bardiya	0.79	0.79	0.83	0.80	0.84
Rukum	0.34	0.59	0.31	0.27	0.48
Darchula	0.71	0.97	0.70	0.72	0.85
Surkhet	0.54	0.69	0.41	0.25	0.64
Jhapa	0.34	0.28	0.46	0.72	0.30
Doti	0.31	0.42	0.32	0.37	0.36
Kavre	0.41	0.44	0.50	0.60	0.41
Ramechhap	0.78	1.08	0.59	0.41	0.99
Baitadi	0.54	0.72	0.48	0.46	0.69
Banke	0.18	0.17	0.23	0.37	0.19
Chitwan	0.21	0.30	0.17	0.17	0.27
Kailali	0.56	0.53	0.62	0.65	0.59
Makawanpur	0.59	0.66	0.56	0.52	0.68
Siraha	0.66	0.73	0.67	0.73	0.72
Rank total	48	67	57	63	65
Weighted average	2.40	3.35	2.85	3.15	3.25
Rank of average	1	5	2	3	4

Table 5.7 Anderson Darling Goodness-of-Fit Test Statistics of QR Wheat Yields Series

District	Normal	Log-normal	Beta	Weibull	Gamma
Rupandehi	0.49	0.52	0.53	0.77	0.50
Kapilbastu	0.36	0.35	0.43	0.56	0.36
Bajura	1.45	2.03	1.20	0.85	1.81
Parsa	0.26	0.24	0.33	0.61	0.23
Mugu	0.49	0.70	0.56	0.56	0.60
Bara	1.20	0.98	1.45	2.02	1.03
Bardiya	0.33	0.23	0.46	0.88	0.25
Rukum	0.93	1.43	0.72	0.45	1.25
Darchula	0.64	1.02	0.56	0.51	0.85
Surkhet	0.99	1.18	0.84	0.63	1.11
Jhapa	0.50	0.47	0.60	0.82	0.49
Doti	0.37	0.53	0.37	0.41	0.45
Kavre	0.83	1.12	0.78	0.74	1.00
Ramechhap	0.84	1.16	0.63	0.42	1.06
Baitadi	0.58	0.78	0.54	0.51	0.73
Banke	0.27	0.24	0.38	0.62	0.25
Chitwan	0.21	0.30	0.18	0.20	0.26
Kailali	0.40	0.51	0.36	0.35	0.48
Makawanpur	0.77	0.87	0.71	0.64	0.89
Siraha	0.64	0.69	0.70	0.81	0.68
Rank total	53	72	53	58	64
Weighted average	2.65	3.60	2.65	2.90	3.20
Rank of average	2	5	1	3	4

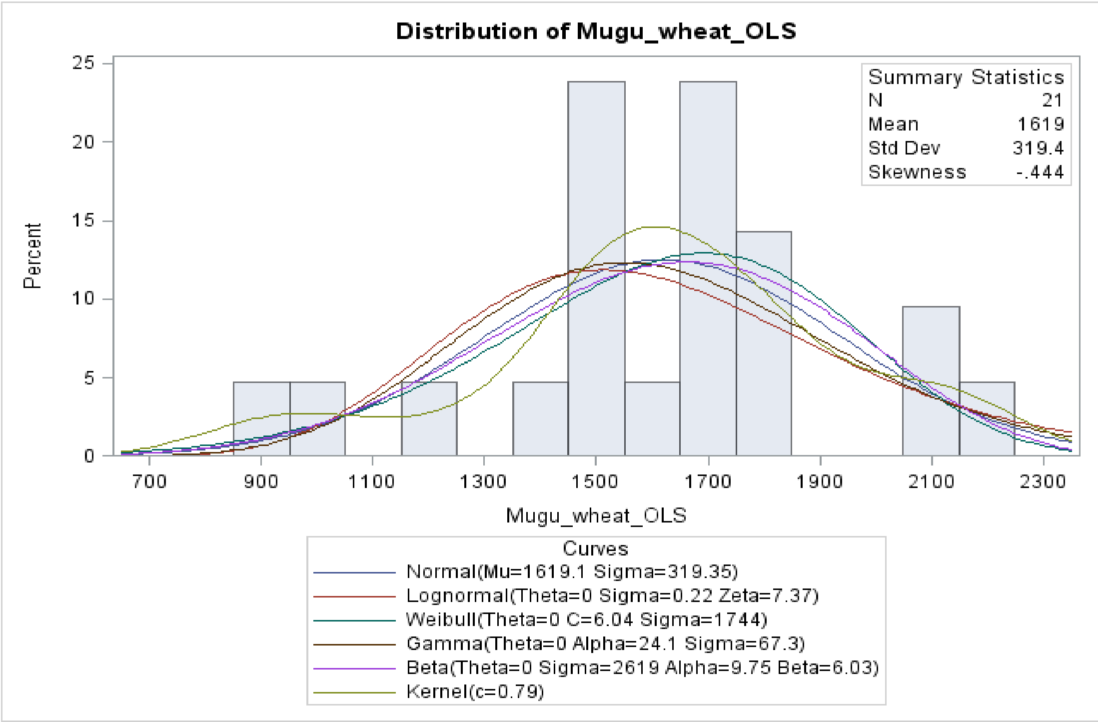

Figure 5.8 Probability Density Functions of Six Probability Distributions of OLS wheat Yield Series at Mugu District.

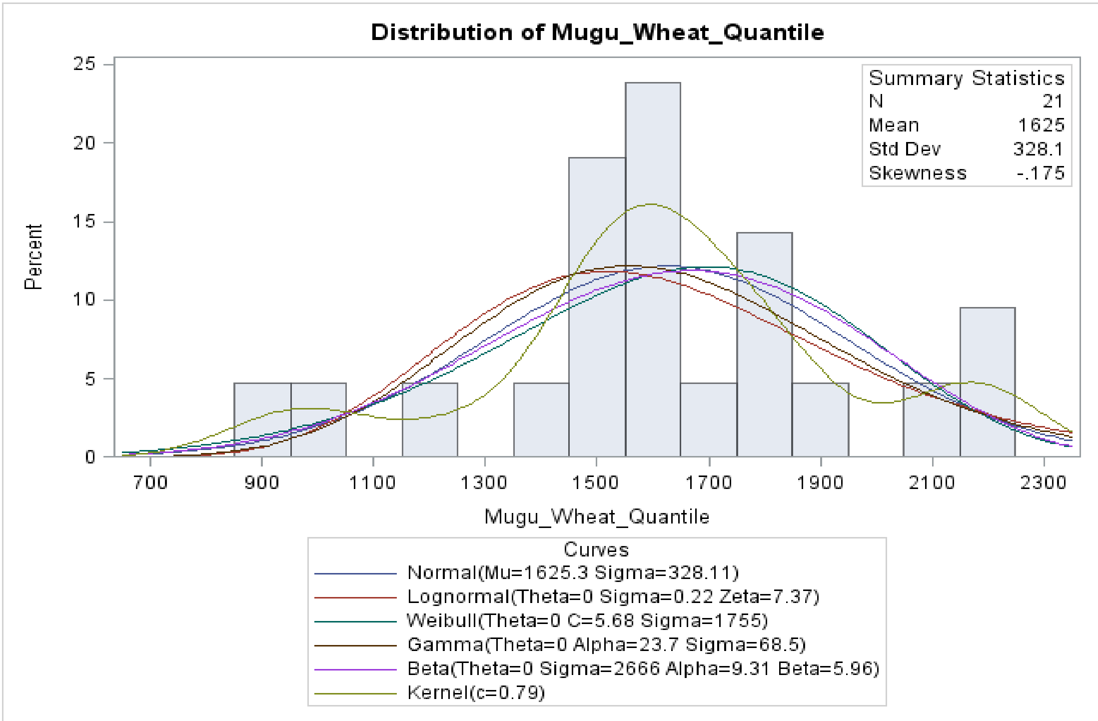

Figure 5.9 Probability Density Functions of Six Probability Distributions of QR wheat Yield Series at Mugu District.

5.2.2 Parameters of Yield Distribution

The shape and scale parameters of parametric distributions for rice, maize, and wheat yield series were estimated by using maximum likelihood estimation (MLE) methods. For this, this study applied log likelihood method. The log likelihood equation (4.5) was applied to estimate shape and scale parameters of Lognormal distribution. Likewise, log likelihood equation (4.6) was applied to estimate the two shape and a scale parameters of Beta distributions. Similarly, shape and scale parameters of Weibull distribution were estimated by using the log likelihood equation (4.7) and log likelihood equation (4.8) was applied to estimate the shape and scale parameters of Gamma distribution.

In addition, the parameters of Normal distribution, such as, the mean and standard deviation were estimated by using simple estimation procedure. Similarly, the standardized bandwidth of the Kernel distribution was estimated by using simple estimation procedure.

The parameters of distributions are presented in Appendix C. The mean and standard deviation of Normal distribution for OLS and QR yield series of rice, maize, and wheat are presented in Table A10, A11, and A12, respectively. Similarly, shape and scale parameters of Lognormal distribution for rice, maize and wheat in both OLS and QR yield series are presented in Table A13, A14, and A15, respectively. Likewise, one scale and two shape parameters of Beta distribution of rice, maize, and wheat for both series are presented in the Table A16, A17, and A18, respectively. The scale and shape parameters of both yield series of rice, maize, and wheat area presented in Table A19, A20, and A21, respectively. In addition, the shape and scale parameters of Gamma distribution of rice, maize, and wheat for both series are presented in Table A22, A23, and A24, respectively. The standardized bandwidth parameter of Kernel distribution of both yield series of rice, maize, and wheat area presented in Table A25, A26, and A27, respectively.

These estimated parameters were applied to construct the shape of probability density function of yield series, which was finally applied to assess the probability of yield loss in calculating the pure premium rates. The probability of yield loss at a guaranteed yield level was estimated by using the procedure of area under the curve in the parametric distribution, whereas a trapezoidal rule was applied in case of non-parametric distribution.

5.3 Pure Premium Rate

Premium rate estimation is the main issue of insurance. We estimated the pure premium rate or theoretical premium rate of area yield insurance of rice, maize, and wheat in Nepal. Probability of yield loss and average yield loss (loss occur) was multiplied to get the expected yield loss. This is also called a premium value in the physical unit, i.e., kilogram per hectare. However, the premium rate is expressed in term of percentage of total liability. The pure premium rate was estimated based on equation (4.10).

Setting of coverage level of yields is major function in premium rate estimation. Risk management agency (RMA) in the USA provides area yield insurance contract at coverage levels of 70, 75, 80, 85, and 90 % of the expected yield. The assumption behind the maximum coverage level at 90% is to minimize moral hazard. Principally, there will be some probabilities of moral hazard at 100% coverage because farmers will not bear any loss at this level if yields fall below the coverage level. However, at the below 100% coverage level, the farmer also need to bear some loss. Therefore, the farmer does not commit to use lower input after buying insurance contract.

Following coverage levels of yield on area yield insurance used by RMA and some previous studies (Deng *et al.*, 2007; Ozaki *et al.*, 2008), this study estimated pure premium rates at coverage level of 70, 75, 80, 85, and 90% expected yields. However, the probability of yield loss or loss occur observed zero in most of the sampled yield series at 85% or below coverage levels. Therefore, only premium rates with coverage level 90% are resulted in this section. The pure premium rates were estimated based on both OLS yield series and QR yield. Moreover, the premium rates presented in this study are percentage of liability. The liability was measured in kilogram per hectare instead of USD per hectare because the prices of rice, maize, and wheat were not available for the year 2011 in Nepal.

5.3.1 Pure Premium Rates of Rice

5.3.1.1 OLS Yield Series

The pure premium rates of OLS rice yield series at 90% coverage level are presented in Table 5.8. The rates were estimated by Normal, Lognormal, Beta, Weibull, Gamma, and Kernel distributions. In case OLS rice yield series, the results showed premium rate estimates were found in a range, such as, 0 to 1.37, 0 to 1.53, 0 to 1.31, 0 to 1.16, 0 to 1.47, and 0 to 1.31% for Normal, Lognormal, Beta, Weibull, Gamma, and Kernel distributions, respectively.

On an average, the premium rates observed were 0.25, 0.26, 0.24, 0.25, 0.25, and 0.24% for Normal, Lognormal, Beta Weibull, Gamma, and Kernel distributions, respectively. Premium rates were found above 1% at Banke district only, below 1% at 18 districts, and 0% at Syanja district.

Table 5.8 Pure Premium Rate (%) at 90% Coverage Level for OLS Rice Yield Series in 2011-2012

Districts	Normal	Lognormal	Beta	Weibull	Gamma	Kernel
Banke	1.37	1.53	1.31	1.16	1.47	1.31
Kapilbastu	0.60	0.66	0.58	0.66	0.61	0.58
Surkhet	0.16	0.17	0.15	0.13	0.16	0.15
Rupandehi	0.24	0.26	0.23	0.22	0.24	0.23
Dhanusha	0.30	0.32	0.27	0.22	0.32	0.27
Kavre	0.23	0.22	0.24	0.30	0.22	0.24
Dhading	0.07	0.07	0.07	0.09	0.07	0.07
Dang	0.38	0.40	0.37	0.36	0.39	0.37
Salyan	0.05	0.05	0.05	0.06	0.05	0.05
Ramechhap	0.15	0.16	0.15	0.15	0.15	0.15
Dailekh	0.01	0.00	0.01	0.02	0.01	0.01
Ilam	0.59	0.60	0.58	0.64	0.59	0.58
Pyuthan	0.12	0.14	0.12	0.11	0.13	0.12
Sindhupalchok	0.15	0.14	0.16	0.21	0.14	0.16
Okhaldhunga	0.28	0.28	0.22	0.28	0.27	0.23
Dadeldhura	0.07	0.06	0.07	0.08	0.06	0.07
Gulmi	0.01	0.01	0.01	0.02	0.01	0.01
Udayepur	0.11	0.13	0.11	0.12	0.11	0.11
Doti	0.06	0.06	0.06	0.08	0.06	0.06
Syanja	0.00	0.00	0.00	0.00	0.00	0.00
Min	0.00	0.00	0.00	0.00	0.00	0.00
Max	1.37	1.53	1.31	1.16	1.47	1.31
Average	0.25	0.26	0.24	0.25	0.25	0.24
Std. Dev.	0.32	0.35	0.30	0.28	0.34	0.30

5.3.1.2 QR Yield Series

The premium rates of QR rice yield series are presented in Table 5.9. The results revealed that premium rates were distributed in a range from 0 to 1.46, 0 to 1.70, 0 to 1.34, 0 to 1.07, 0 to 1.60, and 0 to 1.31 for Normal, Lognormal, Beta, Weibull, Gamma, and Kernel distributions, respectively. The results showed premium rates at Syanja district 0% and about 1.31% at Banke district and 0-1% at the rest of districts in all fitted distributions.

The averages of premium rates for Normal, Lognormal, Beta, Weibull, Gamma, and Kernel distributions were 0.24, 0.26, 0.23, 0.21, 0.25, and 0.23, respectively. The premium rates were found above 1% at Banke district, 0 % at Syanja, and below 0.74% at the remaining 18 districts for all 6 distributions.

Our pure premium rate results for OLS and QR rice yield series were found substantially smaller than the premium rate results of corn, soybean, and wheat presented by Ozaki et al. (2008). Unfortunately, we were unable to compare the results for rice crop since they did not present it in their results.

Table 5.9 Pure Premium Rate (%) at 90% Coverage Level for QR Rice Yield Series in 2011-2012

Districts	Normal	Lognormal	Beta	Weibull	Gamma	Kernel
Banke	1.46	1.70	1.34	1.07	1.60	1.31
Kapilbastu	0.62	0.66	0.59	0.57	0.63	0.74
Surkhet	0.34	0.39	0.31	0.24	0.36	0.24
Rupandehi	0.31	0.32	0.29	0.30	0.31	0.36
Dhanusha	0.31	0.36	0.29	0.23	0.33	0.27
Kavre	0.15	0.14	0.15	0.19	0.14	0.14
Dhading	0.08	0.07	0.08	0.09	0.07	0.03
Dang	0.47	0.53	0.43	0.35	0.49	0.41
Salyan	0.07	0.07	0.07	0.09	0.06	0.05
Ramechhap	0.22	0.24	0.21	0.21	0.22	0.15
Dailekh	0.00	0.00	0.01	0.01	0.00	0.01
Ilam	0.01	0.01	0.01	0.01	0.00	0.01
Pyuthan	0.12	0.14	0.12	0.11	0.13	0.10
Sindhupalchok	0.14	0.13	0.15	0.20	0.13	0.11
Okhaldhunga	0.18	0.19	0.18	0.19	0.18	0.24
Dadeldhura	0.08	0.08	0.08	0.09	0.07	0.09
Gulmi	0.02	0.02	0.02	0.03	0.02	0.03
Udayepur	0.11	0.12	0.11	0.12	0.11	0.15
Doti	0.09	0.08	0.09	0.11	0.08	0.10
Syanja	0.00	0.00	0.00	0.00	0.00	0.00
Min	0.00	0.00	0.00	0.00	0.00	0.00
Max	1.46	1.70	1.34	1.07	1.60	1.31
Average	0.24	0.26	0.23	0.21	0.25	0.23
Std. Dev.	0.33	0.38	0.30	0.24	0.36	0.31

5.3.2 Pure Premium Rates of Maize

5.3.2.1 OLS Yield Series

The pure premium rate results of OLS maize yield series are presented in Table 5.10. The premium rates results showed they were distributed in a range. The ranges of premium rates were 0 to 0.40, 0 to 0.45, 0 to 0.38, 0 to 0.36, 0 to 0.40, and 0 to 0.40% for Normal, Lognormal, Beta, Weibull, Gamma, and Kernel distributions, respectively. The premium rates in Dhankuta district were found about 0.40% in all distributions, which was the highest among sample districts in case of OLS maize. Similarly, premium rates were 0% at Khotang and Taplejung and 0 to 0.25 % at rest of the districts.

The average premium rates were 0.08, 0.09, 0.08, 0.08, 0.08, and 0.09 % for Normal, Lognormal, Beta, Weibull, Gamma, and Kernel distributions, respectively. The average premium rates in OLS maize yield series were found lower than rice yield series in this study.

Table 5.10 Pure Premium Rate (%) at 90% Coverage Level for OLS Maize Yield Series in 2011-2012

Districts	Normal	Lognormal	Beta	Weibull	Gamma	Kernel
Syanja	0.11	0.14	0.14	0.16	0.14	0.17
Myagdi	0.21	0.24	0.20	0.19	0.22	0.17
Dhankuta	0.40	0.45	0.38	0.36	0.40	0.40
Jhapa	0.02	0.02	0.02	0.02	0.02	0.03
Baglung	0.03	0.03	0.03	0.04	0.03	0.05
Ramechhap	0.03	0.03	0.03	0.04	0.03	0.04
Surkhet	0.00	0.00	0.00	0.01	0.00	0.00
Khotang	0.00	0.00	0.00	0.00	0.00	0.00
Solukhumbu	0.03	0.03	0.03	0.03	0.03	0.04
Bara	0.16	0.15	0.17	0.21	0.15	0.19
Nawalparasi	0.22	0.22	0.21	0.23	0.22	0.27
Lamjung	0.07	0.07	0.07	0.00	0.07	0.09
Tanahun	0.07	0.07	0.07	0.07	0.06	0.09
Taplejung	0.00	0.00	0.00	0.00	0.00	0.00
Kaski	0.04	0.04	0.04	0.05	0.04	0.06
Nuwakot	0.02	0.03	0.03	0.03	0.02	0.03
Dailekh	0.03	0.04	0.03	0.02	0.03	0.03
Sindhupalchok	0.01	0.02	0.02	0.03	0.01	0.01
Gulmi	0.06	0.06	0.06	0.07	0.06	0.09
Okhaldhunga	0.09	0.10	0.07	0.11	0.09	0.06
Min	0.00	0.00	0.00	0.00	0.00	0.00
Max	0.40	0.45	0.38	0.36	0.40	0.40
Average	0.08	0.09	0.08	0.08	0.08	0.09
Std. Dev.	0.10	0.11	0.10	0.10	0.10	0.10

5.3.2.2 QR Yield Series

The premium rate results of QR maize yield series are present in Table 5.11. Results showed premium rates were found in a range from 0 to as high as 0.47%. The highest premium rate is observed at Dhankuta district with the value of about 0.45%. Zero % premium rates were estimated at Khotang and Taplejung districts and lower than 0.30% at the remaining 17 districts.

The premium rates of QR maize yield series were observed 0 to 0.44, 0 to 0.47, 0 to 0.37, 0 to 0.39, 0 to 0.45, and 0 to 0.44% for Normal, Lognormal, Beta, Weibull, Gamma, and Kernel distributions, respectively. Likewise, the average premium rates were 0.09, 0.09, 0.08, 0.09, 0.09, and 0.10% for Normal, Lognormal, Beta, Weibull, Gamma, and Kernel distributions, respectively.

The premium rates for both OLS and QR yield series of maize in this study were observed lower than Ozaki et al. (2008). They presented 6.33% premium rate in Normal, 9.82% in Beta, and 7.99 to 9.91% in Kernel distribution at the Gaurapuava county of Brazil, which seemed substantially greater than our results.

Table 5.11 Pure Premium Rate (%) at 90% Coverage Level for QR Maize Yield Series in 2011-2012

Districts	Normal	Lognormal	Beta	Weibull	Gamma	Kernel
Syanja	0.14	0.14	0.14	0.16	0.14	0.17
Myagdi	0.21	0.23	0.20	0.19	0.21	0.17
Dhankuta	0.44	0.47	0.37	0.39	0.45	0.44
Jhapa	0.01	0.01	0.01	0.01	0.01	0.02
Baglung	0.03	0.03	0.03	0.04	0.02	0.01
Ramechhap	0.04	0.04	0.04	0.05	0.04	-[1]
Surkhet	0.00	0.00	0.00	0.01	0.00	0.00
Khotang	0.00	0.00	0.00	0.00	0.00	0.00
Solukhumbu	0.05	0.05	0.05	0.06	0.05	0.07
Bara	0.17	0.16	0.18	0.23	0.16	0.18
Nawal	0.21	0.22	0.20	0.21	0.21	0.27
Lamjung	0.08	0.08	0.08	0.09	0.08	0.10
Tanahun	0.07	0.07	0.07	0.07	0.07	0.10
Taplejung	0.00	0.00	0.00	0.00	0.00	0.00
Kaski	0.04	0.04	0.04	0.05	0.04	0.06
Nuwakot	0.04	0.04	0.05	0.07	0.04	0.05
Dailekh	0.03	0.04	0.03	0.02	0.03	0.04
Sindhupalchok	0.01	0.01	0.02	0.03	0.01	0.01
Gulmi	0.08	0.08	0.08	0.10	0.08	0.10
Okhaldhunga	0.08	0.09	0.07	0.07	0.08	0.05
Min	0.00	0.00	0.00	0.00	0.00	0.00
Max	0.44	0.47	0.37	0.39	0.45	0.44
Average	0.09	0.09	0.08	0.09	0.09	0.10
Std. Dev.	0.11	0.11	0.09	0.10	0.11	0.11

[1] could not estimate the probability of yield loss.

5.3.3 Premium Rates of Wheat

5.3.3.1 OLS Yield Series

The premium rate results of OLS wheat are presented in Table 5.12. Results showed premium rates in were observed in a range, such as, 0 to 1.25, 0 to 1.42, 0 to 1.22, 0 to 1.15, 0 to 1.35, and 0 to 1.10 for Normal, Lognormal, Beta, Weibull, Gamma, and Kernel distributions, respectively. Likewise, the average premium rates for OLS wheat were 0.34, 0.38, 0.34, 0.33, 0.36, and 0.33% for Normal, Lognormal, Beta, Weibull, Gamma, and Kernel distributions, respectively.

The premium rates at Mugu district were observed above 1% of liability based on six distributions, 0 % premium rate at Bara and Bardiya districts, and 0 to 0.90% at the rest of 17 districts.

Table 5.12 Pure Premium Rate (%) at 90% Coverage Level for OLS Wheat Yield Series in 2011-2012

Districts	Normal	Lognormal	Beta	Weibull	Gamma	Kernel
Rupandehi	0.08	0.08	0.09	0.12	0.08	0.08
Kapilbastu	0.02	0.25	0.25	0.29	0.24	0.28
Bajura	0.82	1.00	0.78	0.63	0.91	0.71
Parsa	0.04	0.04	0.04	0.05	0.03	0.04
Mugu	1.25	1.42	1.22	1.17	1.35	1.10
Bara	0.00	0.00	0.00	0.01	0.00	0.00
Bardiya	0.00	0.00	0.00	0.00	0.00	0.00
Rukum	0.69	0.73	0.68	0.65	0.73	0.66
Darchula	0.65	0.74	0.63	0.60	0.70	0.41
Surkhet	0.06	0.07	0.06	0.06	0.06	0.09
Jhapa	0.02	0.02	0.02	0.03	0.02	0.02
Doti	0.51	0.57	0.49	0.47	0.53	0.48
Kavre	0.41	0.43	0.41	0.43	0.42	0.34
Ramechhap	0.51	0.57	0.48	0.41	0.53	0.47
Baitadi	1.06	1.14	0.98	0.96	1.10	1.09
Banke	0.02	0.02	0.02	0.02	0.02	0.03
Chitwan	0.08	0.08	0.08	0.08	0.08	0.11
Kailali	0.21	0.22	0.21	0.21	0.21	0.27
Makawanpur	0.13	0.13	0.12	0.12	0.12	0.19
Siraha	0.14	0.15	0.14	0.15	0.14	0.18
Min	0.00	0.00	0.00	0.00	0.00	0.00
Max	1.25	1.42	1.22	1.17	1.35	1.10
Average	0.34	0.38	0.34	0.32	0.36	0.33
Std. Dev.	0.38	0.43	0.36	0.34	0.41	0.34

5.3.3.2 QR Wheat Yield Series

The pure premium rate results of QR wheat yield series are presented in Table 5.13. Results showed premium rates were found in a range, i.e., 0.01 to 1.25, 0.01 to 1.43, 0.02 to 1.22, 0.01 to 1.20, 0.01 to 1.34, and 0.01 to 1.07% for Normal, Lognormal, Beta Weibull, Gamma, and Kernel distributions, respectively. The average of premium rates were 0.36, 0.41, 0.35, 0.33, 0.38, and 0.32 for Normal, Lognormal, Beta, Weibull, Gamma, and Kernel distributions, respectively. Premium rates at Mugu district were observed greater than 1% in all distributions and lower than 1% at the rest 19 districts.

Our results for both OLS and QR yield series of wheat were found smaller than the results of Ozaki et al. (2008). They presented premium rates equal to 4.96% for Normal, 8.43% for Beta, and 7.29 to 7.85% in Kernel distribution for area yield insurance of wheat at Tabagi county in Brazil.

Table 5.13 Pure Premium Rate (%) at 90% Coverage Level for QR Wheat Yield Series in 2011-2012

Districts	Normal	Lognormal	Beta	Weibull	Gamma	Kernel
Rupandehi	0.09	0.10	0.09	0.12	0.09	0.09
Kapilbastu	0.22	0.23	0.22	0.25	0.22	0.24
Bajura	0.74	0.90	0.69	0.51	0.84	0.53
Parsa	0.04	0.04	0.04	0.05	0.03	0.04
Mugu	1.25	1.43	1.22	1.20	1.34	1.04
Bara	0.01	0.01	0.01	0.02	0.01	0.01
Bardiya	0.02	0.02	0.02	0.03	0.02	0.02
Rukum	0.81	0.94	0.76	0.63	0.89	0.59
Darchula	0.68	0.81	0.65	0.59	0.73	0.45
Surkhet	0.08	0.09	0.07	0.08	0.08	0.09
Jhapa	0.04	0.04	0.04	0.06	0.04	0.05
Doti	0.46	0.52	0.45	0.42	0.49	0.41
Kavre	0.52	0.57	0.50	0.49	0.54	0.36
Ramechhap	0.50	0.52	0.47	0.40	0.52	0.44
Baitadi	1.08	1.17	1.04	1.00	1.13	1.07
Banke	0.02	0.02	0.02	0.03	0.02	0.03
Chitwan	0.09	0.10	0.09	0.10	0.08	0.11
Kailali	0.31	0.34	0.29	0.29	0.31	0.35
Makawanpur	0.16	0.17	0.16	0.15	0.16	0.26
Siraha	0.15	0.15	0.15	0.17	0.15	0.17
Min	0.01	0.01	0.01	0.02	0.01	0.01
Max	1.25	1.43	1.22	1.20	1.34	1.07
Average	0.36	0.41	0.35	0.33	0.38	0.32
Std. Dev.	0.38	0.43	0.36	0.33	0.41	0.31

This study revealed that the estimated premium rates of area yield insurance in rice, maize, and wheat in Nepal in both OLS and QR yield series were substantially lower than the previous studies. In some cases, the results observed to 0% premium rates at 90% coverage level. The reason for lower premium rates may be due to lower CV of normalized yield series in this study.

Botts and Boles (1958) illustrated the relationship of coefficient of variation (CV) and premium rate and indicated that coefficient of variation plays a major role in premium rate estimation. Likewise, Skees et al. (1997) explained that the coefficient of variation plays an important to the premium rates even though yields follow the non-normal distribution. Accordingly, they explained the lower level of CV will have lower premium rates. Our data of normalized yield series showed very low CV for example, about 10 % in rice, 8% in maize, and 11% in both OLS and QR yield series as shown in Table 5.1. Thus, our premium rates observed were very low compared to the previous studies. The reason of lower CV in our study is due to reduction of CV in yield correction, and normalization process, which is illustrated in Table 5.1.

To illustrate the relationship between CV and premium rate, this study examined the correlation between CVs and premium rates. The results indicated that there were significant relationships between CVs and premium rates of examined yield series. The result of correlation between CVs and premium rate are presented in Table A28. Moreover, the graphical presentations of positive relationships of CV and premium rates are presented in Figures A1, A2, and A3 for rice, maize, and wheat, respectively.

The results revealed 0% premium rates in some districts. The reason for this result is that observed yield series were not found lower than the coverage level of yields (90% of the expected yield) during the 1990-91 to 2010-11. Importantly, due to a shortness of the data in this study, we were unable to capture catastrophic yields. Consequently, it impacted on the premium rate. If there is no catastrophic yield in the sample period, apparently, the premium rate estimation will be lower. This is major limitations to apply the shorter data length in the actuarial estimation.

Apart from the pure premium rate in %, the study also estimated pure premium in kilogram per hectare, which is presented in Appendix E Tables A29, A30, A31, A32, A33, and A34 for OLS and QR yield series of rice, maize, and wheat yields, respectively.

5.4 Comparison of Pure Premium Rates

5.4.1 Between Probability Distributions

This section examines the pure premium rates difference based on different probability distributions. Thus, we compared the pure premium rates between Normal, Lognormal, Beta, Weibull, Gamma, and Kernel distributions to examine whether the distribution plays significant role in the premium rates estimation in case of rice, maize, and wheat in Nepal. Besides, we also evaluated the significant difference in the premium rate between different goodness fitting statuses of the distributions.

Moreover, the Gamma distribution was rarely applied for the actuarial estimation in the previous studies; therefore, this study examined the premium rate estimates by fitting Gamma distribution and compared premium rates with Normal, Lognormal, Beta, Weibull, and Kernel distributions.

Wilcoxon sign rank test was used to examine the differences of premium rates between distributions. This test is a nonparametric test that examines median difference of two related samples. Sherrick et al. (2004) applied this test to evaluate the premium rate estimates based on five parametric probability distributions for multi-peril crop insurance products in corn and soybean.

Mean percentage difference was used to examine the differences in premium rates between two distributions. The mean percentage difference is the difference between two values divided by the average of the two values. It examines the mean percentage difference of premium rates based on two probability distributions and also evaluates statistical test of median difference of premium rates between two probability distributions.

5.4.1.1 Rice

5.4.1.1.1 OLS Yield Series

The mean percentage difference and its significant test results of OLS rice yield series are presented in Table 5.14. The mean percentage difference of premium rate between the Normal and Lognormal distribution, Normal and Beta, Normal and Kernel were found -1.52, 0.98, and 0.93%, respectively and all of them were statistically found statistically significant at 0.05 level. Additionally, the mean percentage difference of premium rate between Lognormal and Beta distribution, Lognormal and Gamma, and Lognormal and Kernel were 2.50, 0.97, and 2.44, and were significant 0.01 and 0.05 levels, respectively. Further, the mean percentage difference of premium rate between Beta and Gamma distribution was -1.53% and it was significant at 0.1 level. In addition, the mean percentage difference of premium rate between Gamma and Kernel distribution was 1.48% and it was significant at 0.1 level.

Based on Wilcoxon signed rank test results, premium rates of Lognormal distribution were observed larger than Normal, Beta, Gamma, and Kernel distributions and those rates of Normal distribution were larger than Beta and Kernel distributions. Similarly, premium rates of Beta distribution were found smaller than Gamma and premium rates of Weibull distribution were found larger than Kernel distribution. In case of Kernel distribution, the premium rates were found significantly lower than Normal, Lognormal, and Gamma distributions.

Table 5.14 Mean Percentage Difference of Pure Premium Rates (%) of OLS Rice Yield Series

	Lognormal	Beta	Gamma	Weibull	Kernel
Normal	-1.52**[1]	0.98**[1]	-0.55	0.20	0.93**[1]
Lognormal		2.50**[1]	0.97***[1]	1.72	2.44**[1]
Beta			-1.53*[1]	-0.78	-0.05
Gamma				0.75	1.48*[1]
Weibull					0.72

[1] ***, **, and * indicate significant difference of premium rates between two probability distributions at 0.01, 0.05, and 0.1 levels, respectively.

5.4.1.1.2 QR Yield Series

The mean percentage difference and Wilcoxon signed rank test results of QR rice yields series are presented in Table 5.15. The mean percentage difference of premium rate between Normal and Lognormal and Normal and Beta distributions were -2.34% and 1.34% and were found statistically significant at 0.1 level. Similarly, the mean percentage difference of premium rates between Lognormal and Beta and Lognormal and Gamma distributions were 3.68% and 1.57% and were statistically significant at 0.10 and 0.01 levels, respectively.

Based on statistical significant results, premium rates of Lognormal distribution were found larger than Normal, Beta, and Gamma distributions and those of Normal distribution were larger than Beta distribution. In case of Kernel distribution, the premium rates were observed difference with other distributions.

Table 5.15 Mean Percentage Difference of Pure Premium Rates (%) of QR Rice Yield Series

	Lognormal	Beta	Gamma	Weibull	Kernel
Normal	-2.34*[1]	1.34*[1]	-0.77	3.17	1.29
Lognormal		3.68*[1]	1.57***[1]	5.50	3.63
Beta			-2.11	1.83	-0.06
Gamma				3.94	2.06
Weibull					-1.89

[1]***, **, and * indicate significant difference of premium rates between two probability distributions at 0.01, 0.05, and 0.1 levels, respectively.

5.4.1.2 Maize

5.4.1.2.1 OLS Yield Series

The mean percentage difference and Wilcoxon rank test results of OLS maize are presented in Table 5.16. The mean percentage difference of premium rates between Normal and Lognormal and Normal and Kernel distribution were -2.10 and -3.22% and both were found statistically significant at 0.05 level. Likewise, the mean percentage difference of premium rates between Lognormal and Beta and Lognormal and Gamma distribution were 2.10 and 1.79% and were found statistically significant at 0.1 and 0.01 levels, respectively. Additionally, the mean percentage difference of premium rate between Beta and Kernel and between Gamma and Kernel distribution were -3.22 and -2.92% and were seen statistically significant at 0.05 level.

Based on statistical significant results, premium rates for Lognormal distribution were larger than Normal, Beta, and Gamma distribution and those for Normal distribution were found smaller than the Kernel distributions. Besides, premium rates for Beta and Gamma distributions were observed smaller than the Kernel distribution. Likewise, premium rates of Kernel distribution were observed significantly lower than Normal, Lognormal, and Gamma distributions.

Table 5.16 Mean Percentage Difference of Pure Premium Rates (%) of OLS Maize Yield Series

	Lognormal	Beta	Gamma	Weibull	Kernel
Normal	-2.10**[1]	0.00	-0.31	-1.07	-3.22**[1]
Lognormal		2.10*[1]	1.79***[1]	1.03	-1.12
Beta			-0.31	-1.07	-3.22**[1]
Gamma				-0.76	-2.91**[1]
Weibull					-2.15

[1]***, **, and * indicate significant difference of premium rates between two probability distributions at 0.01, 0.05, and 0.1 levels, respectively.

5.4.1.2.2 QR Yield Series

The results of mean percentage difference of premium rates and Wilcoxon signed rank test for QR maize yield are presented in Table 5.17. The mean percentage difference of premium rates between Normal and Lognormal, Normal and Weibull, and Normal and Kernel were -0.99, -1.68, and -2.82%, respectively and all were these results were statistically significant at 0.10 level. Additionally, the mean percentage difference of premium rates between Lognormal and Gamma distribution was 1.14% and it was significant at 0.05 level. Likewise, the mean percentage difference in premium rates between Beta and Weibull and Beta and Kernel distribution were -2.71 and –3.85 % and were found significant at 0.01 and 0.1levels, respectively. Similarly, the mean percentage differences in premium rates between Gamma and Weibull and Gamma and Kernel distributions were -1.82 and -2.96% and were significant at 0.1 level.

Based on statistical significant results, premium rates of Normal distribution were smaller than Lognormal, Weibull, and Kernel; those of Lognormal distribution were larger than Gamma distribution. Premium rates of Beta and Gamma distribution were found smaller than Weibull and Kernel distributions individually. Similarly, the premium rates of Kernel distribution were observed significantly lower than Normal, Lognormal, and Gamma distributions.

Table 5.17 Mean Percentage Difference of Pure Premium Rate (%) of QR Maize Yield Series

	Lognormal	Beta	Gamma	Weibull	Kernel
Normal	-0.99*[1]	1.03	0.14	-1.68*[1]	-2.82*[1]
Lognormal		2.02	1.14**[1]	-0.68	-1.83
Beta			-0.89	-2.71***[1]	-3.85*[1]
Gamma				-1.82*[1]	-2.96*[1]
Weibull					-1.15

[1]***, **, and * indicate significant difference of premium rates between two probability distributions at 0.01, 0.05, and 0.1 levels, respectively.

5.4.1.3 Wheat

5.4.1.3.1 OLS Yield Series

The mean percentage difference and Wilcoxon sign rank test results of OLS wheat are presented in Table 5.18. The mean percentage difference of premium rate between Normal and Lognormal, Normal and Beta distribution, Normal and Gamma distributions were -3.34, 0, and -2.04% and were found statistically significant at 0.01, 0.1 and 0.05 levels, respectively. Similarly, the mean percentage difference of premium rate between Lognormal and Beta, Lognormal and Gamma, and Lognormal and Weibull distributions were 3.34, 1.31, and 4.25% and were statistically significant at 0.01, 0.01, and 0.10

levels, respectively. Additionally, the mean percentage difference of premium rate between Beta and Gamma distribution was -2.04% and it was statistically significant at 0.1 level.

The statistical significant results indicated premium rates for Lognormal distribution were larger than those of Normal, Beta, Gamma, and Weibull distribution. Similarly, premium rates of Normal distribution were larger than those of Beta and smaller than Gamma distributions. Besides, premium rates of Beta distributions were smaller than those of Gamma distribution. In case of Kernel distribution, we found no significant difference in the premium rates as compared to other distributions.

Table 5.18 Mean Percentage Difference of Pure Premium Rate (%) of OLS Wheat Yield Series

	Lognormal	Beta	Gamma	Weibull	Kernel
Normal	-3.34***[1]	0.00*[1]	-2.04**[1]	0.91	0.57
Lognormal		3.34***[1]	1.31***[1]	4.25*[1]	3.91
Beta			-2.04*[1]	0.91	0.57
Gamma				2.95	2.60
Weibull					-0.35

[1]***, **, and * indicate significant difference of premium rates between two probability distributions at 0.01, 0.05, and 0.1 levels, respectively.

5.4.1.3.2 QR Yield Series

The mean percentage difference and Wilcoxon sign rank test results of QR wheat yield series are presented in Table 5.19. The mean percentage difference of premium rates between Normal and Lognormal, Normal and Beta, and Normal and Gamma distributions were -2.91%, 1.02%, and -1.40%, respectively and were statistically significant at 0.01, 0.01, and 0.05 level, respectively. Likewise, the mean percentage difference of premium rate between Lognormal and Beta, Lognormal and Gamma, and Lognormal and Weibull distribution were 3.93, 1.51, and 5.35% and were found statistically significant at 0.01, 0.01, and 0.05 levels, respectively. In addition, the mean percentage difference of premium rate between Beta and Gamma distribution was -2.42% and it was statistically significant at 0.05 level.

The statistical significant results indicated that premium rates for Lognormal distribution were larger than those of Normal, Beta, Gamma, and Weibull distributions. Similarly, the premium rates for Normal distribution were larger than those of Beta and smaller than Gamma distributions. The premium rate for Beta distribution was smaller than those of Gamma distribution. In case of Kernel distribution, the study observed no significant difference in the premium rates as compared to other distributions.

Table 5.19 Mean Percentage Difference of Pure Premium Rate (%) of QR Wheat Yield Series

	Lognormal	Beta	Gamma	Weibull	Kernel
Normal	-2.91***[1]	1.02***[1]	-1.40**[1]	2.45	3.38
Lognormal		3.93***[1]	1.51***[1]	5.35**[1]	6.27
Beta			-2.42**[1]	1.44	2.36
Gamma				3.85	4.77
Weibull					0.93

[1]***, **, and * indicate significant difference of premium rates between two probability distributions at 0.01, 0.05, and 0.1 levels, respectively.

Wilcoxon sign rank test results revealed in most of the cases that the premium rates for Lognormal distribution were larger than the premium rates for Normal, Beta, Gamma, and Weibull distributions irrespective of crops and yield prediction approaches. Similarly, in most of the cases, premium rates for Beta distribution were observed smaller than Normal, Lognormal, Gamma, Weibull, Kernel distributions irrespective of crops and yield prediction approaches. The Beta distribution was ranked the best fitted distribution in both OLS and QR maize and QR wheat yield series. Although Normal distribution was observed best fitted distribution in OLS and QR rice and OLS wheat yield series and the second best fitted with the rest of yield series, premium rates for Normal distribution were observed larger than Beta distribution in most of the cases. Similarly, premium rates for Normal distribution were smaller than Weibull and Gamma distributions, whereas mixed results were found with Kernel distribution.

As a result, Beta distribution presented the lowest premium rates and the Normal distribution estimated the second lowest premium rates in most of the cases. Lognormal distribution estimated the highest premium rates. Our results are comparable with Sherrick et al. (2004) that they presented the lowest premium rates based on the best fitted Logistic distribution in soybean yields.

Moreover, the premium rates based on Gamma distribution were found smaller than Lognormal and Weibull, larger than Beta and Normal, and mixed results with the Kernel. This distribution presented the premium rates results in between the lowest and the highest premium rates.

In case of kernel distribution, it did not illustrate any noticeable and interesting premium rate results as compared to other distributions. However, it showed significantly higher premium rate than Beta, Normal, and Gamma distribution in both maize yield series.

5.4.2 Between OLS and QR Yield Series

This study assumed different yield prediction approaches may generate different yield series, thereby; it may generate difference in premium rate. Therefore, we examined the difference in the premium rates between OLS and QR yield series. For this, we examined the mean percentage difference of premium rates by using the Wilcoxon sign rank test for OLS and QR yield series of rice, maize, and wheat.

5.4.2.1 Rice

The mean percentage difference and statistical significant results for OLS and QR yield series are presented in Table 5.20. The results revealed that the premium rates based on OLS yield series were seen larger than QR yield series; however, there were no significant difference in premium rates in all tested six distributions.

Table 5.20 Mean Percentage Difference of Pure Premium Rates (%) between OLS and QR Rice Yield Series

QR / OLS	Normal	Lognormal	Beta	Weibull	Gamma	Kernel
Normal	0.87					
Lognormal		0.50				
Beta			1.24			
Weibull				3.84		
Gamma					0.65	
Kernel						1.24

5.4.2.2 Maize

In the case of maize, the mean percentage difference results are presented in Table 5.21. The results showed a negative sign between the OLS and QR yield series indicated the premium rates for OLS were smaller in all distributions; however, a statistical significant difference result at 0.1 level was observed in the case of Normal distribution only. The result indicated that QR premium rates were larger than OLS premium rates in Normal distribution.

Table 5. 21 Mean Percentage Difference of Pure Premium Rates (%) between OLS and QR Maize Yield Series

QR / OLS	Normal	Lognormal	Beta	Gamma	Weibull	Kernel
Normal	-1.95*[1]					
Lognormal		-0.85				
Beta			-0.92			
Gamma				-1.50		
Weibull					-2.56	
Kernel						-1.83

[1]* indicates significant difference of premium rates between two yield prediction approach at 0.1 level.

5.4.2.3 Wheat

The mean percentage difference results are presented in Table 5.22. The results showed premium rates from OLS were seen smaller than QR yield series in Normal, Lognormal, Beta, Gamma probability distributions but larger in the Kernel distribution. However, the Wilcoxon sign rank test results showed significant differences was observed for Normal, Lognormal, Beta, Gamma distribution at 0.1 level. Based on the results, the premium rates using QR yield series were larger than OLS for Normal, Lognormal, Beta, Gamma distributions in case of wheat.

Table 5. 22 Mean Percentage Difference of Pure Premium Rates (%) between OLS and QR Wheat Yield Series

OLS \ QR	Normal	Lognormal	Beta	Gamma	Weibull	Kernel
Normal	-2.04*[1]					
Lognormal		-1.61*[1]				
Beta			-1.02*[1]			
Gamma				-1.40*[1]		
Weibull					-0.50	
Kernel						0.78

[1]* indicates significant difference of premium rates between two regression model at 0.1 level, respectively.

Out of comparisons of premium rate under 3 crops and six distributions for each crop and all together 18 test carried out, 5 tests results showed a statistically significant difference between the OLS and QR yield series and the rest 13 showed there were no significant difference. Importantly, we could not observe any difference in the premium rates between OLS and QR yield series in rice. The differences were observed in case of maize and wheat yield series only. Those results were which were found significant difference showed higher mean percentage difference of premium rates for QR yield series compared to OLS yield series. Thus, based on the results, actuarial estimation based on QR predicted yield series may generate larger premium rate than the OLS approach at least in case of maize and wheat in Nepal.

In the case of maize, non-normal Beta distribution was the best fitted distribution in both OLS and QR yield series. Similarly, non-normal Beta distribution was the best fitted distribution in QR wheat yield series. In both maize and wheat we observed some differences in premium rate between OLS and QR yield series.

The quantile regressions are robust over OLS in handling the extreme value points; thus, the quantile regression approach might have generated more yields in the lower tail side as compared to the OLS. Thus, based on the results, if the yield series is more towards non-normal distribution, it may generate higher premium rate as compared to OLS yield series.

5.5 Performance of Area Yield Insurance

The overall motive of the crop insurance is to minimize the yield risk and increase the probability of income of the producers. Thus, this study evaluated the performance of the area yield insurance in terms of the variance reduction and increment of the certainty equivalent of the revenues comparing the results without and with insurance conditions.

Miranda (1991) indicated that the variance reduction performance of area yield insurance depends on how the yields of a farm are associated with the area yields. According to him, higher the correlation of yields between farm and area yields, higher the risk reduction will be and vice versa.

The efficiency evaluation of area yield insurance is done at the farm level because risk reduction and revenues measurement can only be done at the farm level. However, we do not have farm yield data for this study. Therefore, we made some assumptions to precede the analysis and compare the risk reduction and revenues results without and with insurance conditions.

We assumed three hypothetical farms with one hectare land area having three categories of yield farms average yield farms, lower yield farms, and higher yield farms. The mean and variance of the yield series were assumed to be equal to the area yield for the average farms, whereas as 10% lower mean yield for the lower yield farms, and 10% higher mean yield for the higher yield farms but we kept variance same as of district yield. The reason behind this is to examine the effect of insurance of the farms with different yields but with the same premium rate. Three districts, i.e., Kapilbastu for rice, Nawalparasi far maize, and Mugu for wheat were selected in a random basis. Kapilbastu district is the second highest ranking district, Nawalparasi district is eleventh ranking district, and Mugu district is fifth highest ranking district for rice, maize and wheat, respectively based on CV. Accordingly, we evaluated the performance of area yield insurance in 3 farms for each crop. Thus, we evaluated performance in 9 farms altogether.

In the next step, we simulated OLS yield series and generated 10000 observations for each model farm by fitting the Beta distribution. The Beta distribution was selected because this distribution showed one of the best fitted distributions in overall ranking and also it illustrated the lowest premium rates among the distributions tested.

In addition, we assumed the initial wealth of USD 10000 for each farm, which is similar to the condition of Nepalese farm. Since the national/district average price of rice, maize, and wheat could not access in Nepal; FAO producer price in 2007 (FAO, 2012) was taken as proxy price. The FAO prices of rice, maize, and wheat were USD 0.168/kg, 0.1739 USD/kg, and 0.2055 USD/kg, respectively. Further, we assumed the farmers were moderate risk averter. So, this study considered the constant relative risk aversion (CRRA) =1 and 2 for the certainty equivalent of revenues (CERs) estimation. Thus, we estimated the CERs separately for CRRA=1 and CRRA=2 conditions.

5.5.1 Risk Reduction

This study applied equation (4.16) for risk reduction analysis. The risk reduction results are presented in Table 5.23. We measured the risk reduction in terms of variance of yield reduction due to insurance contract. The results revealed that risk reduction were observed with insurance contract in all 9 farms; however, the scale of risk reduction varied in different yield farms. The higher risk reduction was observed in lower yield farms and lower risk reduction was observed in higher yield farms. For example, about 68% risk reduction was observed for the lower yield farm and about 19% for the higher yield farm, whereas about 40% risk reduction for average rice farm at Kapilbastu district for rice. Similar results were observed in the case of maize and wheat farms at Nawalparasi and Mugu district, respectively.

Table 5.23 Efficiency of Area Yield Insurance Measured by Risk Reduction and Certainty Equivalent of the Revenues at CRRA=1 and 2

Crop/ District	Farm	Premium (USD /ha)	Risk Reduction (%)	Certainty Equivalent of the Revenues			
				Without Insurance		With Insurance	
				CRRA=1	CRRA=2	CRRA=1	CRRA=2
Rice (Kapilbastu)	Average Farm	2.76	40.09	10528.71	10528.44	10537.26	10537.10
	Lower Yield Farm	2.76	68.00	10475.84	10475.57	10502.94	10502.86
	Higher Yield Farm	2.76	18.64	10581.58	10581.32	10582.47	10582.26
Maize (Nawalparasi)	Average Farm	1.01	30.44	10525.89	10525.74	10530.57	10530.47
	Lower Yield Farm	1.01	67.60	10473.31	10473.16	10494.40	10494.35
	Higher Yield Farm	1.01	7.72	10578.47	10578.33	10578.36	10578.23
Wheat (Mugu)	Average Farm	3.67	47.19	10332.93	10332.73	10342.02	10341.92
	Lower Yield Farm	3.67	67.48	10299.59	10299.41	10320.83	10320.77
	Higher Yield Farm	3.67	29.04	10366.21	10366.02	10368.41	10368.27

The results indicated that area yield insurance contract was seen effective in risk reduction but it varied the risk reduction magnitudes in different farms and also in different crops. Higher (lower) expected yield farms got lower (greater) benefits of risk reduction compared the lower (higher) and average expected yield farms.

The yield risk of a farmer is decomposed in two parts, i.e., systemic risk (risk to all farmers of the area) and the non-systemic residual component (risk of individual farm) (Miranda, 1991). Area yield insurance only helps to minimize the systemic risk. This study revealed the result of a substantial yield risk reduction. Thus, the pure premium rates for area yield insurance were found helpful in yield reduction in rice, maize, wheat in Nepal.

5.5.2 Certainty Equivalent of the Revenues

Importantly, the study also compared the certainty equivalent of the revenue (CERs) without and with insurance contracts. The CER provides the basis for producer’s welfare analysis. The CERs were examined in two moderate risk aversion conditions, i.e., CRRA=1 and 2. The equation (4.18) and (4.20) were applied for CRRA=1 and equation (4.17) and (4.19) for CRRA=2, respectively.

The results presented in Table 5.23 showed CERs in all farms in both cases of CRRA=1 and CRRA=2 were seen higher with insurance contract except in higher yield farm of maize yield at Nawalparasi district. In this farm, the CER with insurance contract was found slightly smaller with without contract.

The main concern of crop insurance is economic sustainability. Many governments are diverting a huge amount of their revenues to provide premium subsidy. In one hand, the amount of premium is mostly higher and farmers are not motivated to buy insurance contracts with high premium rates. On the other hand, the catastrophic risks, such as, drought, floods spread over a large area. Therefore, risk pooling is very low. Therefore, private insurance is difficult to sustain. Thus, subsidy on premium will make the premium affordable to farmers; thus, it encourages farmers to buy a contract.

However, in our study the premium rate was observed very affordable to the farmers. Moreover, the premium rate is seemed helpful to reduce the yield risk and increase the CER. Thus, based on the risk reduction and CERs results, the area yield insurance is seemed beneficial to the rice, maize, and wheat farmers in Nepal.

6. Concluding Remarks

The conventional insurance, particularly multiple peril yield and revenue crop insurance (MPCI) products seems inefficient for actuarial performance. The experience of the implementing countries showed premium collections mostly were lower than indemnity payment and its administrative costs. As a result, governments invested a huge amount of money to cover the losses. The major reason indicated for poor actuarial performance is moral hazard and adverse selection. These two problems arise due to asymmetry in information but hard to minimize them in the MPCI product. Thus, an alternative insurance product—area yield insurance product was suggested. This product is considered less vulnerable to moral hazard and adverse selection problems because the premium rates and indemnities are estimated based on the area yield. Therefore, there will have no effect of individual producer on it. Thus, these products are suggested as an alternative product not only in the developed countries but also suggested suitable for developing countries where government cannot afford a huge amount of money to the premium subsidy for the crop insurance products.

Most importantly, under and over rating of premium also indicated a cause of poor actuarial performance, which arises due to inaccurate yield estimation procedure. The bias rating could emerge due to many factors; however, major one been inaccurate expected yield and probability of its shortfall estimation. Although the quantile regressions (QR) are considered robust over OLS, if the data are non-normally distributed, it is rarely applied for yield prediction in crop insurance rate making studies. On the other hand, one of the reasons of non-emergence of the crop insurance market in developing countries is the absence of suitable actuarial methodology in the condition of a small number of observations available.

Considering the present study limitations and the small number of observations available in developing countries, the overall objective of this dissertation was to accurately estimate the pure premium rate for the area yield insurance of rice, maize, and wheat in Nepal and evaluate its performance. To achieve overall objective, this study set five approaches were followed as: (1) to estimate area yields of rice, maize, and wheat in Nepal by ordinary least square and quantile regression approaches; (2) to examine the potential probability distribution functions of area yields of rice, maize, and wheat in Nepal; (3) to estimate the pure premium rates of area yield insurance of rice, maize, and wheat in Nepal; (4) to examine the difference of pure premium rates between probability distributions and yield estimation approaches; and (5) to evaluate the performance of area yield insurance in terms of variance reduction and certainty equivalent of the revenues. The study selected the rice, maize, and wheat crops in Nepal for the analysis because these are the important staple crops in Nepal and no actuarial estimation has been conducted before.

6.1 Findings

The results based on the AD test statistics of yield distribution modeling showed the Beta distribution was the best fitted distribution for OLS and QR maize and QR wheat yield series and the Normal was the best fitted with the rest yield series. Therefore, Normal distribution was the best fitted distribution in rice yield series, Beta was the best fitted distribution in maize yield series. However, in case of wheat, it depended on the yield prediction approach followed. On the other hand, Weibull, Gamma, and Lognormal were found the least fitted distribution in rice, maize, and wheat yield series, respectively. The result of Gamma distribution showed the second and third ranks in goodness-of-fit in OLS and QR rice yield series and fourth ranks in wheat yield series.

The premium rate estimates observed were very small mostly less than 1% of liability, except in rice at Banke district and wheat at Mugu district irrespective of distributions applied and yield prediction approaches followed. The main reason for low premium rates is because of lower coefficient of variation (CV) in the normalized yields.

As in previous studies, our study results also showed that the probability distribution function played a significant role to generate premium rate difference. The premium rate estimates observed were significantly lower for best fitted Beta distribution among fitted distributions, whereas the opposite result were observed in the case of Lognormal distribution. Moreover, premium rates based on the rest of the distributions were in between the Beta and Lognormal distribution. Gamma distribution revealed higher premium rate than Beta and lower than Lognormal and mixed results with other distributions. Thus, Gamma distribution can be a modestly feasible distribution for premium rate estimation, at least in the case of rice, maize, and wheat in Nepal.

In the case of Kernel distribution, it did not show any specific and interesting premium rate results in comparison to other distributions. However, it showed significantly higher premium rate than Beta, Normal, and Gamma distribution in both maize yield series.

The comparison of premium rates based on OLS yield and quantile yield series showed somehow interesting results. In case of rice, quantile approach predicted yield series generated no significant different premium rates than OLS yield series. However, QR yield series showed larger premium rate and significantly different in case of maize and wheat. In the case of maize, non-normal Beta distribution was the best fitted distribution in both OLS and QR yield series. Similarly, the non-normal Beta distribution was the best fitted distribution in QR wheat yield series. In both maize and wheat we observed some significant differences in the premium rate between OLS and QR yield series. Thus, based on the results, quantile regression approach may generate larger premium rate than the OLS approach if the yield series is fitted well with non-normal distribution.

The premium rates were observed very low; however, they were enough to reduce the yield risk substantially. Similarly, higher CERs observed with area yield insurance contracts in rice, maize, and wheat in Nepal that presented the indication of the higher welfare of a farmer due to area yield contract. Thus, findings can be implemented in Nepal and other countries having similar production situation.

6.2 Contributions

Firstly, this study will contribute to present literature as it estimated the premium rates for the first time for area yield insurance in Nepal. Secondly, present literatures have rarely applied Gamma distribution for actuarial estimation in the crop insurance products. Our results showed the Gamma distribution performed better goodness of fit results in rice and wheat yield series goodness-of-fitness than Lognormal distribution. Similar results were observed in the case of premium rate estimation and illustrated the premium rates somehow in the between Lognormal and Beta distribution. Thus, Gamma distribution can cautiously be applied to actuarial estimation. Thirdly, the quantile regressions were rarely applied for yield prediction in the crop insurance purposes. This study successfully applied the quantile regression for yield prediction and premium rate and revealed that quantile regression approach may generate larger premium rate than the OLS approach if the yield series is fitted well with non-normal distribution.

6.3 Further Research

Literature have agreed that weather index insurance is economically sustainable and less vulnerable to moral hazard and adverse selection similar to area yield insurance. However, the product is not well documented for methodological procedures for actuarial estimation, particularly in the case of developing countries where there are limited climate and yield data are available. Moreover, present literature have rarely compared the premium rates and welfare effect to the producer between these two crop insurance products. Thus, further research need to be focused on designing and rating of weather index insurance, compare the premium rates, and risk reduction and welfare effects between area yield insurance and index insurance products.

7. References

Adhikari, S. 2011. *Essays on Crop Insurance Yield Guarantee and Product Choices* (A Ph.D. Dissertation). Retrieved on April 20, 2012, from the World Wide Web: http://repositories.tdl.org/ttuir/bitstream/handle/2346/ETD-TTU-2011-08-1606/Adhikari_Shyam_Thesis.pdf?sequence=2.

Adhikari, S., T. O. Knight, and E. J. Belasco. 2012. Evaluation of Crop Insurance Yield Guarantees and Producer Welfare with Upward-Trending Yields. *Agricultural and Resource Economics Review* 41(3): 367–376.

AICC (Agriculture Information and Communication Center). 2004-05. *Executive-summary of agriculture statistics*. Agriculture Information and Communication Centre, Ministry of Agriculture and Cooperatives. Retrieved on March 5, 1013 from the World Wide Web: http://aicc.gov.np

Anderson, T. W. and D. A. Darling. 1952. Asymptotic Theory of Certain Goodness of Fit Criteria Based on Stochastic Processes. *Annals of Mathematical Economics* 23(2):193-212.

Babcock, B. and D. Hennessy. 1996. Input Demand under Yield and Revenue Insurance. *American Journal of Agricultural Economics* 78: 416–27.

Barnett, B. J., J. R. Black, Y. Hu, and J. R. Skees. 2005. Is Area Yield Insurance Competitive with Farm Yield Insurance? *Journal of Agricultural and Resource Economics* 30(2): 285-301.

Barnett, B.J. and O. Mahul. 2007. Weather Index Insurance for Agriculture and Rural Areas in Lower-Income Countries. *Journal of Agricultural and Resource Economics* 89: 1241-1247.

Barry, J. B., J. R. Black., Y. Hu, and J. R. Skees. 2005. Is Area Yield Insurance Competitive with Farm Yield Insurance? *Journal of Agricultural and Resource Economics* 30(2):285-301.

Barry, P.J, P. N. Ellinger, J. A. Hopkin, and C. B. Baker. 1995. *Financial Management in Agriculture.* Fifth edition, Interstate Publishers Inc, Danville, Illinois, USA.

Batra, R. N. and A. Ullah. 1974. Competitive Firm and the Theory of Input Demand under Price Uncertainty. *Journal of Political Economy* 82 (3): 537-548.

Botts, R. and J. N. Boles. 1958. Use of Normal-Curve Theory in Crop Insurance Rate Making. *Journal of Farm Economics* 40(3): 733-740.

Carriquiry, M.A., B.A. Babcock, and C.E. Hart. 2008. Using a Farmer's Beta for Improved Estimation of Expected Yields. *Journal of Agricultural and Resource Economics* 33(1): 52–63.

Chambers, R.G. 1989. Insurability and Moral Hazard in Agricultural Insurance Market. *American Journal of Agricultural Economics* 71: 604-616.

Chavas, J. P. 2004. *Risk Analysis in Theory and Practice*. Elsevier Academic Press, California, USA, 5-16.

Coble, K.H., T.O. Knight, R.D. Pope, and J.R. Williams. 1997. An Expected Indemnity Approach to the Measurement of Moral Hazard in Crop Insurance. *American Journal of Agricultural Economics* 79:216-216.

Corder, G. W. and D. I. Foreman.2009. *Nonparametric Statistics for Non-Statisticians: A Step-by-Step Approach*. John Wiley and Sons, 264.

D'Agostino, R. B. and M. A. Stephens. 1986. *Goodness-of-Fit Techniques*. Statistics: A Series of Textbooks and Monographs, Vol. 68, Marcel Dekker, 576.

Dalal, A. J. and M. Alghalith. 2009. Production Decision under Joint Price and Production Uncertainty. *European Journal of Operational Research* 197: 84-92.

Day, R.H. 1965. Probability Distributions of Field Crop Yields. *Journal of Farm Economics* 47(3): 713–741.

Deng, X., B. J. Barnett, and D. V. Vedenov. 2007. Is there a Viable Market for Area-Based Crop Insurance? *American Journal of Agricultural Economics* 89(2): 508-519.

FAO. 2012. FAOSTAT-Agriculture. Food and Agricultural Organization of the United Nations. Retrieved on April 12, 2012, from the World Wide Web: http://faostat.fao.org/ site/339/default.aspx.

Field, J. E., S. K. Mishra, and O. Ramirez. 2003. Evaluating Crop and Revenue Insurance Products as Risk Management Tools for Texas Cotton Producers. *Journal of Agricultural and Applied Economics* 35(1): 39-52.

Finger, R. 2010. Evidence of Slowing Yield Growth-The Example of Swiss Cereal Yields. *Food Policy* 35:175-182.

Fischer, T., B. Su, Y. Luo, and T. Scholten. 2012. Probability Distribution of Precipitation Extremes for Weather Index–Based Insurance in the Zhujiang River Basin, South China. *Journal of Hydrometeorology* 13:1023-1037.

Gallagher, P. 1987. U.S. Soybean Yield: Estimation and Forecasting with Nonsymmetric Disturbances. *American Journal of Agricultural Economics* 69(4): 796-803.

GoN (Government of Nepal). 2004. *National Agricultural Policy-2004*. Government of Nepal, Singha Darbar Kathmandu, Nepal. Retrieved on April 12, 2012, from the World Wide Web: http://moad.gov.np/downloadfile/nationalAgri%20Policy%202061%20(Nepali)_1298620284.pdf.

GoN (Government of Nepal). 2012. Agricultural Development Strategy, Assessment Report. Government of Nepal, Singha Darbar Kathmandu, Nepal. Retrieved on May 12, 2013, from the World Wide Web:http://moad.gov.np/content.php?id=259.

Goodwin, B. K. 1994. Premium Rate Determination in the Federal Crop Insurance Program: What Do Averages Have to Say About Risk? *Journal of Agricultural and Resource Economics* 19: 382–395.

Goodwin, B. K. and O. Mahul. 2004. *Risk Modeling Concepts Relating to the Design and Rating of Agricultural Insurance Contracts*. The World Bank, Washington DC.

Goodwin, B.K. and A.P. Ker. 1998. Nonparametric Estimation of Crop Yield Distributions: Implications for Rating Group-Risk Crop Insurance Contracts. *Journal of Agricultural and Resource Economics* 80: 139–153.

Halcrow, H.G. 1949. Actuarial Structures for Crop Insurance. *Journal of Farm Economics* 31:418-443.

Hardaker, J. B., R. B. M. Huirne, J. R. Anderson, and G. Lien. 2004. *Coping with Risk in Agriculture*. CABI Publishing, UK.

Harri, A., K.H. Coble, A. P. Ker, and Barry J. Goodwin. 2011. Relaxing Heteroscedasticity Assumptions in Area-Yield Crop Insurance Rating. *American Journal of Agricultural Economics* 93(3): 703-713.

Harwood, J., R. Heifner, K. Coble, J. Perry, and A. Somwaru. 1999. *Managing Risk in Farming: Concepts, Research, and Analysis*. Agricultural economics Report No. 774, USDA, Washinton, DC.

Hazell, P.B.R. 1992. The appropriate role of agricultural insurance in developing countries. *Journal of International Development* 4:567-581.

Just, R. E. and Q. Weninger. 1999. Are Crop Yields Normally Distributed? *American Journal of Agricultural Economics* 81: 287–304.

Just, R. E., L. Calvin, and J. Quiggin. 1999. Adverse Selection in Crop Insurance: Actuarial and Asymmetric Information Incentives. *American Journal of Agricultural Economics* 81: 834-849.

Kay, R. D.; W. M. Edwards, and P. A. Duffy. 2008. *Farm Management*. McGraw-Hill, Singapore.

Ker, A. 1996. *Rating and Yield Predicting Procedures for the Group Risk Federal Crop Insurance Program: A Non-parametric Approach.* (PhD Dissertation Submitted to North Carolina State University).

Ker, A.P. and K. Coble. 1998. *On the Use of the Beta for Modeling Yields*. Working paper, May 1998. University of Arizona.

Ker, A. P. and K. Coble. 2003. Modeling conditional yield densities. *American Journal of Agricultural Economics* 85: 291–304.

Ker, P. A. and B.K. Goodwin. 2000. Nonparametric Estimation of Crop Insurance Rates Revisited. *American Journal of Agricultural Economics* 83: 463–478.

Knight, F. H. 1921. *Risk, Uncertainty, and Profit*. Hart, Schaffiner, and Marx, New York, USA, 233.

Koenker, R. and G. Bassett. 1978. Regression Quantiles. *Econometrica* 46 (1):33-50.

Krause, M. A., J.H. Lee, and W. W. Koo. 1995. Program and Nonprogram Wheat Acreage Responses To Prices and Risk. *Journal of Agricultural and Resource Economics* 20(1): 96-107.

Law, A. and W.D. Kelton. 2000. *Simulation Modeling and Analysis*. 3rd ed. New York: McGraw-Hill Higher Education, 368.

Linnerooth-Bayer, J., K. Warner, C. Bals, P. Hoppe, I. Burton, T. Loster, and A. Haas. 2009. Insurance, Developing Countries and Climate Change. *The Geneva Papers* 34:381-400.

Lu, Y., O. A. Ramirez, R. M. Rejesus, T. O. Knight, and B. J. Sherrick. 2008. Empirically Evaluating the Flexibility of the Johnson Family of Distributions: A Crop Insurance Application. *Agricultural and Resource Economics Review* 37(1): 79-91.

Mahul O. and C. Stutley. 2010. *Government Support to Agricultural Insurance: Challenges and Options for Developing Countries*. Washington D.C., The World Bank.

Mahul, O. 1999. Optimum Area Yield Crop Insurance. *American Journal of Agricultural Economics* 81(1): 75–82.

Martin, S.W., B.J. Barnett, and K.H. Coble. 2001. Developing and Pricing Precipitation Insurance. *Journal of Agricultural and Resource Economics* 26:261–74.

Miranda, M. J. 1991. Area-Yield Crop Insurance Reconsidered. *American Journal of Agricultural Economic*, 73: 233–242.

MoAD (Ministry of Agriculture Development). 1990-91 to 2010-11. *Statistical Information on Nepalese Agriculture*. Ministry of Agriculture Development. Government of Nepal, Singha Darbar, Kathmandu, Nepal.

MoF (Ministry of Finance). 2009-10 and 2010-11. *Economic Survey*. Ministry of Finance, Government of Nepal, Singha Darbar, Kathmandu, Nepal. Retrieved on April 14, 2012, from the World Wide Web: http://mof.gov.np//en/archive-documents/economic-survey-21.html.

Moss, C. B. and J. S. Shonkwiler. 1993. Estimating yield distributions with a stochastic trend and non-normal errors. *American Journal of Agricultural Economics* 75:1056-62.

Nelson, C. H. 1990. The Influence of Distributional Assumptions on the Calculation of Crop Insurance Premia. *North Central Journal of Agricultural Economics* 12:71-78.

Nelson, C. H., and P. V. Preckel. 1989. The Conditional Beta Distribution as a Stochastic Production Function. *American Journal of Agricultural Economics*, 71: 370-78.

NPC (National Planning Commission). 2008-09. *Three Year Interim Plan*. National Planning Commission, Government of Nepal, Singha Darbar, Kathmandu, Nepal. Retrieved on April 12, 2012, from the World Wide Web: http://npc.gov.np/new/uploadedFiles/allFiles/11tyip_eng.pdf.

Ozaki, V. A., B. K. Goodwin, and R. Shirota. 2008. Parametric and Nonparametric Statistical Modeling of Crop Yield: Implication for Pricing Crop Insurance Contracts. *Applied Economics* 40:1151-1164.

Pannell, D. J., and T. L. Nordblom. 1998. Impact of Risk Aversion on Whole-Farm Management in Syria. *Australian Journal of Agricultural and Resource Economics* 42(3): 227-247.

Poudel, S., K. Kotani. 2012. Climatic impacts on crop yield and its variability in Nepal: do they vary across seasons and altitudes? *Climatic Change* 116(2): 327-355.

Quiggin, J., G. Karagiannis, and J. Stanton. 1994. Crop Insurance and Crop Production: An Empirical Study of Moral Hazard and Adverse Selection. In: *Economics of Agricultural Crop Insurance*. Hueth, D. L. and W. H. Furtran (eds.), Kluwer Academic Publishers, Norwell, MA, 253-272.

Ramirez, O.A. 1997. Estimation of a Multivariate Parametric Model for Simulating Heteroskedastic, Correlated, Non-Normal Random Variables: The Case of Corn-Belt Corn, Soybeans and Wheat Yields. *American Journal of Agricultural Economics* 79:191-205.

Ramirez, O.A., S.K. Misra, and J.E. Field. 2003. Crop Yield Distributions Revisited. *American Journal of Agricultural Economics* 85: 108-20.

Ramirez, O.A., T.U. McDonald, and C.E. Carpio. 2010. A Flexible Parametric Family for the Modeling and Simulation of Yield Distributions. *Journal of Agricultural and Applied Economics* 42(2): 1-17.

Sarkar, M.A.R., K. Alam, and J. Gow. 2012. Exploring the relationship between climate change and rice yield in Bangladesh: an analysis of time series data. *Agricultural System* 112: 11-16.

Seog, S. H. 2010. *The Economics of Risk and Insurance*. Wiley-Blackwell Publishing, John Wiley and Sons, Singapore, 1-4.

Sherrick, B.J., F. C. Zanini, G.D. Schnitkey, and S.H. Irwin. 2004. Crop Insurance Valuation under Alternative Yield Distributions. *American Journal of Agricultural Economics* 86(2): 406-419.

Sigurdson, D. and R. Sin 1994. An Aggregate Analysis of Canadian Crop Insurance Policy. In: *Economics of Agricultural Crop Insurance: Theory and Evidence*, D.L. Hueth and W.H. Furtan (eds.), Boston/Dordrecht/London: Kluwer Academic Publishers, 17-44.

Silverman, B. W. 1986. *Density Estimation for Statistics and Data Analysis*. Chapman and Hall, London, 175.

Skees, J. R., J. R. Black, and B. Barnett. 1997. Designing and Rating an Area Yield Crop Insurance Contract. *American Journal of Agricultural Economics* 79: 430-438.

Skees, J.R. and M.R. Reed. 1986. Rate Making for Farm Level Crop Insurance: Implications for Adverse Selection. *American Journal of Agricultural Economics* 68: 653-659.

Skees, K. R. and H.B.P. Professor. *Agricultural Insurance Programs: Challenges and Lesson Learned.* Paper presented on Income Risk Management: From Risk Pooling to Safety Nets Systems, OECD, Paris, 15-16 May, 2000.

Smith, B H, and B.K. Goodwin. 1996. Crop Insurance, Moral Hazard, and Agricultural Chemical Use. *American Journal of Agricultural Economics* 78: 428-438.

Smith, V. H., H.H. Chouinard, and A. E. Baquet. 1994. Almost Ideal Area Yield Crop Insurance Contracts. *Agricultural and Resource Economics Review* 23(1): 75-83.

Stokes, J. R. 2000. A Derivative Security Approach to Setting Crop Revenue Coverage Insurance Premiums. *Journal of Agricultural and Resource Economics* 25: 159-76.

Taylor, C. R. 1990. Two Practical Procedures for Estimating Multivariate Non-normal Probability Density Functions. *American Journal of Agricultural Economics* 72: 210-217.

The World Bank. 2009. *Agricultural Insurance Feasibility Study for Nepal*. Report No. 46521-NP. Washington, D.C., The World Bank.

USDA, 1997. *Introduction to Risk Management, Understanding Agricultural Risks.* United States Department of Agriculture, Risk Management Agency, USA.

Vedenov, D. V. and B. J. Barnett. 2004. Efficiency of Weather Derivatives as Primary Crop Insurance Instruments. *Journal of Agricultural and Resource Economics* 29(3):387-403.

Victor, R. 2004. *A Risk Perception Primer: A Narrative Research Review of the Risk Perception Literature in Behavioral Accounting and Behavioral Finance.* Working Series, July, 2004. Retrieve on March 25, 2010, from World Wide Web: http://ssrn.com/abstract=566802

Yeh, M. H. and R. Wu. 1966. Premium Rate Making in All Risk Crop Insurance Program. *Canadian Journal of Agricultural Economics* 14 (1): 40–49.

Zhang, Q. and K. Wang. 2010. Evaluating production risks for wheat producers in Beijing. *China Agricultural Economic Review* 2 (2): 200-211.

Zhu, Y., B. K. Goodwin, and S. K. Ghosh. 2011. Modeling Yield Risk under Technological Change: Dynamic Yield Distributions and the U.S. Crop

Insurance Program. *Journal of Agricultural and Resource Economics 36* (1):192–210.

Appendices

Appendix A. Coefficient of Variation (CV) of Original Yields

Table A1 Area and Coefficient of Variation (CV) of Rice Yields in Sample Districts

S.N.	Districts	Area (ha.) (2010-011)	Coefficient of Variation (CV) (1990-91 to 2010-211)
1	Banke	36500	30.09
2	Kapilbastu	72000	23.13
3	Surkhet	13870	21.56
4	Rupandehi	71500	20.24
5	Dhanusha	61972	18.83
6	Kavre	11350	18.55
7	Dhading	16670	17.96
8	Dang	38500	17.83
9	Salyan	6961	17.31
10	Ramechhap	9460	17.23
11	Dailekh	8507	16.54
12	Ilam	14825	16.37
13	Pyuthan	6540	16.28
14	Sindupalchok	12924	15.84
15	Okhaldhunga	5030	15.72
16	Dadeldhura	6221	15.53
17	Gulmi	10426	15.26
18	Udayepur	15500	15.26
19	Doti	7570	14.88
20	Syanja	19455	14.82

Table A2 Area and Coefficient of Variation (CV) of Maize Yields in Sample Districts

S.N.	Districts	Area (ha.) (2010-011)	Coefficient of Variation (CV) (1990-91 to 2010-211)
1	Syangja	30900	31.84
2	Myagdi	11115	25.82
3	Dhankuta	17779	24.94
4	Jhapa	24600	22.69
5	Baglung	20327	21.56
6	Ramechhap	18041	20.71
7	Surkhet	16100	20.69
8	Khotang	23000	20.56
9	Solukhumbu	12955	20.11
10	Bara	7500	19.98
11	Nawalparasi	10750	19.63
12	Lamjung	15900	19.40
13	Tanahun	26029	19.28
14	Taplejung	16075	18.71
15	Kaski	20800	18.01
16	Nuwakot	20115	17.70
17	Dailekh	20150	17.48
18	Sindupalchok	23920	17.16
19	Gulmi	24845	16.97
20	Okhaldhunga	12097	16.81

Table A3 Area and Coefficient of Variation (CV) of Wheat Yields in Sample Districts

S.N.	Districts	Area (ha.) (2010-011)	Coefficient of Variation (CV) (1990-91 to 2010-211)
1	Rupandehi	30500	31.22
2	Kapilbastu	29995	30.83
3	Bajura	4950	20.93
4	Parsa	23600	26.33
5	Mugu	4325	26.14
6	Bara	29000	24.03
7	Bardiya	18890	23.85
8	Rukum	11800	23.20
9	Darchula	5265	23.03
10	Surkhet	16255	22.66
11	Jhapa	11500	22.30
12	Doti	16150	22.25
13	Kavre	9995	21.85
14	Ramechhap	4820	21.84
15	Baitadi	12000	21.59
16	Banke	17913	21.58
17	Chitwan	8728	21.50
18	Kailali	34500	21.40
19	Makawanpur	4213	21.29
20	Siraha	17500	21.04

Appendix B. Descriptive Statistics of Normalized yields

Table A4 Descriptive Statistics of Normalized OLS Rice Yield Series

Districts	N	Mean	Min	Max	Std Dev	Skewn	Kurt
Banke	21	3250.25	2108.55	4134.04	577.67	-0.73	-0.61
Kapilbastu	21	3145.86	2386.61	3934.76	457.69	-0.02	-1.17
Surkhet	21	3350.36	2533.29	3752.84	295.92	-1.35	2.15
Rupandehi	21	3604.47	2858.27	4188.76	387.63	-0.37	-0.83
Dhanusha	21	2551.06	1774.30	2865.05	266.91	-1.50	2.63
Kavre	21	3000.10	2463.76	4244.47	385.96	1.52	4.49
Dhading	21	2739.89	2207.18	3241.03	259.52	0.43	-0.09
Dang	21	3082.34	2281.29	3824.97	375.82	-0.51	0.49
Salyan	21	3092.23	2668.21	3661.25	290.40	0.67	-0.37
Ramechhap	21	2535.88	1928.26	2943.49	254.90	-0.45	0.04
Dailekh	21	3096.57	2716.51	3607.31	194.78	0.64	1.94
Ilam	21	2347.65	1685.59	3284.51	361.55	0.57	1.22
Pyuthan	21	2680.33	1940.52	3051.52	242.38	-1.28	3.12
Sindhupalchok	21	2445.05	1988.49	3204.39	252.46	0.90	3.42
Okhaldhunga	21	2059.10	1673.19	2418.33	206.46	-0.19	-0.60
Dadeldhura	21	2340.43	1932.66	2732.90	197.00	-0.02	-0.14
Gulmi	21	2563.56	2179.66	2877.01	150.26	-0.40	1.36
Udayepur	21	2477.93	1976.24	2827.91	232.79	-0.27	-0.34
Doti	21	2441.17	1995.10	2919.92	212.11	0.17	0.34
Syanja	21	2902.42	2610.72	3353.10	189.15	0.70	0.12

Table A5 Descriptive Statistics of Normalized QR Rice Yield Series

Districts	N	Mean	Min	Max	Std Dev	Skew	Kurt
Banke	21	3000.47	1800.77	3491.35	536.54	-1.22	0.00
Bapilbastu	21	3149.68	2371.97	3815.77	456.22	-0.20	-1.16
Surkhet	21	3267.88	2176.37	3705.16	353.79	-1.83	4.17
Rupandehi	21	3473.23	2610.54	4234.23	391.70	-0.48	0.08
Dhanusha	21	2520.44	1744.41	2855.84	266.61	-1.47	2.63
Kavre	21	3050.17	2633.22	4625.15	432.49	2.52	8.67
Dhading	21	2828.66	2265.82	3320.90	267.71	0.37	-0.07
Dang	21	2962.88	2098.48	3467.50	363.80	-1.26	1.24
Dalyan	21	3184.45	2723.19	3860.38	313.18	0.80	-0.12
Ramechhap	21	2592.25	1880.05	2998.14	274.31	-0.64	1.00
Dailekh	21	3113.13	2749.29	3707.28	197.74	0.97	3.49
Ilam	21	3024.51	2654.60	3339.64	172.12	-0.10	0.59
Pyuthan	21	2632.95	1906.88	3021.01	238.09	-1.26	3.18
Sindhupalchok	21	2476.52	2052.29	3488.38	287.67	2.10	7.51
Okhaldhunga	21	2071.30	1681.70	2432.51	207.82	-0.20	-0.60
Dadeldhura	21	2381.13	1927.71	2807.76	204.99	-0.07	0.37
Gulmi	21	2591.86	2167.66	2917.08	155.69	-0.75	2.41
Udayepur	21	2447.33	1958.42	2789.29	230.07	-0.27	-0.40
Doti	21	2481.48	1991.29	2976.97	219.84	0.00	0.68
Syanja	21	2924.97	2634.00	3374.58	192.21	0.74	0.14

Table A6 Descriptive Statistics of Normalized OLS Maize Yield Series

Districts	N	Mean	Min	Max	Std Dev	Skew	Kurt
Syanja	21	2818.08	2260.18	3442.43	279.90	0.03	0.23
Myagdi	21	2694.01	1854.11	3164.57	277.28	-1.19	3.31
Dhankuta	21	2229.94	1711.72	2688.24	267.13	-0.56	-0.04
Jhapa	21	2523.01	2210.83	2759.38	182.27	-0.35	-1.32
Baglung	21	2485.93	2151.75	2758.64	174.27	-0.51	-0.15
Ramechhap	21	2072.73	1769.40	2320.76	150.94	-0.13	-0.51
Surkhet	21	2345.22	2077.77	2620.03	134.76	0.31	-0.24
Khotang	21	2185.56	1925.36	2376.23	109.18	-0.35	0.17
Solukhumbu	21	2322.45	2017.10	2634.89	197.31	0.04	-1.43
Bara	21	2866.18	2455.75	3789.02	317.52	0.93	2.21
Nawalparasi	21	3022.95	2461.86	3708.23	328.93	-0.03	-0.41
Lamjung	21	2463.12	2096.36	2861.00	233.17	0.13	-1.24
Tanahun	21	2724.29	2289.75	3174.20	236.03	-0.16	-0.83
Taplejung	21	2093.87	1920.12	2282.05	101.96	0.03	-0.93
Kaski	21	2669.38	2285.17	3091.88	208.93	-0.03	-0.34
Nuwakot	21	2477.45	2130.89	2859.86	189.63	0.05	-0.55
Dailekh	21	1970.42	1568.31	2139.69	123.13	-1.73	4.93
Sindupalchok	21	2221.17	1912.79	2662.78	151.21	0.81	2.96
Gulmi	21	2046.04	1697.48	2367.27	168.72	-0.27	-0.32
Okhaldhunga	21	2068.32	1534.38	2278.13	155.84	-1.92	6.36

Table A7 Descriptive Statistics of Normalized QR Maize Yield Series

Districts	N	Mean	Min	Max	Std Dev	Skew	Kurt
Syanja	21	2742.01	2198.63	3321.45	268.04	-0.09	0.11
Myagdi	21	2666.75	1837.04	3144.16	272.93	-1.20	3.42
Dhankuta	21	2177.47	1647.61	2626.69	269.26	-0.59	-0.06
Jhapa	21	2531.5	2249.36	2801.01	181.59	-0.08	-1.19
Baglung	21	2455.85	2135.98	2780.66	169.75	-0.30	-0.04
Ramechhap	21	2058.68	1733.88	2320.45	152.68	-0.28	-0.13
Surkhet	21	2355.71	2079.27	2649.27	134.11	0.28	0.11
Khotang	21	2170.98	1917.26	2363.24	108.85	-0.32	0.16
Solukhumbu	21	2295.17	1966.7	2642.59	201.54	-0.07	-1.16
Bara	21	2870.35	2456.68	3975.86	339.66	1.58	4.72
Nawalparasi	21	2984.31	2440.59	3500.67	312.05	-0.29	-0.71
Lamjung	21	2498.72	2131.31	2988.39	249.12	0.43	-0.72
Tanahun	21	2663.47	2236.18	3055.58	226.38	-0.33	-0.95
Taplejung	21	2073.9	1907.45	2298.1	100.89	0.46	-0.06
Kaski	21	2644.1	2264.09	3075.81	208.99	0.03	-0.27
Nuwakot	21	2485.65	2110.26	3006.99	200.34	0.43	1.25
Dailekh	21	1932.83	1524.6	2080.94	121.86	-2.04	5.66
Sindupalchok	21	2215.1	1914.29	2679.23	153.33	1.03	3.52
Gulmi	21	2014.77	1663.71	2396.48	174.47	-0.08	0.16
Okhaldhunga	21	2065.21	1527.68	2282.54	157.38	-1.85	6.32

Table A8 Descriptive Statistics of Normalized OLS Wheat Yield Series

Districts	N	Mean	Min	Max	Std Dev	Skew	Kurt
Rupandehi	21	3111.83	2587.37	3962.97	287.88	0.86	2.99
Kapilbastu	21	2878.11	2314.68	3731.66	337.13	0.50	0.69
Bajura	21	1782.25	963.18	2188.85	266.17	-1.63	3.47
Parsa	21	3151.24	2668.41	3749.24	248.07	0.38	0.79
Mugu	21	1619.12	889.29	2182.35	319.35	-0.44	0.60
Bara	21	3117.83	2768.11	3686.92	210.21	1.06	1.64
Bardiya	21	2581.96	2368.76	2944.97	187.33	0.41	-1.12
Rukum	21	2013.06	1220.09	2630.11	305.55	-0.60	1.31
Darchula	21	1246.69	728.13	1528.85	186.81	-0.79	1.85
Surkhet	21	2429.93	1991.6	2725.82	180.53	-0.85	0.74
Jhapa	21	2249.77	1951.99	2698.06	179.71	0.68	0.60
Doti	21	1709.76	1086.49	2097.75	244.99	-0.49	0.62
Kavre	21	2269.26	1633.64	2900.54	308.35	0.11	0.66
Ramechhap	21	2002.76	1443.86	2359.41	249.28	-0.96	0.43
Baitadi	21	1531.62	1088.78	1913.62	253.43	-0.28	-0.88
Banke	21	2197.87	1887.84	2479.63	156.83	0.06	-0.42
Chitwan	21	2948.55	2382.06	3349.18	246.71	-0.51	0.04
Kailali	21	2070.34	1699.4	2427.81	240.27	0.08	-1.45
Makawanpur	21	2736.26	2306.37	3150.46	270.37	-0.15	-1.34
Siraha	21	2043.05	1688.79	2381.32	193.52	-0.14	-0.19

Table A9 Descriptive Statistics of Normalized QR Wheat Yield Series

Districts	N	Mean	Min	Max	Std Dev	Skew	Kurt
Rupandehi	21	3091.65	2495.5	3767.49	272.22	0.15	1.48
Kapilbastu	21	2861.28	2313.99	3531.84	322.57	0.23	-0.06
Bajura	21	1704.35	889.96	2008.61	249.96	-2.00	4.90
Parsa	21	3153.39	2670.05	3754.08	248.53	0.39	0.81
Mugu	21	1625.35	923.58	2221.31	328.11	-0.18	0.50
Bara	21	3172.25	2788.03	3907	242.57	1.70	3.92
Bardiya	21	2625.33	2316.66	3220.64	213.06	1.00	1.75
Rukum	21	1945.2	1106.35	2357.08	291.11	-1.46	2.53
Darchula	21	1243.61	711.5	1504	183.91	-1.08	2.42
Surkhet	21	2409.47	1919.36	2750.21	183.74	-1.09	2.06
Jhapa	21	2248	1957.63	2646.01	188.25	0.44	0.19
Doti	21	1723.72	1069.57	2097.19	241.90	-0.66	1.23
Kavre	21	2235.95	1506.86	2775.6	300.11	-0.71	1.66
Ramechhap	21	1966.94	1432.73	2303.25	242.83	-1.02	0.50
Baitadi	21	1496.18	1090.56	1895.15	252.53	-0.25	-0.74
Banke	21	2221.74	1916.4	2517.27	159.89	0.22	-0.04
Chitwan	21	2913.1	2347.51	3390.36	253.05	-0.35	0.18
Kailali	21	2036.08	1575.1	2395.35	231.93	-0.40	-0.35
Makawanpur	21	2694.17	2265.3	3089.77	271.99	-0.24	-1.34
Siraha	21	2037.83	1683.79	2393.56	196.95	-0.04	0.04

Appendix C. Parameters of Parametric and Non-parametric Distribution

Table A10 Parameter Estimates of Normal Distribution of Rice Yield Series

Districts	OLS		QR	
	Mean	Std. Dev.	Mean	Std. Dev.
Banke	3250.25	577.67	3000.47	536.54
Kapilbastu	3145.86	457.69	3149.68	456.22
Surkhet	3350.36	295.92	3267.88	353.79
Rupandehi	3604.47	387.63	3473.23	391.70
Dhanusha	2551.06	266.91	2520.44	266.61
Kavre	3000.10	385.96	3050.17	432.49
Dhading	2739.89	259.52	2828.66	267.71
Dang	3082.34	375.82	2962.88	363.80
Salyan	3092.23	290.40	3184.45	313.18
Ramechhap	2535.88	254.90	2592.25	274.31
Dailekh	3096.57	194.78	3113.13	197.74
Ilam	2347.65	361.55	3024.51	172.12
Pyuthan	2680.33	242.38	2632.95	238.09
Sindhupalchok	2445.05	252.46	2476.52	287.67
Okhaldhunga	2059.10	206.46	2071.30	207.82
Dadeldhura	2340.43	197.00	2381.13	204.99
Gulmi	2563.56	150.26	2591.86	155.69
Udayepur	2477.93	232.79	2447.33	230.07
Doti	2441.17	212.11	2481.48	219.84
Syanja	2902.42	189.15	2924.97	192.21

Table A11 Parameter Estimates of Normal Distribution of Maize Yield Series

Districts	OLS		QR	
	Mean	Std. Dev.	Mean	Std. Dev.
Syanja	2818.08	279.90	2742.01	268.04
Myagdi	2694.01	277.28	2666.75	272.93
Dhankuta	2229.94	267.13	2177.47	269.26
Jhapa	2523.01	182.28	2531.50	181.59
Baglung	2485.93	174.27	2455.85	169.75
Ramechhap	2072.73	150.94	2058.68	152.68
Surkhet	2345.22	134.76	2355.71	134.11
Khotang	2185.56	109.18	2170.98	108.85
Solukhumbu	2322.45	197.31	2295.16	201.54
Bara	2866.18	317.53	2870.35	339.66
Nawalparasi	3022.94	328.93	2984.31	312.05
Lamjung	2463.11	233.17	2498.71	249.12
Tanahun	2724.29	236.03	2663.46	226.38
Taplejung	2093.87	101.96	2073.90	100.89
Kaski	2669.38	208.93	2644.10	208.99
Nuwakot	2477.45	189.63	2485.65	200.34
Dailekh	1970.42	123.13	1932.83	121.86
Sindupalchok	2221.17	151.21	2215.10	153.33
Gulmi	2046.04	168.72	2014.77	174.47
Okhaldhunga	2068.32	155.84	2065.21	157.38

Table A12 Parameter Estimates of Normal Distribution of Wheat Yield Series

Districts	OLS		QR	
	Mean	Std. Dev.	Mean	Std. Dev.
Rupandehi	3111.83	287.88	3091.65	272.22
Kapilbastu	2878.11	337.13	2861.28	322.57
Bajura	1782.25	266.17	1704.35	249.96
Parsa	3151.24	248.07	3153.39	248.53
Mugu	1619.12	319.35	1625.35	328.11
Bara	3117.83	210.21	3172.25	242.57
Bardiya	2581.96	187.33	2625.33	213.06
Rukum	2013.06	305.55	1945.20	291.11
Darchula	1246.69	186.81	1243.61	183.91
Surkhet	2429.93	180.53	2409.47	183.74
Jhapa	2249.77	179.71	2248.00	188.25
Doti	1709.76	244.99	1723.72	241.90
Kavre	2269.26	308.35	2235.95	300.10
Ramechhap	2002.76	249.28	1966.94	242.83
Baitadi	1531.33	253.39	1496.18	252.53
Banke	2197.87	156.83	2221.74	159.89
Chitwan	2948.55	246.71	2913.10	253.05
Kailali	2070.34	240.27	2036.08	231.93
Makawanpur	2736.26	270.37	2694.17	271.99
Siraha	2043.05	193.52	2037.83	196.95

Table A13 MLE Parameter Estimates of Lognormal Distribution of Rice Yield Series

Districts	OLS		QR	
	Scale	Shape	Scale	Shape
Banke	8.07	0.19	7.99	0.20
Kapilbastu	8.04	0.15	8.04	0.15
Surkhet	8.11	0.09	8.09	0.12
Rupandehi	8.18	0.11	8.15	0.12
Dhanusha	7.84	0.11	7.83	0.12
Kavre	8.00	0.12	8.01	0.13
Dhading	7.91	0.09	7.94	0.09
Dang	8.03	0.13	7.99	0.13
Salyan	8.03	0.09	8.06	0.10
Ramechhap	7.83	0.10	7.85	0.11
Dailekh	8.04	0.06	8.04	0.06
Ilam	7.75	0.15	8.01	0.06
Pyuthan	7.89	0.10	7.87	0.10
Sindhupalchok	7.80	0.10	7.81	0.11
Okhaldhunga	7.63	0.10	7.63	0.10
Dadeldhura	7.75	0.08	7.77	0.09
Gulmi	7.85	0.06	7.86	0.06
Udayepur	7.81	0.10	7.80	0.10
Doti	7.80	0.09	7.81	0.09
Syanja	7.97	0.06	7.98	0.06

Table A14 MLE Parameter Estimates of Lognormal Distribution of Maize Yield Series

Districts	OLS		QR	
	Scale	Shape	Scale	Shape
Syanja	7.94	0.10	7.91	0.10
Myagdi	7.89	0.11	7.88	0.11
Dhankuta	7.70	0.13	7.68	0.13
Jhapa	7.83	0.07	7.83	0.07
Baglung	7.82	0.07	7.80	0.07
Ramechhap	7.63	0.07	7.63	0.08
Surkhet	7.76	0.06	7.76	0.06
Khotang	7.69	0.05	7.68	0.05
Solukhumbu	7.75	0.09	7.73	0.09
Bara	7.96	0.11	7.96	0.11
Nawalparasi	8.01	0.11	8.00	0.11
Lamjung	7.80	0.09	7.82	0.10
Tanahun	7.91	0.09	7.88	0.09
Taplejung	7.65	0.05	7.64	0.05
Kaski	7.89	0.08	7.88	0.08
Nuwakot	7.81	0.08	7.82	0.08
Dailekh	7.58	0.07	7.56	0.07
Sindupalchok	7.70	0.07	7.70	0.07
Gulmi	7.62	0.08	7.60	0.09
Okhaldhunga	7.63	0.08	7.63	0.08

Table A15 MLE Parameter Estimates of Lognormal Distribution of Wheat Yield Series

Districts	OLS		QR	
	Scale	Shape	Scale	Shape
Rupandehi	8.04	0.09	8.03	0.09
Kapilbastu	7.96	0.12	7.95	0.11
Bajura	7.47	0.18	7.43	0.18
Parsa	8.05	0.08	8.05	0.08
Mugu	7.37	0.22	7.37	0.22
Bara	8.04	0.07	8.06	0.07
Bardiya	7.85	0.07	7.87	0.08
Rukum	7.60	0.16	7.56	0.17
Darchula	7.12	0.17	7.11	0.17
Surkhet	7.79	0.08	7.78	0.08
Jhapa	7.72	0.08	7.71	0.08
Doti	7.43	0.15	7.44	0.15
Kavre	7.72	0.14	7.70	0.14
Ramechhap	7.59	0.13	7.58	0.13
Baitadi	7.32	0.17	7.30	0.18
Banke	7.69	0.07	7.70	0.07
Chitwan	7.99	0.09	7.97	0.09
Kailali	7.63	0.12	7.61	0.12
Makawanpur	7.91	0.10	7.89	0.10
Siraha	7.62	0.10	7.62	0.10

Table A16 MLE Parameter Estimates of Beta Distribution of Rice Yield Series

Districts	OLS			QR		
	Scale	Alpha	Beta	Scale	Alpha	Beta
Banke	4960.85	11.63	6.15	4190	10.30	4.14
Kapilbastu	4721.71	16.01	8.01	4579	15.30	6.94
Surkhet	4503.41	37.00	12.76	4446	26.23	9.50
Rupandehi	5026.51	25.70	10.15	5081	25.94	12.02
Dhanusha	3438.06	26.99	9.42	3427	26.88	9.70
Kavre	5093.36	22.50	15.62	5550	19.49	15.85
Dhading	3889.24	32.16	13.47	3985	31.68	12.93
Dang	4589.96	22.89	11.20	4161	21.37	8.68
Salyan	4393.50	32.27	13.56	4632	30.87	14.00
Ramechhap	3532.19	29.25	11.50	3598	26.27	10.20
Dailekh	4328.77	70.10	27.88	4449	70.94	30.42
Ilam	3941.41	16.25	10.99	4008	77.81	25.30
Pyuthan	3661.82	36.18	13.27	3625	36.75	13.87
Sindhupalchok	3845.27	31.97	18.26	4186	26.60	18.27
Okhaldhunga	2902.00	29.78	12.19	2919	29.74	12.17
Dadeldhura	3279.48	41.12	16.48	3369	40.19	16.67
Gulmi	3452.41	78.27	27.13	3500	76.39	26.77
Udayepur	3393.49	31.63	11.68	3347	31.49	11.58
Doti	3503.90	40.16	17.47	3572	39.19	17.22
Syanja	4023.72	64.24	24.81	4049	62.66	24.06

Table A17 MLE Parameter Estimates of Beta Distribution of Maize Yield Series

Districts	OLS			QR		
	Scale	Alpha	Beta	Scale	Alpha	Beta
Syanja	4130.92	32.37	15.07	3985.74	33.16	15.04
Myagdi	3797.48	29.56	12.13	3772.99	30.14	12.53
Dhankuta	3225.89	22.61	10.11	3152.03	20.69	8.89
Jhapa	3311.26	48.50	15.15	3361.21	49.62	16.26
Baglung	3310.37	53.88	17.87	3336.79	57.68	20.70
Rramechhap	2784.91	49.80	17.11	2784.54	49.40	17.43
Surkhet	3144.04	77.43	26.36	3179.13	80.55	28.14
Khotang	2851.48	98.52	30.00	2835.89	98.02	30.03
Solukhumbu	3161.87	37.68	13.62	3171.10	36.91	14.08
Bara	4546.82	28.34	16.57	4771.04	25.73	16.96
Nawalparasi	4449.88	27.46	12.96	4200.80	27.55	11.23
Lamjung	3433.20	31.90	12.55	3586.06	29.95	13.01
Tanahun	3809.04	39.31	15.65	3666.69	39.90	15.04
Taplejung	2738.46	102.49	31.53	2757.72	105.10	34.66
Kaski	3710.26	46.80	18.24	3690.97	46.96	18.27
Nuwakot	3431.83	48.37	18.63	3608.39	46.96	21.18
Dailekh	2567.63	68.19	20.71	2497.12	67.07	19.61
Sindupalchok	3195.34	63.13	27.65	3215.08	61.45	27.71
Gulmi	2840.72	42.82	16.64	2875.78	40.66	17.38
Okhaldhunga	2734.00	49.39	15.93	2739.05	48.33	15.80

Table A18 MLE Parameter Estimates of Beta Distribution of Wheat Yield Series

Districts	OLS			QR		
	Scale	Alpha	Beta	Scale	Alpha	Beta
Rupandehi	4755.56	38.15	20.12	4520.98	40.43	18.68
Kapilbastu	4477.99	25.21	13.99	4238.20	25.23	12.12
Bajura	2626.62	15.79	7.55	2410.33	15.58	6.53
Parsa	4499.09	47.69	20.38	4504.90	47.61	20.39
Mugu	2618.82	9.75	6.03	2665.57	9.31	5.96
Bara	4424.30	61.86	25.89	4688.40	50.35	24.01
Bardiya	3533.96	51.08	18.82	3864.76	46.22	21.79
Rukum	3156.13	15.99	9.09	2828.49	15.35	7.02
Darchula	1834.62	14.69	6.95	1804.80	15.01	6.81
Surkhet	3270.98	50.63	17.54	3300.26	50.61	18.72
Jhapa	3237.67	46.43	20.37	3175.21	40.72	16.77
Doti	2517.30	16.05	7.59	2516.63	16.59	7.65
Kavre	3480.65	18.39	9.80	3330.72	18.73	9.19
Ramechhap	2831.29	20.64	8.56	2763.90	20.84	8.47
Baitadi	2286.00	12.32	6.07	2274.18	12.18	6.33
Banke	2975.56	52.20	18.48	3020.73	51.03	18.35
Chitwan	4019.02	40.31	14.64	4068.43	39.11	15.51
Kailali	2913.37	21.72	8.83	2874.42	23.42	9.64
Makawanpur	3780.55	29.38	11.22	3707.73	28.06	10.56
Siraha	2857.58	32.39	12.92	2872.28	31.30	12.80

Table A19 MLE Parameter Estimates of Weibull Distribution of Rice Yield Series

Districts	OLS		QR	
	Scale	Shape	Scale	Shape
Banke	3477.74	7.43	3202.08	8.47
Kapilbastu	3340.64	8.03	3342.05	8.34
Surkhet	3468.98	15.87	3400.53	13.90
Rupandehi	3771.14	11.44	3639.01	10.62
Dhanusha	2655.15	13.96	2624.67	13.63
Kavre	3174.68	6.91	3246.24	5.86
Dhading	2858.86	11.07	2951.04	11.17
Dang	3239.81	9.76	3105.53	11.61
Salyan	3227.07	10.88	3330.02	10.20
Ramechhap	2645.75	12.06	2708.44	11.57
Dailekh	3189.66	14.94	3208.89	13.83
Ilam	2502.29	6.61	3103.78	19.10
Pyuthan	2779.14	14.74	2730.15	14.54
Sindhupalchok	2560.55	8.88	2610.82	7.14
Okhaldhunga	2149.56	11.67	2162.34	11.66
Dadeldhura	2429.07	13.17	2472.87	12.75
Gulmi	2631.13	19.00	2659.93	19.02
Udayepur	2580.09	12.58	2548.34	12.59
Doti	2537.36	12.14	2579.91	12.08
Syanja	2992.95	15.07	3017.19	14.90

Table A20 MLE Parameter Estimates of Weibull Distribution of Maize Yield Series

Districts	OLS		QR	
	Scale	Shape	Scale	Shape
Syanja	2942.19	10.88	2860.14	11.30
Myagdi	2806.80	12.34	2777.73	12.36
Dhankuta	2341.80	10.28	2289.57	10.08
Jhapa	2603.89	17.49	2613.86	16.34
Baglung	2562.42	17.41	2531.67	16.65
Ramechhap	2140.94	15.81	2126.84	15.73
Surkhet	2408.92	18.24	2418.95	18.21
Khotang	2235.13	23.36	2220.49	23.02
Solukhumbu	2411.68	13.67	2385.26	13.27
Bara	3010.58	8.47	3026.41	7.40
Nawalparasi	3167.06	10.31	3119.45	11.46
Lamjung	2568.17	11.97	2612.20	10.65
Tanahun	2829.05	13.45	2762.91	14.34
Taplejung	2141.45	23.01	2122.39	20.71
Kaski	2763.75	14.18	2738.81	13.85
Nuwakot	2563.67	14.42	2578.14	12.20
Dailekh	2019.56	22.63	1979.29	24.78
Sindupalchok	2293.36	13.27	2288.99	12.70
Gulmi	2120.67	14.13	2092.55	12.65
Okhaldhunga	2069.62	18.87	2127.20	18.11

Table A21 MLE Parameter Estimates of Weibull Distribution of Wheat Yield Series

Districts	OLS		QR	
	Scale	Shape	Scale	Shape
Rupandehi	3245.25	9.92	3214.43	11.58
Kapilbastu	3028.24	8.65	3004.32	9.52
Bajura	1881.13	9.63	1793.45	10.68
Parsa	3265.95	12.79	3268.37	12.75
Mugu	1744.16	6.04	1754.94	5.68
Bara	3219.92	13.56	3291.75	11.11
Bardiya	2669.59	14.72	2726.55	11.37
Rukum	2136.76	7.85	2055.03	9.51
Darchula	1321.80	8.20	1315.98	8.71
Surkhet	2506.64	17.26	2485.84	16.57
Jhapa	2334.14	12.24	2335.06	12.20
Doti	1811.08	8.44	1822.89	8.75
Kavre	2401.69	7.95	2358.49	8.89
Ramechhap	2103.22	10.83	2064.31	11.09
Baitadi	1635.38	7.31	1599.62	7.09
Banke	2269.75	15.46	2295.77	14.73
Chitwan	3055.77	14.62	3024.08	13.38
Kailali	2176.26	10.00	2135.09	10.65
Makawanpur	2855.33	12.16	2812.96	12.11
Siraha	2128.52	11.97	2125.25	11.45

Table A22 MLE Parameter Estimates of Gamma Distribution of Rice Yield Series

Districts	OLS		QR	
	Scale	Shape	Scale	Shape
Banke	108.91	29.84	107.94	27.80
Kapilbastu	64.51	48.77	65.03	48.43
Surkhet	27.13	123.51	42.36	77.14
Rupandehi	41.07	87.77	44.13	78.71
Dhanusha	29.89	85.34	30.19	83.48
Kavre	43.41	69.12	49.49	61.63
Dhading	23.07	118.77	23.86	118.53
Dang	46.24	66.66	47.79	61.99
Salyan	25.20	122.70	28.23	112.81
Ramechhap	25.38	99.90	29.33	88.37
Dailekh	11.47	270.07	11.62	267.82
Ilam	51.99	45.16	9.40	321.66
Pyuthan	22.82	117.47	22.40	117.57
Sindhupalchok	23.99	101.91	28.45	87.04
Okhaldhunga	20.14	102.25	20.28	102.11
Dadeldhura	15.93	146.88	17.03	139.80
Gulmi	8.56	299.61	9.22	281.11
Udayepur	21.35	116.05	21.10	115.96
Doti	17.56	139.01	18.76	132.31
Syanja	11.47	252.99	11.73	249.30

Table A23 MLE Parameter Estimates of Gamma Distribution of Maize Yield Series

Districts	OLS		QR	
	Scale	Shape	Scale	Shape
Syanja	26.74	105.38	25.37	108.09
Myagdi	30.05	89.65	29.42	90.64
Dhankuta	32.26	69.13	33.73	64.56
Jhapa	12.78	197.49	12.49	202.62
Baglung	11.95	207.99	11.38	215.86
Ramechhap	10.58	195.83	10.99	187.34
Surkhet	7.32	320.38	7.23	325.82
Khotang	5.27	415.07	5.26	412.40
Solukhumbu	16.00	145.12	17.01	134.95
Bara	32.10	89.29	35.19	81.56
Nawalparasi	34.56	87.47	31.97	93.35
Lamjung	20.99	117.33	23.23	107.55
Tanahun	19.77	137.82	18.74	142.12
Taplejung	4.73	442.40	4.62	448.51
Kaski	15.69	170.10	15.81	167.27
Nuwakot	13.87	178.63	15.21	163.45
Dailekh	7.91	249.25	8.00	241.69
Sindupalchok	9.57	232.02	9.78	226.50
Gulmi	13.53	151.27	14.58	138.20
Okhaldhunga	12.44	166.30	12.68	162.87

Table A24 MLE Parameter Estimates of Gamma Distribution of Wheat Yield Series

Districts	OLS		QR	
	Scale	Shape	Scale	Shape
Rupandehi	24.58	126.60	22.95	134.74
Kapilbastu	36.92	77.96	34.57	82.76
Bajura	46.53	38.30	44.63	38.19
Parsa	18.42	171.04	18.47	170.72
Mugu	67.28	24.06	68.52	23.72
Bara	13.01	239.60	16.51	192.09
Bardiya	12.76	202.33	15.83	165.84
Rukum	48.71	41.33	49.76	39.09
Darchula	30.06	41.47	30.06	41.37
Surkhet	13.37	181.72	14.18	169.89
Jhapa	13.33	168.72	14.80	151.91
Doti	36.06	47.41	35.50	48.55
Kavre	40.58	55.91	42.04	53.19
Ramechhap	32.41	61.80	31.43	62.59
Baitadi	42.01	36.45	42.70	35.04
Banke	10.69	205.69	10.92	203.52
Chitwan	20.34	144.93	21.52	135.38
Kailali	26.63	77.75	26.21	77.67
Makawanpur	25.84	105.90	26.71	100.88
Siraha	17.77	114.98	18.37	110.94

Table A25 Standardized Bandwidth (c) Estimates of Kernel Distribution of Rice Yield Series

Districts	OLS	QR
Banke	0.61	0.40
Kapilbastu	1.14	1.12
Surkhet	0.66	0.51
Rupandehi	0.98	0.56
Dhanusha	0.70	0.66
Kavre	0.93	0.81
Dhading	0.45	0.44
Dang	0.85	0.48
Salyan	0.85	0.55
Ramechhap	1.18	0.56
Dailekh	0.66	0.63
Ilam	0.90	0.59
Pyuthan	0.81	0.85
Sindhupalchok	0.70	0.86
Okhaldhunga	1.23	1.24
Dadeldhura	0.66	1.03
Gulmi	0.45	0.70
Udayepur	1.28	1.29
Doti	1.16	1.10
Syanja	1.08	1.06

Table A26 Standardized Bandwidth (c) Estimates of Kernel Distribution of Maize Yield Series

Districts	OLS	QR
Syanja	0.80	0.75
Myagdi	0.91	0.90
Dhankuta	0.82	0.86
Jhapa	0.66	1.19
Baglung	0.91	0.87
Ramechhap	1.18	1.13
Surkhet	0.82	0.89
Khotang	1.18	1.17
Solukhumbu	0.83	0.95
Bara	0.58	0.70
Nawalparasi	0.98	0.99
Lamjung	0.98	1.05
Tanahun	0.71	0.66
Taplejung	1.18	1.09
Kaski	1.22	1.21
Nuwakot	1.07	0.93
Dailekh	0.82	0.74
Sindupalchok	0.87	0.88
Gulmi	1.20	0.93
Okhaldhunga	0.88	0.81

Table A27 Standardized Bandwidth (c) Estimates of Kernel Distribution of Wheat Yield Series

Districts	OLS	QR
Rupandehi	0.76	0.62
Kapilbastu	0.99	0.62
Bajura	0.45	0.55
Parsa	1.02	1.00
Mugu	0.78	0.62
Bara	0.94	0.70
Bardiya	0.44	1.07
Rukum	1.01	0.74
Darchula	0.44	0.53
Surkhet	0.83	0.65
Jhapa	1.10	0.49
Doti	0.75	0.78
Kavre	0.61	0.61
Ramechhap	0.78	0.76
Baitadi	0.57	0.51
Banke	1.28	0.87
Chitwan	1.18	1.01
Kailali	0.74	1.11
Makawanpur	0.55	0.47
Siraha	0.45	0.48

Appendix D. Correlation between CV and Premium Rate

Table A28 Correlation Coefficients between CV and Premium Rate of Beta Distribution

Premium \ CV	OLS Rice	OLS Maize	OLS Wheat	QR Rice	QR maize	QR wheat
OLS rice	0.90***[1]					
OLS maize		0.87***[1]				
OLS wheat			0.97***[1]			
QR rice				0.84***[1]		
QR maize					0.88***[1]	
QR wheat						0.98***[1]

[1]*** indicates significant at 0.01 level.

Appendix E. Pure Premium (kg/ha)

Table A29 Premium of OLS Rice Yield Series in kg/ha at 90% Coverage for 2011-2012

Districts	Normal	Lognormal	Beta	Gamma	Weibull	Kernel
Banke	40.11	44.72	38.27	42.90	33.82	38.27
Kapilbastu	17.03	18.76	16.40	17.31	18.56	16.40
Surkhet	4.79	5.09	4.41	4.86	3.82	4.41
Rupandehi	7.77	8.52	7.46	7.72	7.24	7.46
Dhanusha	6.88	7.24	6.27	7.24	4.98	6.27
Kavre	6.31	5.93	6.46	5.96	8.08	6.46
Dhading	1.80	1.65	1.82	1.68	2.18	1.82
Dang	10.49	11.05	10.14	10.75	10.03	10.14
Salyan	1.41	1.34	1.45	1.30	1.78	1.45
Ramechhap	3.50	3.63	3.37	3.48	3.39	3.37
Dailekh	0.19	0.12	0.21	0.15	0.42	0.21
Ilam	12.41	12.75	12.32	12.46	13.42	12.32
Pyuthan	3.01	3.48	2.83	3.08	2.63	2.83
Sindupalchok	3.38	3.05	3.49	3.17	4.66	3.49
Okhaldhunga	5.35	5.44	4.11	5.21	5.45	4.31
Dadeldhura	1.40	1.33	1.39	1.31	1.69	1.39
Gulmi	0.27	0.23	0.28	0.23	0.48	0.28
Udayepur	2.56	2.81	2.49	2.47	2.63	2.49
Doti	1.31	1.27	1.32	1.23	1.68	1.32
Syanja	0.00	0.00	0.00	0.00	0.01	0.00

Table A30 Premium of QR Rice Yield Series in kg/ha at 90% Coverage for 2011-2012

Districts	Normal	Lognormal	Beta	Weibull	Gamma	Kernel
Banke	39.47	45.78	36.28	28.78	43.17	35.46
Kapilbastu	17.57	18.79	16.75	16.06	18.00	21.01
Surkhet	9.93	11.61	9.03	6.98	10.72	6.94
Rupandehi	9.58	10.14	9.22	9.22	9.63	11.26
Dhanusha	7.11	8.06	6.51	5.26	7.48	6.02
Kavre	4.08	3.74	4.19	5.30	3.75	3.92
Dhading	1.93	1.88	1.96	2.33	1.81	0.89
Dang	12.44	14.05	11.55	9.39	13.16	10.81
Salyan	2.00	1.88	2.03	2.51	1.84	1.54
Ramechhap	5.22	5.58	4.99	4.91	5.25	3.53
Dailekh	0.12	0.12	0.16	0.36	0.12	0.16
Ilam	0.16	0.14	0.17	0.31	0.13	0.28
Pyuthan	2.95	3.26	2.79	2.64	3.02	2.45
Sindupalchok	3.12	2.85	3.28	4.44	2.83	2.41
Okhaldhunga	3.43	3.49	3.32	3.47	3.34	4.52
Dadeldhura	1.66	1.63	1.65	2.01	1.56	1.90
Gulmi	0.41	0.40	0.42	0.68	0.37	0.66
Udayepur	2.53	2.56	2.46	2.58	2.44	3.31
Doti	1.93	1.90	1.92	2.39	1.82	2.24
Syanja	0.00	0.00	0.00	0.00	0.00	0.00

Table A31 Premium of OLS Maize Yield Series in kg/ha at 90% Coverage for 2011-2012

Districts	Normal	Lognormal	Beta	Weibull	Gamma	Kernel
Syanja	2.69	3.59	3.61	4.17	3.52	4.20
Myagdi	5.09	5.82	4.82	4.63	5.27	4.21
Dhankuta	7.95	9.09	7.61	7.28	8.11	7.97
Jhapa	0.44	0.38	0.43	0.46	0.40	0.64
Baglung	0.77	0.63	0.76	0.89	0.71	1.20
Ramechhap	0.54	0.50	0.55	0.68	0.49	0.78
Surkhet	0.06	0.06	0.07	0.13	0.05	0.06
Khotang	0.05	0.03	0.05	0.10	0.03	0.10
Solukhumbu	0.63	0.64	0.63	0.70	0.59	0.84
Bara	4.22	3.95	4.32	5.47	3.99	5.02
Nawalparasi	5.95	5.92	5.83	6.25	5.85	7.23
Lamjung	1.53	1.50	1.52	0.00	1.46	2.06
Tanahun	1.66	1.62	1.63	1.82	1.57	2.20
Taplejung	0.00	0.00	0.00	0.00	0.00	0.00
Kaski	0.99	0.92	1.00	1.26	0.92	1.43
Nuwakot	0.55	0.61	0.56	0.72	0.50	0.77
Dailekh	0.54	0.76	0.49	0.40	0.51	0.59
Sindupalchok	0.29	0.32	0.32	0.61	0.25	0.29
Gulmi	1.14	1.03	1.12	1.28	1.07	1.60
Okhaldhunga	1.70	1.93	1.31	1.97	1.75	1.19

Table A32 Premium of QR Maize Yield Series in kg/ha at 90% Coverage for 2011-2012

Districts	Normal	Lognormal	Beta	Weibull	Gamma	Kernel
Syanja	3.47	3.51	3.42	3.89	3.35	4.15
Myagdi	4.94	5.53	4.70	4.55	5.14	4.18
Dhankuta	8.57	9.25	7.20	7.71	8.79	8.55
Jhapa	0.26	0.25	0.27	0.32	0.24	0.41
Baglung	0.58	0.55	0.58	0.77	0.52	0.31
Ramechhap	0.78	0.76	0.78	0.95	0.72	-[1]
Surkhet	0.08	0.07	0.09	0.17	0.06	0.09
Khotang	0.04	0.03	0.04	0.09	0.03	0.09
Solukhumbu	1.08	1.06	1.06	1.16	1.01	1.50
Bara	4.44	4.17	4.58	5.95	4.12	4.57
Nawalparasi	5.69	5.87	5.50	5.53	5.61	7.12
Lamjung	1.81	1.75	1.81	2.10	1.70	2.29
Tanahun	1.66	1.67	1.62	1.70	1.58	2.30
Taplejung	0.00	0.00	0.00	0.00	0.00	0.00
Kaski	1.00	0.96	0.89	1.29	0.92	1.44
Nuwakot	1.00	0.94	1.03	1.51	0.90	1.20
Dailekh	0.58	0.64	0.51	0.41	0.57	0.68
Sindupalchok	0.28	0.24	0.31	0.60	0.24	0.27
Gulmi	1.46	1.45	1.46	1.77	1.38	1.88
Okhaldhunga	1.49	1.70	1.37	1.31	1.54	0.93

[1] could not estimate the probability of yield loss.

Table A33 Premium of OLS Wheat Yield Series in kg/ha at 90% Coverage for 2011-2012

Districts	Normal	Lognormal	Beta	Weibull	Gamma	Kernel
Rupandehi	2.32	2.12	2.42	3.43	2.12	2.38
Kapilbastu	0.64	6.54	6.39	7.42	6.18	7.26
Bajura	13.14	16.11	12.52	10.11	14.55	11.38
Parsa	1.01	1.05	1.05	1.51	0.92	1.18
Mugu	18.24	20.74	17.84	17.10	19.73	15.96
Bara	0.12	0.14	0.14	0.26	0.10	0.11
Bardiya	0.00	0.00	0.00	0.00	0.00	0.00
Rukum	12.55	13.29	12.24	11.81	13.29	12.02
Darchula	7.33	8.26	7.07	6.69	7.85	4.57
Surkhet	1.36	1.62	1.31	1.38	1.30	1.91
Jhapa	0.36	0.32	0.38	0.56	0.33	0.44
Doti	7.82	8.72	7.50	7.18	8.18	7.41
Kavre	8.41	8.81	8.28	8.77	8.48	6.85
Ramechhap	9.16	10.29	8.58	7.43	9.55	8.40
Baitadi	14.55	15.72	13.51	13.27	15.19	15.07
Banke	0.35	0.33	0.36	0.48	0.31	0.52
Chitwan	2.16	2.22	2.10	2.22	2.09	2.82
Kailali	3.95	4.13	3.83	3.89	3.89	4.97
Makawanpur	3.15	3.15	3.06	3.07	3.05	4.73
Siraha	2.61	2.70	2.57	2.84	2.50	3.34

Table A34 Premium of QR Wheat Yields in kg/ha at 90% Coverage for 2011-2012

Districts	Normal	Lognormal	Beta	Weibull	Gamma	Kernel
Rupandehi	2.56	2.72	2.60	3.43	2.41	2.61
Kapilbastu	5.75	5.86	5.69	6.32	5.61	6.28
Bajura	11.39	13.79	10.64	7.89	12.83	8.17
Parsa	1.01	1.07	1.05	1.51	0.91	1.17
Mugu	18.26	20.90	17.90	17.61	19.53	15.21
Bara	0.30	0.22	0.34	0.59	0.25	0.16
Bardiya	0.47	0.43	0.50	0.77	0.41	0.52
Rukum	14.14	16.49	13.36	10.98	15.51	10.37
Darchula	7.56	9.06	7.23	6.57	8.18	4.99
Surkhet	1.66	1.93	1.58	1.73	1.63	2.04
Jhapa	0.82	0.78	0.85	1.13	0.75	1.04
Doti	7.20	8.07	6.91	6.54	7.57	6.41
Kavre	10.42	11.55	10.10	9.88	10.92	7.18
Ramechhap	8.83	9.21	8.25	7.02	9.24	7.80
Baitadi	14.58	15.75	13.99	13.46	15.22	14.37
Banke	0.43	0.41	0.46	0.64	0.38	0.50
Chitwan	2.32	2.54	2.27	2.56	2.23	2.84
Kailali	5.64	6.23	5.40	5.29	5.67	6.49
Makawanpur	3.90	4.05	3.76	3.69	3.81	6.30
Siraha	2.79	2.69	2.76	3.13	2.69	3.13

Appendix F. Relation between Premium Rate and CVs

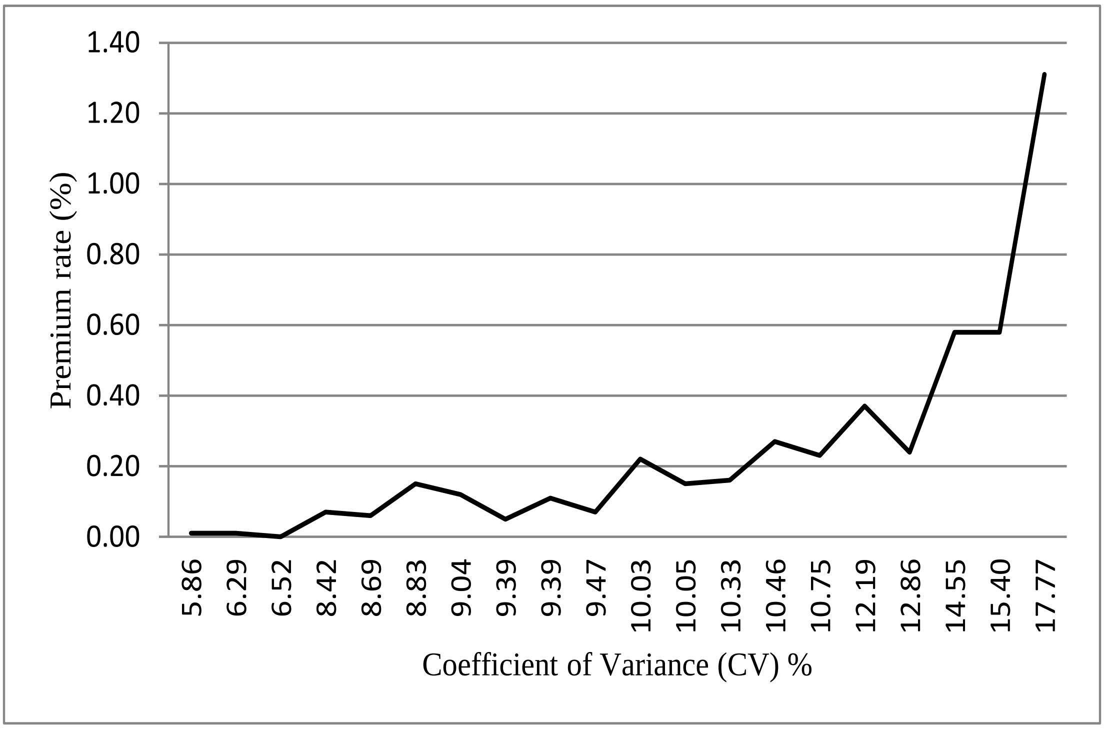

Figure A1 Relation between Premium Rate of Beta Distribution and CV of OLS Rice yield series.

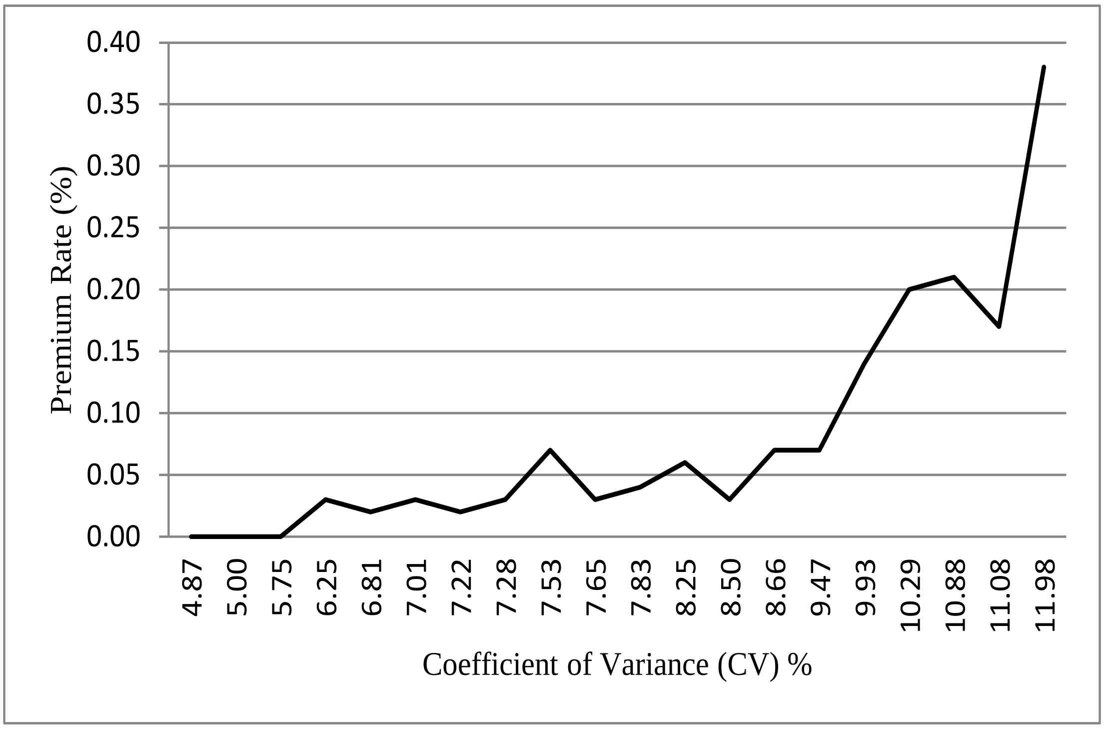

Figure A2 Relation between Premium Rate of Beta Distribution and CV of OLS Maize yield series.

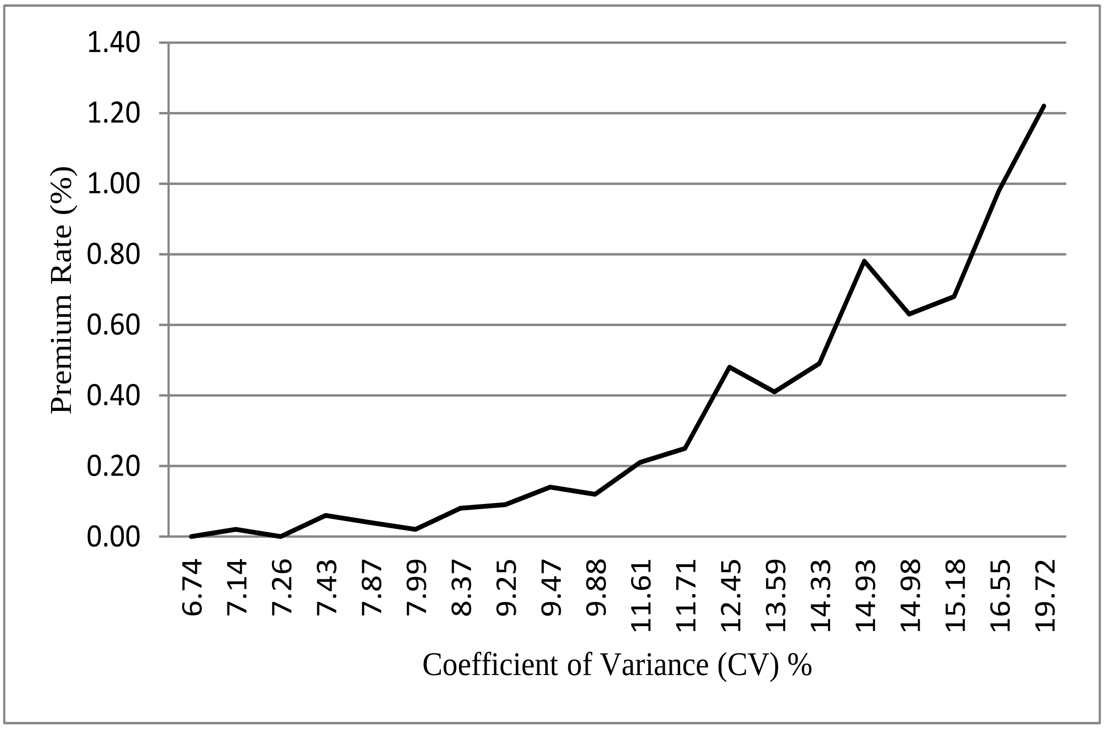

Figure A3 Relation between Premium Rate of Beta Distribution and CV of OLS Wheat yield series.

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Publications (Journal Articles)

Poudel, M. P. and S.E. Chen. 2012. Effect of Production on Large Cardamom Price Variability in Nepal. Journal of International Agricultural Trade and Development, Vol. 8, No.1, pp. 99-108.

Poudel, M. P. and S.E. Chen. 2012. Trends and Variability of Rice, Maize, and Wheat Yields in South Asian Countries: A Challenge for Food Security, Asian Journal of Agriculture and Rural Development, Vol. 2, No. 4, pp. 584 - 597.

Poudel, M. P., S.E. Chen, and R. Ghimire, R., 2013. Rice Yield Distribution and Risk Assessment in South Asian Countries: A Statistical Investigation. International Journal of Agricultural Management and Development, Vol. 3. No. 1, pp.53-63.

Papers delivered at professional meetings

Price Variability of Large Cardamom in Nepal. Rural Economics Society of Taiwan (REST), Annual meeting, Taipei, Taiwan, December 11, 2010.

Rice Yield Distribution and Risk Assessment in South Asian Countries. Rural Economics Society of Taiwan (REST), Annual meeting, Taipei, Taiwan, December 8, 2012.

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