International Journal of Agricultural Management & Development (IJAMAD)
Available online on: www.ijamad.com
ISSN: 2159-5852 (Print)
ISSN:2159-5860 (Online)

Rice Yield Distribution and Risk Assessment in South Asian Countries: A Statistical Investigation

Mahadeb Prasad Poudel [1,2*], Shwu-En Chen[1] and Raju Ghimire [3]

Received: 2 February 2013 ,
Accepted: 27 February 2013

Abstract

In the last decades, rice yields in South Asian countries grew tremendously in one hand and a noticeable yield fluctuation on the other. The objective of this study was to examine the rice yield distributions, estimate yield risks at country level, and compare risks between five countries namely Afghanistan, Bangladesh, Nepal, Sri Lanka, and Pakistan. Anderson Darling (AD) test was applied to test the goodness-of-fit for four distributions by using country level de-trended rice yields from 1961 to 2010. Results showed the Normal distribution was fitted well in Afghanistan and Sri Lanka, whereas the Weibull distribution in Bangladesh, Nepal, and Pakistan. The average yield risks at 85% of the expected yield were found 5.29, 4.27, 3.86, 1.55, and .15% in Afghanistan, Sri Lanka, Pakistan, Nepal, and Bangladesh, respectively. Wilcoxon signed rank test results of mean absolute percentage differences showed yield risk in Bangladesh was significantly lower than the rest four counties and that in Afghanistan was significantly higher than Nepal and Bangladesh at 0.1 level. The outcome of this study could give policy implications for designing and implementing the risk reducing programs in the countries with higher yield risk.

Keywords:
Yield risk, Yield distribution, Maximum likelihood estimation, South Asia, Rice

[1] Department of Tropical Agriculture and International Cooperation, 1, Shuefu Road, Neipu, Pingtung 912, Taiwan, R.O.C.
[2] Department of Agriculture, Ministry of Agriculture Development, Government of Nepal, Harihar Bhaban, Lalitpur, Nepal.
[3] Department of Agribusiness Management, National Pingtung University of Science and Technology, 1, Shuefu Road, Neipu, Pingtung 912, Taiwan, R.O.C.
* Corresponding author's email: mahadeb200@hotmail.com

INTRODUCTION

Rice is one of the most important food grains for more than half of the world's population (IRRI, 2006). Similarly, in South Asian region, rice is ranked as the first major staple food in Bangladesh, Bhutan, India, Maldives, Nepal, and Sri Lanka and the second major food in Pakistan and Afghanistan (FAO, 2012). As an industry[1], this crop is also a substantial contributor to the national economy in this region. Considering the importance of this crop, research and development activities were intensified on it in the last six decades. The devoted efforts on research and development made tremendous achievements on yield growths (Alauddin and Quiggin 2008). The observed average annual growth rates during 1961 to 2010 were 2.25, 3.11, 2.36, 0.80, 2.4, and 2.35 in Afghanistan, Bangladesh, India, Nepal, Pakistan, and Sri Lanka, respectively (FAO, 2012).

In the last decades, rice yield in South Asian countries grew tremendously in one hand and a noticeable yield fluctuation on the other. Larson *et al.,* (2004) supported yield instability was increased during the Green Revolution period along with the yield level. In Afghanistan, rice yield was 3375 kilograms per hectare in 2006, it went down to 3247 in 2007 and it further decreased to 3221 in 2008 and climbed to 3395 in 2009. Likewise, in Bangladesh, rice yield was 4144 kilograms per hectare in 2008, 4204 in 2009 and it decreased to 4183 in 2010. In India, the rice yield was 3116 kilograms per hectare in 2001 and it decreased to 2616 in 2002 and rose to 3118 in the next year. Similarly, in Nepal it was 2857 in 2004; it down to 2783 in 2005 and further decreased in 2007 to 2575 and again increased to 2907 kilograms per hectare in 2009. In addition, the fluctuation was also severe in Pakistan as it was 3318 kilograms per hectare in 2007, 3581 in 2009 and 3059 in 2010. Similarly, in Sri Lanka the rice yield was 3834 in 2007, it decreased to 3680 in 2008 and again increased to 4056 kilograms per hectare in 2010 (FAO, 2012).

The physical observations of yields indicate instabilities exist in this region. Many factors play role for yield fluctuations. One of the major factors is climate. South Asia is considered a vulnerable place for climate change. Past studies indicated a change in rainfall patterns as well as gradual increase on average temperatures in South Asian region. Moreover, studies also indicated climate change showed the influence on rice yields (Lobell *et al.,* 2011; Poudel and Kotani, 2012; Sarker *et al.,* 2012). In general, if higher instability exists, farmers will be reluctant to apply costly inputs to the risky crop. Consequently, a potential production capacity will be underutilized in the risky crop and attain a low level of production. The low production ultimately perpetuates the loss for farmers as well as the nation. Therefore, farmers, agriculturalists, and policy makers are concerned to minimize the yield instability. Thus, it is necessary to assess yields risk of rice at country level to help to develop risk mitigating measures such as crop insurance products.

There are limited studies on risk quantification. More specifically, rice yield risk assessment studies in South Asian region are rare. Therefore, the objective of this study was set to examine the rice yield distributions, estimate yield risks at country level, and compare risks between five countries namely Afghanistan, Bangladesh, Nepal, Sri Lanka, and Pakistan in South Asian region. The next section of this paper presents the material and methods. The third section is about results and discussion and last section concludes the study.

MATERIALS AND METHODS

In literature, bulks of studies are carried out to estimate the yield fluctuations in different crops at the farm and area levels. They applied different estimation methods. Larson *et al.,* (2004) and Ghosh (2010) used the coefficient of variation to estimate yield fluctuations, whereas other applied probability distributions. The limitation in coefficient of variation approach is it only compares the yield variation in relation to mean. However, the probability distribution approach estimates yield risk at different levels of expected yield. Accordingly, probability distribu-

[1] *This study considers rice as an "industry", which is a combination of different classes and varieties of rice produced at country level in South Asia.*

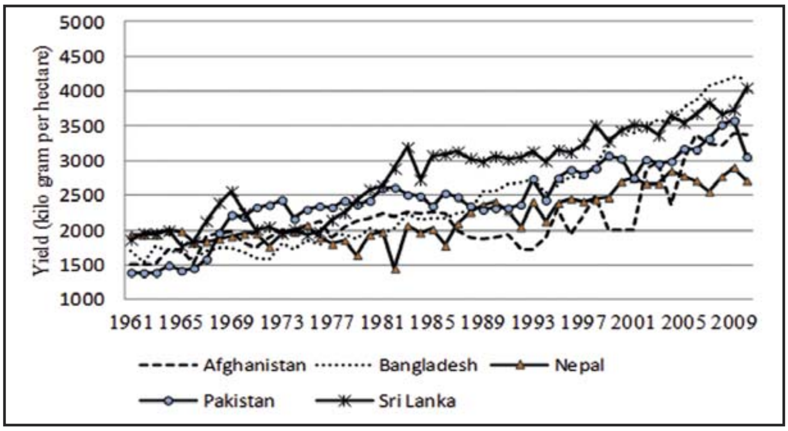

Figure 1: Rice Yield Trends during 1961-2010. Source: FAO (2012)

tion methods are broadly applied in the literature for yield risk assessment and crop insurance rate making (Just and Weninger, 1999; Ramirez, 2000; Ramirez *et al.*, 2003; Goodwin and Mahul, 2004; Sherrick *et al.*, 2004; Ozaki *et al.,* 2008; Ghosh, 2010; Ramirez *et al.*, 2010; Zhu *et al.*, 2011).

Further, different studies applied different probability distribution functions to crop yield distribution modeling. Just and Weninger (1999), Ozaki and Goodwin (2008) applied the Normal distribution in yield modeling. Likewise, Sherrick *et al.,* (2004) applied the Normal, the Beta, the Weibull, the Lognormal, and the Logistic distributions to the yield distribution modeling. Zhang and Wang (2010) tested nine distribution functions including the Normal, the Gamma, the Weibull, and the Lognormal. For the precision, we applied the most frequently applied four distributions[2] -- the Normal, the Lognormal, the Gamma, and the Weibull.

The Normal distribution is a non-flexible type of distribution because it contains fixed value of skewness, 0 and kurtosis, 3. However, other three non-normal distributions exhibit more flexible and permit the varying values of skewness and kurtosis. The Lognormal and the Gamma allow varying magnitudes of positive skewness, whereas the Weibull distribution permits both positive and negative values of skewness.

Sources of Data

This study primarily focused on agricultural economics aspects of the crop "rice," thus; we considered the rice as an "industry", which is a combined form of different classes and varieties of rice produced at national level. The rice yield in this study is defined as the total rice production including all types in a country is divided by its total harvested area. This paper is to examine the goodness-of-fit of the rice yield distributions in five countries to give policy implications of the rick-reduce programs; the classification may not be an important issue. In addition, the rice classifications in South Asia are similar and the data of rice classifications in these 5 countries are not available. Moreover, some previous studies applied rice as a collective form of all rice types and compared yield trends in different countries (Hobbs, and Morris, 1996; Hafner, 2003). Therefore, the rice classification would not be adopted in this paper. We utilized time series yield data of rice for 50 years from 1961 to 2010 in five South Asian countries namely Afghanistan, Bangladesh, Nepal, Pakistan, and Sri Lanka[3]. The yield data were taken from the website of Food and Agricultural Organization (FAO, 2012) and transferred to kilograms per hectare.

Figure 1 shows the yield trends of rice in five

[2]This study primarily focuses to realize yield distribution considering average country level time series yields. This study assumes temporal yield dynamism collectively examines the yield response of all factors. In the similar analysis, Gallaghar (1987) applied linear time trend yield for the U.S. soybean yield distribution modeling. Based on the above reason and following previous literature, we think a univariate statistical analysis could be helpful for analyzing a dynamic multivariate system for yield response functions.

[3]There are 8 countries in South Asia namely Afghanistan, Bangladesh, Bhutan, India, Maldives, Nepal, Pakistan, and Sri Lanka. Rice data in Maldives cannot be accessed probably because of rice is not cultivated in the Maldives. Similarly, in case of Bhutan, the yield data shows a constant value for many years that is not very relevant to yield risk analysis. India is a big country having a large area under rice production; therefore, it is not meaningful to compare rice yield risk in India with other small countries. So, this study selected only five South Asian countries.

South Asian countries. The yield levels in all countries changed drastically during 1961-2010. It increased 2.21 times in Afghanistan (1519 in 1961 to 3360 kilograms per hectare in 2010), 2.46 times in Bangladesh (1701 in 1961 to 4183 kilograms per hectare in 2010), 1.40 times in Nepal (1938 in 1961 to 2716 kilograms per hectare in 2010), 2.2 times in Pakistan (1392 in 1961 to 3959 kilograms per hectare in 2010), and 2.18 times in Sri Lanka (1863 in 1961 to 4056 kilograms per hectare in 2010).

Likewise, the figure also presents the rice yield fluctuations in different countries during the study period. Yield fluctuations are seen in every country but more severe in Afghanistan.

Model specifications

In the present study, we consider rice as the study crop in South Asian countries, which is one of the good examples of continuous increment of yields over the study period. Therefore, it is not reliable to simply compare the yields of different periods, i.e. 1961 and 2010. To overcome this problem, a method of yield detrending is carried out, by which yields in different periods are made comparable.

Recent studies applied a deterministic trend to capture the yield dynamism of the expected yields. The trend part is usually controlled for prior to examining the yield distribution. For this, different functional form regressions such as linear and/or polynomial OLS regression, quartile regression, smoothing splines, karnel regression, and partial linear models are applied. Just and Wagener (1999) stated a deterministic component may be sufficient to model the yield distribution. Therefore, we considered the linear and polynomial OLS (ordinary least square) regression, cubic splines, and quantile regression[4]. These models are applied in present agricultural economics literatures to capture the yield dynamism and yield estimation (Goodwin and Ker, 1998; Goodwin and Mahul, 2004; Sherrick *et al.*, 2004; Zhu *et al.*, 2011). The trend model for regressions is

$$y_{jt}= m(x_t)+ u_{jt} \qquad (1)$$

where y_{jt} represents the yields in country j; $m(x_t)$ denotes the regression function, $E\ (Y_t /X_t=x)$; x_t represents linear or nonlinear time indexes representing trend; t stands for time (t=1,….,T); and is the residuals that are assumed to be independently distributed with mean zero and u_{jt} standard deviation, σ_u.

We applied OLS, cubic splines, and quantile regression models to estimate the yields. Accordingly, we also estimated the residuals by $\hat{u}_t=y_{jt}-\acute{m}(x_t)$. Kolmogorov-Smirnove (K-S) two-sample goodness-of-fit (GOF) test suggests that residuals are not significantly different between these three models. As goodness-of-fit results indicated there are no differences on the residuals, we selected OLS regression models since it is convenient to apply.

Further, we should be careful about which OLS model is appropriate. Past studies suggested linear model gives good result in short period data, whereas polynomial regression is better for the longer period. Considering 50 years data length in our data set, we applied polynomial regression model. The polynomial regression model is

$$y_{jt}=\beta_{j0}+\beta_{j1}\, t+\beta_{j2}\, t^{2}+\beta_{j3}t^{3}+\beta_{j4}t^{4}+ujt \qquad (2)$$

where y_{jt} represents the yields in country j; β_{j0}, β_{j1}, β_{j2}, β_{j3} and β_{j4} are parameters; ujt is the residual term, and t stands for the time index.

The results showed the fourth and the third order coefficients were insignificant at .1 level of rice yields in Bangladesh; therefore, this study selected the second order polynomial regression in Bangladesh. Similarly, fourth, third, and second order coefficients were insignificant in Sri Lanka at .1 level and we selected first order polynomial regression for this country. Likewise, the study selected third order polynomial regression model for Afghanistan and Nepal because fourth order coefficients were insignificant in those countries. We selected fourth order polynomial regression in Pakistan because all four coefficients were significant at .1 level.

Furthermore, the second stage in yield detrending is the process of the yield normaliza-

[4] One anonymous reviewer mentioned about use of S-curve functional form for yield estimation. To our knowledge, this functional form is generally applied to evaluate the effect of multiple input variables on yields. We are considering only time factor, which is assumed a technology factor. Therefore, we think the S-curve functional form may not give the good results for this study.

tion. The normalization process is applied to address the potential temporal heteroskedasticity problem in the yield data. Yield normalization is a type of rescaling based on the reference yield. Although an ad hoc approach, it is commonly used to address the potential heteroskedasticity problem in the recent literature (Ozaki *et al*., 2008; Zhu *et al.*, 2011). In doing this, last observation of the sample data is considered a reference yield to express the yield in terms of technology. The model we applied for yield normalization is

$$\tilde{y}_{jt}=(1+\varepsilon_{jt})*\, y_{j2010} \qquad (3)$$

where $\tilde{y}_{jt}$ is the normalized yield in county *j*, ε_t is the ratio of residual to the respective predicted yield, and y_{j2010} is the observed yield in 2010.

In the next step, we applied yield distribution modeling by fitting the normalized yield of the particular country to a specific probability distribution function. For this, Goodness of fit test was applied to examine the best fitting probability distribution function for the rice yield in each country. Some frequently applied goodness-of-fit tests are Chi Squared, Shapiro-Wilk, Kolmogorov-Smirnov, and Anderson Darling tests. This study applied Anderson Darling (AD) tests because this test is able to test goodness-of-fit for multiple distributions. Moreover, it is a reliable test that provides a good result even in small numbers of samples. This test measures the distance between each sample point in the empirical cumulative distribution function (CDF) and the fitted probability distribution at that point and examines whether the yield distribution fits closely with theoretical probability distribution. Sherrick *et al.,* (2004) applied the AD test in the similar type of research to evaluate the best fitting models in their models. More explanations about the AD test can be found in Sherrick *et al*. (2004).

After a goodness-of-fit test, we applied maximum likelihood (ML) estimation method was applied to estimate the parameters of each distribution. For this, we used the log likelihood models for all fitted distributions.

The log likelihood model for the Normal distribution is

$$LL_N = -\frac{n}{2}\ln(2\pi) - n\ln(\sigma) - \frac{1}{2\sigma^2}\sum_{i=1}^{n}(\tilde{y}_{jt}-\mu)^2 \qquad (4)$$

where $\tilde{y}_{jt}$ is the normalized yield in country *j*, n is the number of observations, μ is the mean of yield, σ is the standard deviation of yield (σ >0), and π is the Pi.

The log likelihood model for the Log normal distribution is

$$LL_{LN} = -\frac{n}{2}\ln(\tilde{y}_{jt}-\theta) - \frac{n}{2}\ln(2\pi) - n\ln(\sigma)$$

$$-\frac{1}{2\sigma^2}\sum_{i=1}^{n}(\ln(\tilde{y}_{jt}-\theta)-\zeta)^2 \qquad (5)$$

where $\tilde{y}_j$ is the normalized yield in country j, n is the number of observations, θ is the threshold parameter ($\theta = 0$), σ is the shape parameter (σ > 0), ζ is the scale parameter (− ∞< ζ < ∞).

The log likelihood model for the Weibull distribution is

$$LL_W = n\ln(c) - nln(\sigma) + (c-1)\sum_{i=1}^{n}(\ln(\tilde{y}_{jt}-\theta)$$

$$-\ln(\sigma)) - \sum_{i=1}^{n}\left(\frac{\tilde{y}_{jt}-\theta}{\sigma}\right)^c \qquad (6)$$

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

The log likelihood model for the Gamma distribution is

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

$$\sum_{i=1}^{n}\left(\frac{\tilde{y}_{jt}-\theta}{\sigma}\right) - nln\Gamma(\alpha) - n\ln(\sigma) \qquad (7)$$

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

To estimate the probability of yield loss or

Table 1: Descriptive Statistics of the Normalized Rice Yields (kilograms per hectare), 2061-2010

Countries	N	Minimum	Maximum	Mean	Std Dev	Skewness	Kurtosis
Afghanistan	50	2784.47	3871.66	3360.89	307.01	-0.11	-0.93
Bangladesh	50	3808.69	4492.54	4183.18	174.58	-0.48	-0.35
Nepal	50	2006.48	3057.31	2716.63	182.60	-1.37	3.79
Pakistan	50	2470.33	3891.61	3062.98	240.45	0.17	2.28
Sri Lanka	50	3319.61	4942.24	4057.31	336.92	0.12	0.62

Source: Authors estimation based on FAO (2012)

yield risk, we applied the cumulative distribution functions. In literature, probability distribution functions are broadly applied for yield risk assessment and insurance rate making at different expected yield levels. Goodwin and Mahul (2004) and Ozaki *et al.,* (2008) used the expected yield loss equation as

$$\text{Expected yield loss} = F(\lambda Y^e)[\lambda Y^e - E(y|y < \lambda Y^e] \quad (8)$$

$$\text{Expected yield loss} = \text{prob}\,[y< \lambda Y^e\,][\lambda Y^e - E(y|y < \lambda Y^e] \quad (9)$$

where y^e represents expected yield, y is the observed yield, *F*(.) is the cumulative distribution function of the Normal, the Log normal, the Gamma, and the Weibull distribution, λ ($0<\lambda>1$) is the coefficient for yield at different levels i.e. .55, .60, .65, .70, .75, .80, .85, .90, and .95.

We followed the idea of Zhang *et al.,* (2009) and Zhang and Wang (2010) for yield risk i.e. the probability of yield loss. Accordingly, we examined the probability of yield loss rather than a complete equation of the expected yield loss. The probability of the yield loss equation that was applied by Zhang *et al.,* (2009) and Zhang and Wang (2010) is

$$\text{Probability of yield loss} = \text{Prob}\,[y<\lambda Y^e] = F(\lambda Y^e) \quad (10)$$

RESULTS AND DISCUSSION

The summary statistics of the normalized yields in the study countries are presented in Table 1. The mean of the normalized yield in the South Asian countries varied from as low as of 2716.63 kilograms per hectare in Nepal to as high as of 4183.18 kilograms per hectare in Bangladesh. Rice yields showed negative skewness in three countries namely Afghanistan, Bangladesh, and Nepal. The negative skewness in distribution indicates yields in those countries have a long tail on the left side of the distribution. In addition, the kurtosis values of the nor-

Table 2: Goodness of –Fit Measures and Ranking of Alternative Distributions of Rice Yield Based on Anderson-Darling Test Statistics

		Normal	Log normal	Weibull	Gamma
Afghanistan	Statistics	.36	.42	.48	.42
		(.25)	(.36)	(.23)	(.25)
	Rank	1	3	4	2
Bangladesh	Statistics	.55	.66	.21	.63
		(.15)	(.08)	(.25)	(.10)
	Rank	2	4	1	3
Nepal	Statistics	.97	1.38	.33	1.20
		(.02)	(.01)	(.25)	(.00)
	Rank	2	4	1	3
Pakistan	Statistics	.64	.78	1.54	.71
		(.09)	(.04)	(.25)	(.07)
	Rank	2	4	1	3
Sri Lanka	Statistics	.39	.44	.99	.41
		(.25)	(.23)	(.01)	(.25)
	Rank	1	3	4	2
Weighted Average		1.6	3.6	2.2	2.6
Rank of Average		1	4	2	3

Note: Numerical values in parentheses are p- values.

malized yield were greater than 3 in Nepal and lesser than 3 in the rest four countries. This reveals the rice yield distributions had shorter tails in Nepal and flat tails in the rest four countries. (Table 1)

Crop yield distributions modeling

The Anderson Darling (AD) test statistics and assigned ranks of four probability distributions are presented in Table 2. Yield distributions of Afghanistan, Bangladesh, and Sri Lanka could not reject the null hypothesis of normality at .1 level indicates the yields in those countries were fitted well to the Normal distribution. Similarly, the test could not reject the Lognormal distribution at .1 level in Afghanistan and Sri Lanka, which depicts yields in Afghanistan and Sri Lanka were fitted to the Log normal distribution. Likewise, yields in Afghanistan, Bangladesh, Nepal, and Pakistan were fitted to the Weibull distribution since the test could not reject the Weibull distribution at .1 level. Additionally, yield distributions of Afghanistan and Sri Lanka were fitted to the Gamma distribution because the test could not reject the Gamma distribution at .1 level.

Moreover, based on the lowest to the highest AD test statistics, the best fittings to the least fitting probability distributions are assigned to the yield distribution of individual country, Table 2. Yields in Afghanistan and Sri Lanka were fitted well to the Normal distribution because the yields in those countries could not reject the Normal distribution at .1 level and presented the lowest test statistics. Similarly, Yields in Bangladesh, Nepal, and Pakistan fitted well to the Weibull distribution because yields in these countries showed the lowest test statistics among the insignificant results and also could not reject the null hypothesis of the Weibull distribution at .1 level.

In the overall ranking, the Normal distribution was the best fitted model, the Weibull was the second, the Gamma was the third, and the Lognormal was the fourth rank, respectively. Sherrick *et al.,* (2004), who conducted a yield distribution modeling in corn and soybean yields based on farm level data, presented the Weibull was the first best fitting and the Normal was in the fourth fitting distribution out of five applied distributions. Our results showed differences to Sherrick *et al.,* (2004) result. The difference in both results may be due to the aggregation of data at the national level that we have applied in this study. However, the interesting result is Sherrick *et al.,* (2004) and this study both assigned the Lognormal as the least fitted distribu-

Table 3: Maximum- Likelihood Estimates of Parameters of Probability Distributions

	Afghanistan	Bangladesh	Nepal	Pakistan	Sri Lanka
		Normal			
Mean	3360.89	4183.18	2716.63	3062.979	4057.307
Std	307.01	174.58	182.60	240.4536	336.9197
		Lognormal			
Mean	3360.89	4183.29	2717.02	3063.23	4057.66
Std	307.01	176.66	193.44	242.25	339.21
Zeta	8.12	8.34	7.90	8.02	8.30
Sigma	0.09	0.04	0.07	0.08	0.08
		Weibull			
Mean	3359.28	4182.10	2716.17	3040.67	4040.02
Std	324.48	182.07	174.77	308.31	399.24
Sigma	3499.21	4262.72	2792.83	3173.25	4211.96
C	12.60	28.76	19.24	11.98	12.31
		Gamma			
Mean	3360.89	4183.18	2716.63	3062.98	4057.31
Std	305.97	174.10	187.42	238.60	334.21
Sigma	27.86	7.25	12.93	18.59	27.53
Alpha	120.66	577.29	210.10	164.80	147.38

Table 4: Summary of Rice Yield Risks at Different Expected Yield Levels (%)

	Expected Yield Levels								
	95	90	85	80	75	70	65	60	55
Afghanistan									
Normal	29.21	13.68	5.03	1.43	0.31	0.05	0.01	0.00	0.00
Log Normal	30.50	13.67	4.33	0.89	0.11	0.01	0.00	0.00	0.00
Weibull	26.89	14.65	7.42	3.53	1.58	0.66	0.26	0.10	0.03
Gamma	29.87	13.42	4.39	0.98	0.14	0.01	0.00	0.00	0.00
Range	3.61	1.23	3.09	2.64	1.47	0.65	0.26	0.1	0.03
Average	29.12	13.86	5.29	1.71	0.54	0.18	0.07	0.03	0.01
Bangladesh									
Normal	11.54	0.83	0.02	0.00	0.00	0.00	0.00	0.00	0.00
Log Normal	11.62	0.67	0.01	0.00	0.00	0.00	0.00	0.00	0.00
Weibull	12.38	2.75	0.54	0.09	0.01	0.00	0.00	0.00	0.00
Gamma	11.35	0.67	0.01	0.00	0.00	0.00	0.00	0.00	0.00
Range	1.03	2.08	0.53	0.09	0.01	0.00	0.00	0.00	0.00
Average	11.72	1.23	0.15	0.02	0.00	0.00	0.00	0.00	0.00
Nepal									
Normal	22.85	6.84	1.28	0.15	0.01	0.00	0.00	0.00	0.00
Log Normal	24.64	7.41	1.22	0.10	0.00	0.00	0.00	0.00	0.00
Weibull	19.60	7.42	2.53	0.80	0.23	0.06	0.01	0.00	0.00
Gamma	23.76	6.98	1.16	0.10	0.00	0.00	0.00	0.00	0.00
Range	5.04	0.58	1.37	0.65	0.22	0.06	0.01	0.00	0.00
Average	22.71	7.16	1.55	0.29	0.06	0.02	0.00	0.00	0.00
Pakistan									
Normal	26.21	10.14	2.80	0.54	0.07	0.01	0.00	0.00	0.00
Log Normal	27.09	9.77	2.18	0.27	0.02	0.00	0.00	0.00	0.00
Weibull	27.71	15.62	8.21	4.06	1.89	0.83	0.34	0.13	0.05
Gamma	26.54	9.63	2.25	0.31	0.02	0.00	0.00	0.00	0.00
Range	1.5	5.99	6.03	3.79	1.87	0.83	0.34	0.13	0.05
Average	26.89	11.29	3.86	1.30	0.50	0.21	0.09	0.03	0.01
Sri Lanka									
Normal	27.35	11.42	3.54	0.80	0.13	0.02	0.00	0.00	0.00
Log Normal	28.33	11.11	2.83	0.42	0.03	0.00	0.00	0.00	0.00
Weibull	27.28	15.10	7.78	3.77	1.72	0.74	0.30	0.11	0.04
Gamma	27.76	10.95	2.92	0.49	0.05	0.00	0.00	0.00	0.00
Range	1.05	4.15	4.95	3.35	1.69	0.74	0.30	0.11	0.04
Average	27.68	12.15	4.27	1.37	0.48	0.19	0.08	0.03	0.01

tion for the yield distributions.

The results of maximum likelihood estimate are presented in table 3. The study estimated the mean and standard deviations of the Normal and mean, standard deviation, shape, and scale parameters of the Lognormal, the Weibull, and the Gamma distributions.

Yield risk

The study estimated the yield risk from 55 to 95% at every 5% difference of expected yield i.e. 55%, 60%, 65%, 70%, 75%, 80%, 85%, 90%, and 95% as presented in the table 4. The results present a very nominal risk at 70 or lesser % of expected yield in most of the study countries. Sherrick *et al.* (2004) selected 85% of the expected yields to compare the results. By observing the results at different percentage, we also selected this level because it seems appropriate to compare results. We observed variations in results based on the different probability distributions. In Afghanistan, at 85% of the expected yield, the probabilities of yield loss estimates were 5.03, 4.33, 7.42 and 4.39% based on the Normal, the Lognormal, the Weibull, and the Gamma distributions, respectively. Similarly, in Bangladesh at the same level of expected yield, the risks were .02, .01, .54, and .01% for the Nor-

Table 5: Mean Absolute Difference of the Yield Risks between Countries.

	Afghanistan	Bangladesh	Nepal	Pakistan	Sri Lanka
Bangladesh	47*	-			
Nepal	27*	41*	-		
Pakistan	8	46*	21*	-	
Sri Lanka	5	47*	23*	3	-

Note: * indicates significant at .1 level.

mal, the Lognormal, the Weibull, and the Gamma distributions, respectively. Moreover, it was 1.28, 1.22, 2.53, and 1.16% in Nepal based on the Normal, the Lognormal, the Weibull, and the Gamma distributions, respectively. Likewise, in Pakistan it was found 2.8, 2.18, 8.21, and 2.25% based on the Normal, the Lognormal, the Weibull, and the Gamma distributions, respectively. In the similar way, 3.54, 2.83, 7.78, and 2.92% risk was observed in Sri Lanka based on the Normal, the Lognormal, the Weibull, and the Gamma distributions, respectively.

At 85% of expected yield, the yield risks were found 5.03 and 3.54% in Afghanistan, and Sri Lanka based on best fitted Normal distribution in those countries. Similarly, 0.54, 2.53, and 8.21% yield risks were found in Bangladesh, Nepal, and Pakistan, respectively, based on the best fitted Weibull distribution. In most of the countries, the risk percentage was the lowest from the Lognormal distribution; whereas the highest from the Weibull distributions. To make the yield risk comparisions, we averaged the yield risks from all distributions. The average values of risks were 5.29, 0.15, 1.55, 3.86, and 4.27% in Afghanistan, Bangladesh, Nepal, Pakistan, and Sri Lanka, respectively.

The results in table 4 showed yield risks in Afghanistan was the highest, whereas it was found the lowest in Bangladesh at every level of expected yield irrespective of the probability distribution functions. The probability of yield loss depends on how yields deviate to the left hand side of the expected yield. The result of the lowest yield risk in Bangladesh was due to the higher closeness of yield distributions to the expected yield, whereas the opposite is true in the case of Afghanistan. The average rice yield risk estimation from four probability distributions in the study countries were ranged from 0.15 to 5.29% at 85% of the expected yield. Zhang *et al*. (2009) presented corn yield risks at a range from 3.89 to 19.03% at medium risk level (85 to 75% of the expected yield) in different provinces of China. Likewise, Zhang and Wang (2010) presented about 0.43 to 11.49% of wheat yield risks in Beijing area of China. Therefore, our results of rice yield risks in studies counties at 85% are smaller than corn yield risks in China and wheat yield risk in the Beijing area of the same country.

Finally, the average yield risks of each country were compared by using the absolute mean percentage difference[5]. Wilcoxon Signed Rank test was applied to evaluate the differences of the yield risks between two countries. This test compares the yield risk between two regions or between two distributions. This test was applied by Sherrick *et al.* (2004) in the similar study to compare the crop insurance rates estimated from different probability distributions. The absolute mean difference results presented in Table 5 indicate the yield risks between Afghanistan-Pakistan, Afghanistan- Sri Lanka, and Pakistan-Sri Lanka were not significantly different at .1 level. In contrast, the results were significantly different between Bangladesh-Afghanistan, Bangladesh-Nepal, Bangladesh-Pakistan, Bangladesh- Sri Lanka, Nepal-Afghanistan, Nepal-Pakistan, and Nepal-Sri Lanka at .1 level. As a result, the yield risk in Bangladesh was significantly lower than Afghanistan by 47, Nepal by 41, Pakistan by 46, and Sri Lanka by 47%. Similarly, rice yield risk in Nepal was significantly lower than Afghanistan by 27, Pakistan by 21, and Sri Lanka by 23%.

CONCLUSIONS

Rice is the most important crop to supply food in the South Asian countries. Moreover, it is also an important industry that contributes a substantial share in the national economies in those

[5] *Average of risk estimated from four probability distribution models*

countries. However, the production of rice in this region appeared unstable. Therefore, a right assessment of yield risk vis a vis production risk was necessary. Thus, this study examined the rice yield distribution, estimated the yield risk, and compared the yield risks in five countries within a South Asian region.

Anderson Darling test results showed the Normal distribution fitted well with yields in Afghanistan and Sri Lanka, whereas the Weibull distribution fitted well with the yields in Bangladesh, Nepal, and Pakistan. The overall weighted results presented the Normal, the Weibull, the Gamma, and Lognormal distributions were ranked the first, the second, the third, and the fourth best fitting distributions for the rice yields in the study countries. Rice yield risks in the study countries were found nominal on the 70 or lesser % of the expected yield. At the 85% level, observed yield risks were 5.03 and 3.54% in Afghanistan and Sri Lanka based on best fitted Normal distribution. Similarly, 0.54, 2.53, and 8.21% yield risk were found in Bangladesh, Nepal, and Pakistan, respectively, based on the best fitted Weibull distribution. The observed average yield risks from all distributions were 5.29, 0.15, 1.55, 3.86, and 4.27% in Afghanistan, Bangladesh, Nepal, Pakistan, and Sri Lanka, respectively. As a result, the highest yield risk was observed in Afghanistan and the lowest in Bangladesh at every level of expected yield irrespective of the probability distribution functions. Based on Wilcoxon Signed rank test results, the yield risk was the lowest in Bangladesh, second lowest in Nepal and the highest in Afghanistan among five study countries.

The outcomes of this study could be helpful for policy implications to design and implement the risk management programs in the countries with higher yield risks. Based on the results, Afghanistan, Sri Lanka and Pakistan need to develop risk mitigating measures such as crop insurance products for rice because crop insurance protects farmers' from loss. Moreover, releasing of more resistant varieties for adverse weather, disease and pests, and improving crop husbandry are also best tools to minimize the effects of yield risks in those countries.

ACKNOWLEDGEMEN

The authors would like to thank to Edgardo Reyes Calderon for his help to run software and data analysis. In addition, the authors would like to thank two anonymous reviewers for their valuable comments and suggestions.

REFERENCES

1- Alauddin, M. & John, Q. (2008). Agricultural Intensification, Irrigation and the Environment in South Asia: Issues and Policy Options. Ecological Economics, 65, 111-124.

2- FAO. (2012). FAOSTAT-Agriculture. Food and Agricultural Organization of the United Nations. Accessed April 12, 2012. http://faostat. fao. org/ site/ 339/default.aspx.

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

4- Ghosh, B. K. (2010). Growth and Variability in the Production of the Crops in West Bengal Agriculture. Trends in Agricultural Economics. 3(3): 135-146.

5- Goodwin, B. K. and Mahul, O. (2004). Risk Modeling Concepts Relating to the Design and Rating of Agricultural Insurance Contracts. Working Paper - 3392, The World Bank.

6- Goodwin, B.K. & Ker, A.P. (1998). Nonparamertic Estimation of Ccrop Yield Distributions: Implication for Rating Group Risk Crop Insurance Contracts. American Journal of Agricultural Economics. 80: 139–153.

7- Hafner, S. (2003). Trends in Maize, Rice, and Wheat Yields for 188 Nations Over the Past Years: Prevalence of Linear Growth. Agriculture, Ecosystem and Environment. 97: 275-283.

8- Hobbs, P. & Morris, M. (1996). Meeting South Asia's Future Food Requirements from Rice-Wheat Cropping Systems: Priority Issues Facing Researchers in the Post-Green Revolution Era. Mexico: CIMMYT.

9- IRRI (International Rice Research Institute). (2006). Bringing hope, improving lives: Strategic Plan 2007–2015.

10- Just, R. E. & Weninger, Q. (1999). Are Crop Yields Normally Distributed? American Journal of Agricultural Economics. 81: 287–304.

11- Larson, D.W., Jones, E., Pannu, R.S. & Sheokand, R.S. (2004). Instability in Indian Agriculture - a

Challenge to the Green Revolution Technology. Food Policy. 29: 257-273.
12- Lobell, D. B., Schlenker, W. & Costa-Roberts, J. (2011). Climate Trends and Global Crop Production Since 1980. Science. 333: 616-620.
13- Ozaki, V.A., Goodwin, B.K. & Shirota, R. (2008). Parametric and Nonparametric Statistical Modeling of Crop Yield: Implication for Pricing Crop Insurance Contracts. Applied Economics. 40: 1151-1164.
14- Poudel, S. & Kotani, K. (2012). Climatic Impacts on Crop Yield and Its Variability in Nepal: do they vary across seasons and altitudes? Climate Change, DOI 10.1007/s10584-012-0491-8.
15- Ramirez, O. A. (2000). Parametric Modeling and Simulation of Joint Price-Production Distributions under Non-Normality, Autocorrelation and Heteroscedasticity: A Tool for Assessing Risk in Agriculture. Journal of Agricultural and Applied Economics. 42: 283–297.
16- Ramirez, O.A., Misra, S. & Field, J. (2003). Crop Yield Distributions Revisited. American Journal of Agricultural Economics. 85(1): 108–120.
17- Ramirez, O.A., McDonald, T. U. & Carpio, C.E. (2010). A Flexible Parametric Family for the Modeling and Simulation of Yield Distributions. Journal of Agricultural and Applied Economics. 42(2): 1-17.
18- Sarkar, M.A.R., Alam, K. & Gow, J. (2012). Exploring the Relationship between Climate Change and Rice Yield in Bangladesh: An Analysis of Time Series Data. Agricultural System. 112: 11-16.
19- Sherrick, B.J., Zanini, F. C., Schnitkey, G.D. & Irwin, S.H. (2004). Crop Insurance Valuation under Alternative Yield Distributions. American Journal of Agricultural Economics. 86(2): 406–419.
20- Zhang, Q. & Wang, K. (2010). Evaluating Production Risks for Wheat Producers in Beijing. China Agricultural Economic Review. 2(2): 200 – 211.
21- Zhang, Q., Wang, K. & Boyd, M. (2009). Corn Production Risk Analysis and Assessment in China. New Perspectives on Risk Analysis and Crisis Response. October 19-21, 2009.
22- Zhu, Y, Goodwin, B. K. & Ghosh, S.K. (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.