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Developing Area Yield Crop Insurance under Alternative Parametric Methods: Case Study for Wheat in East Azarbaijan Province, Iran

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Abstract

In crop insurance design, the yield guarantee and the premium are very important parameters, both of which depend upon the yield distribution. Accordingly, the accurate modeling of yield distribution is essential for designing crop insurance contracts. This study employs historical county-level yield data for irrigated and dry wheat in East Azarbaijan Province, Iran for 1975-2013 to evaluate the effects of five alternative parametric distributions and generate the area yield crop insurance premiums. Results indicated that, in almost all cases, the premium rates with alternative distributions significantly differed from each other and that the beta distribution fitted the data the best except for some series for which the weibull distribution was the best. The results showed that premiums for wheat vary from 246,000 IRR per hectare in the coverage of 65% for Miyaneh to 460,000 IRR per hectare for Tabriz, and for dry wheat they vary from 265,000 IRR per hectare for Tabriz to 680,000 IRR per hectare for Maragheh. Moreover, it was found that the calculated premiums were less than traditional premiums, which would be affordable for both insured and insurers. The insured will pay lower premiums, and because the new methods are used to calculate the indemnities in this contract, and therefore there is no need for attending in individual farms to calculate the loss; it will be useful for the insurers, too.

Keywords:
area-yield crop insurance, parametric distribution, premium rate, wheat

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INTRODUCTION

In an effort to overcome risks from unexpected events, agricultural producers purchase crop insurances to protect their income from fluctuations. The pricing of crop insurance affects both farmer's participation rates and also relative indemnities paid by the crop insurance companies. If crop insurance rates are too high, farmers may choose other methods to manage risk; conversely, the rates which are too low encourage adverse selection, which will increase the amount of indemnities, relative to the premiums paid. In adverse selection, the producers whose theses rates are low for them relative to the expected indemnities, will buy crop insurance more than producers whose rates are high for them. For agricultural insurance the actuarial premium should have conformity to the risk level of the insured crop and need accurate evaluations of agricultural production risk (Zhang & Wang, 2010). In modeling risk exposures, it is of crucial importance to characterize the shape of the yield distribution and, in fact, insurance it is like an input to rate making in designing crop because in yield-based crop insurance contracts the indemnity will be paid to the producer when yields fall below a guaranteed level. The setting of this level requires an accurate representation of the crop yield probability density function. The shape of the distribution of agricultural yields has been a controversial subject in the literature for many years. Although some researchers such as Just and Weninger (1999) concluded that agricultural yields have normal distribution, Day (1965), Taylor (1990), Ramirez (1997) and Ramirez et al. (2003) found evidences against normality.

In crop insurance designing of each insurance contract, two parameters are important: the yield guarantee which establishes total liability as related to the expected yield and the premium that should be paid by the insured for the coverage offered under the contract which reflects the likelihood and expected level of loss. Both parameters depend upon the yield distribution. Therefore, the accurate modeling of crop yield distribution, particularly their lower tails, is essential for the crop insurance contracts (Chen & Miranda, 2008; Goodwin & Mahul, 2004; Lanoue, 2010). The challenges associated with the statistical modeling of yield for the rating of crop insurance have been highlighted by extensive studies, some of which have used parametric or nonparametric methods whilst the others have used both of them to find the best method.

Although the literature on distribution choice varies remarkably in the selection of the model, yet very little literature have evaluated the comparison of distributions directly. A notable exception is Sherrick et al. (2004) that directly evaluated how distribution selection can affect the expected yield probabilities and premium rates (Burton, 2014). Sherrick et al. (2004) evaluated five alternative distributions (normal, logistic, weibull, beta, and lognormal). They fitted these parametric distribution to the farm-level corn and soybean production data and the results showed large differences in expected payouts, which were caused by the parameterization chosen for the yield distributions and for their data, more flexible parametric distributions such as the weibull and beta fit better than the others. Sherrick et al. (2014) examined the commonly used parametric (beta, weibull, normal), semi-parametric, and non-parametric distributions to identify implications for the choice of parameterization of yield distributions in modeling crop insurance for farm-level corn yield data in Illinois in the period of 1972 to 2008. Some of their results showed that the beta distribution consistently resulted in the overstated rates while the weibull resulted in understated rates. Zhang and Wang (2010) evaluated the production risks for wheat producers in Beijing in 13 districts. The results showed that, except for two areas for which the Johansen family distribution was the best, the burr distribution was appropriate for modeling the risks of winter wheat. Chen and Miranda (2008) formulated and estimated regime-switching models for Texas county-level dry land cotton yields and their results showed that this new model and conventional parametric distribution models did not generate the premium rate estimation of GRP[1] crop insurance and were significantly dif-

[1] Group Risk Program

ferent. In an attempt to price the area-yield crop insurance for corn, soybean and wheat aggregated yield data, Ozaki et al. (2008) compared parametric and nonparametric statistical methods in Brazil. They showed that the rates were higher in the nonparametric approach than those in empirical rate approach. Goodwin and Ker (1998) used nonparametric methods to evaluate the yield risk and insurance premium rates in county level crop yield for wheat and barley and found that they would modify the performance of crop insurance programs better. As mentioned before, although alternative yield-model distribution could impact quantitative evaluation of insurance values, few studies have focused on the economic importance of the commonly used alternative yield distribution assumptions directly, especially in area yield crop insurance contract, and it has been subjected to no study on any crop or in any region in Iran. The only two studies which correspond to the area yield crop insurance in Iran are Abdullahi Ezzatabadi and Bakhshudeh, (2007) and Torkamani and Vazirzadeh (2007).

There are different crop insurance policies based on different characteristics. Some of them pay indemnities based on individual level losses. Other policies pay indemnities based on shortfalls in an index (e.g. an area yield or weather measure). Some policies protect only against yield losses while the others consider the product of yield and price and protect against revenue losses (Barnett, 2014). The Federal Crop Insurance Corporation (FCIC) was started in 1938. At first, it was a pilot project and its activities were very limited until by the act of Federal Crop Insurance in 1980, it was extended to more crops and regions. FCIC's traditional policies are generally either yield-based or revenue-based in which a producer can receive an indemnity if there is a yield or revenue loss relative to the farmer's historical yield or revenue (Shields, 2015). Given the problems in these traditional crop insurance such as adverse selection (Just et al., 1999; Quiggin et al., 1993; Skees & Reed, 1986), moral hazard (Chambers, 1989; Coble et al., 1997; Smith and Goodwin, 1996) and transaction costs (Skees & Barnett, 1999), index-based crop insurance was introduced. Index insurance, unlike traditional insurance (which pays the indemnity based on individual losses), pay the indemnity based on the observed value of a specified "index" (area-level yield or some objective weather event or measure such as temperature or rainfall) or some other closely related variables. An index is a random variable. It is neutrally observable, reliably measurable, and highly correlated with the losses of the insured, and moreover the insured cannot influence it (Miranda & Farrin, 2012). The area yield crop insurance have been implemented in many countries including the United States, Canada and Mongolia whose results were satisfactory (Zhang et al., 2011). Three factors are important in offering the agricultural insurance products ranges in each country: the willingness of the government to subsidize them, the existence of a viable infrastructure for providing insurance (including regulatory structures, trained loss adjusters, product delivery mechanisms, etc.) and the information and data available to do the actuarial analysis (Smith & Glauber, 2012).

In Iran, agricultural insurance is offered particularly through the government institution, the Agricultural Insurance Fund and its activities have been started since 1984 and there is a broad variety of agricultural insurance products. The state institution offers Multi-Peril Crop Insurance (MPCI), crop income insurance, greenhouse insurance, and forestry insurance products. Aquaculture is insured through a special program and livestock insurance is available against accident and mortality from epidemic disease. Agricultural insurance is supported by the government through premium subsidies that are available for both crop and livestock insurance programs and agricultural insurance premiums are exempt from sales taxes. Evaluating the indicators of the development of agricultural insurance in the twelve years leading to the growing season of 2013-2014 shows that during this period the level of insured crops has increased to 9.3 million hectare from 2 million hectare and horticultural crops from 12 to 550 thousand hectares (Agricultural Insurance Fund, 2013; Ministry of Agriculture-Jahad, 2013). In Iran, premium subsidies amounted to 69 percent of total premiums. The absence of a suitable method for designing crop insurance has been noted as one of the main problems for the development of an agricultural insurance market and now the Agricultural Insurance Fund is looking for professional advice to train national experts on actuarial principles applied to calculate premium rates (Mahul & Stutley, 2010; Rasulof, 2004).

Wheat is one of the most important and most strategic agricultural products with an important role in food security. It has been covered by the Agricultural Insurance Fund for many years. In crop year of 2013-2014, a great portion of insured level of agronomy subsector belonged to wheat (irrigated and rain fed) which is about 59% of total level, and East Azarbaijan Province has been ranked the sixth in wheat planting area (6.4%) in the country. The amount of wheat production in this province is 227,034 ton for wheat and 190,154 ton for dry wheat which accounts for 3.9% of the country's total wheat production in the crop year of 2013-2014. Therefore, in this study we undertook a statistical case study of wheat and dry wheat yield data in East Azarbaijan Province which is ranked the thirteenth and fifth in insured level of wheat and dry wheat in the country in the crop year of 2013-2014. The statistics reported by the Agricultural Insurance Fund of East Azarbaijan Province shows that in the crop year of 2013-2014, the total received premium was about 6,969 million IRR and the indemnity paid was about 18,989 million IRR for wheat, and they were about 45,565 million IRR and about 65,588 million IRR for dry wheat, respectively. Using the Agricultural Insurance Fund statistics for East Azarbaijan Province, we can see during the crop years of 2008-2009 to 2013-2014, indemnities paid for these two crops to producers exceeded premiums collected in almost every year (see Figure 1)[1] .

Moreover, our calculations show that although the producer loss ratio (indemnities divided by producer-paid premiums) and loss ratio (indemnities divided by total premium, including government subsidies) have been decreasing in this period, these ratios are greater than one (see Figure 2). With respect to these data, it is necessary to use a better actuarially method to reduce these ratios to lower than one. At the moment, the Agricultural Insurance Fund uses a specific formula and they do not use statistical modeling for calculating the traditional premium rates. Indeed, there has been no research about alternative parametric statistical modeling for pricing crop insurance contract in Iran. It should be mentioned that the area yield crop insurance is performed for three crops in three provinces in Iran as a pilot and it is not available for these crops in East Azarbaijan Province. Thus, given the advantages of the area yield crop insurance relative to traditional insurance such as adverse selection and moral hazard and its satisfied outcomes in the other countries, it seems that this kind of crop insurance product would be effective

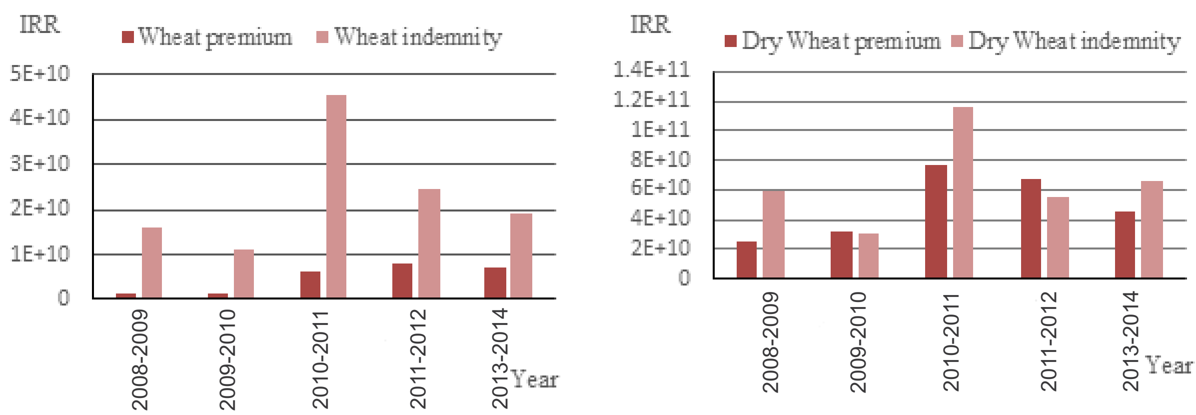

Figure1: Premium and indemnity for wheat and dry wheat in East Azarbaijan Province, 2008-2009 to 2013-2014

[1] *The data for 2012-2013 was not available totally*

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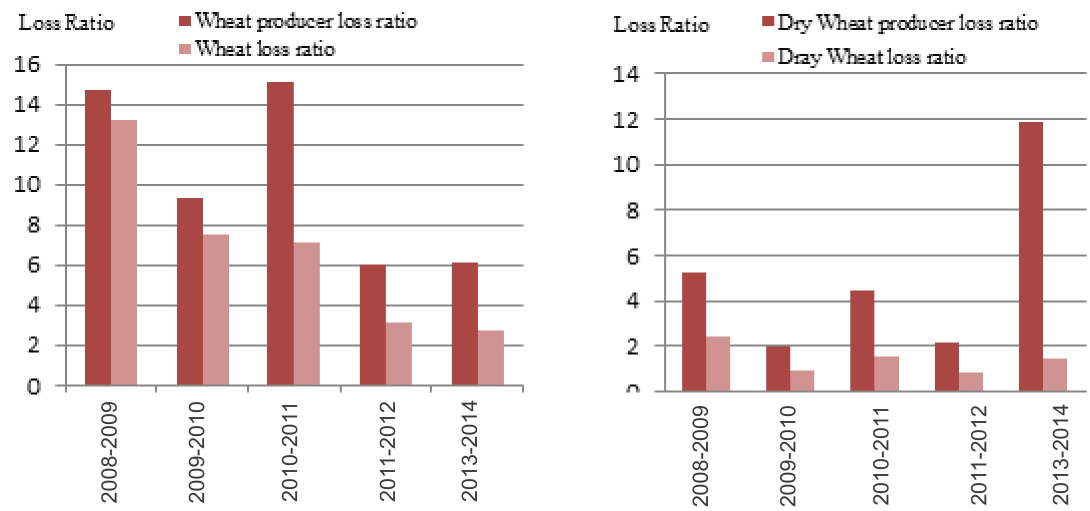

Figure 2: Producer loss ratio versus loss ratio for wheat and dry wheat in East Azarbaijan Province, 2008-2009 to 2013-2014

for developing countries such as Iran. Therefore, the objective of this study was to evaluate five parametric yield distributions suggested by previous empirical evidence (beta, logistic, normal and weibull) and to assess their implications for the valuation of two crop-insurance products (wheat and dry wheat) in Iran based on regional agricultural yield (area-yield crop insurance (GRP)). Thus, two crops yield data (wheat, and dry wheat) in six important producer counties in East Azarbaijan Province were used to generate the GRP premiums and evaluate the effects of alternative distributions.

MATERIALS AND METHODS

Designing an insurance contract is a mechanism for determining the probability of loss and the expected level of loss when losses occur. More clearly, one is interested in measuring the Probability Density Function (PDF) underlying the events that trigger losses. Thus, in designing and rating a crop insurance contract, the concept of modeling yield risk means modeling the probability distribution for the crop yield and estimating the parameters or descriptions of patterns which depict the stochastic nature of random yields (Goodwin & Mahul, 2004).

By adopting improved production techniques, the data-generating process underlying yield realizations are changing over time and these technical changes cause challenges for accurate modeling of yield distributions in rating crop insurance products. Therefore, a common procedure for modeling yield risk has been to first detrend the time-series yield data and then estimate the yield distribution. These procedures are often mentioned as “two-stage” methods; the first stage fits a trend model to the data, and the second stage uses the detrended data to model the distribution (Zhu et al., 2011). Thus, a variety of methods for detrending yield data have been adopted (Goodwin & Mahul, 2004) such as autoregressive integrated moving average models (Goodwin & Ker, 1998; Ker & Goodwin, 2000), linear spline (Chen & Miranda, 2008; Ker & Coble, 2003; Skees et al., 1997) and first and higher-ordered polynomials (Deng et al., 2008; Ozaki et al., 2008; Sherrick et al., 2004; Sherrick et al., 2014). Therefore, in this study, like the studies outlined above, we use a two-step estimation process for modeling yield distribution. First, trend yields are estimated using ordinary least-squares. It is performed with a first or second order deterministic trend model (in t), in particular we have:

$$y_t=\alpha_0+\alpha_1 t+\alpha_2 t^2+u_t \quad (1)$$

where y_t is the realized yield for wheat and dry wheat at the counties level in year t and t=1975,1976,…., 2013. Series with significant slope coefficient (at the 10% level) were detrended. For some series, the log-linear trend equation was used based on cox-box test results.

Given the trend yields, the detrended county-level were computed by normalizing observed yields to the last year 2013 equivalents as follows (Chen & Miranda, 2008; Deng et al., 2007; Ye et al., 2015):

$$y_t^{det}=yt/\hat{y}_t \cdot \hat{y}_T \qquad (2)$$

where, y_t^{det} is the detrended yield in year t, y_t is the realized yield in year t and $\hat{y}_t$ is the fitted trend yield in year t and T = 2013. Second, these detrended series are used for modeling yield risk. As mentioned before, in designing and rating a crop insurance contract, the modeling yield risk is fully analogous to modeling the probability distribution for the crop yield and significantly depends on the distribution function. There are three approaches for modeling yield densities and distributions, parametric, non-parametric and semi-parametric methods which have different advantages and disadvantages (Goodwin & Mahul, 2004; Ramirez et al., 2010).

A major advantage of using a parametric approach is the ease of estimation of the distribution parameters. A parametric method is more efficient than a non-parametric method if the true distributional form is known (Burton, 2014). The parametric distribution method estimates specific parameters and presumes that the data-generating process can be adequately represented by them. Therefore, the main disadvantage of this procedure is the possible error resulting from this assumption because these specific parameters may not be flexible enough to properly display the data and the main advantage of this procedure is that, if the presumed distribution can adequately display the data-generating process, it performs well even with small sample data. The Beta, the logistic, the log-normal, the normal and the weibull are the basic distributions for parametric method (Ramirez et al., 2010). These parametric distributions are different due to their flexibility and their ability to characterize the inherent properties of various crop yields. Therefore, they differ in terms of their suitability for modeling crop yield densities (Goodwin & Mahul, 2004). In literature, alternative parametric distribution models have been used for the crop yield data such as beta and normal distribution (Nelson, 1990), beta, normal, and gamma (Turvey & Zhao, 1999), normal, logistic, weibull, beta, and lognormal (Sherrick et al., 2004), normal, lognormal, and beta (Chen & Miranda, 2008), normal, lognormal, logistic, beta, burr, gamma, and weibull (Zhang & Wang, 2010), and normal, lognormal, gamma, and weibull (Poudel et al., 2013). Considering the literature in this study, the five parametric distributions examined were beta, logistic, lognormal, normal, and weibull distributions whose structures are as follow (Sherrick et al., 2004; Zanini et al., 2001):

Beta distribution: parameters $\alpha,\gamma>0$

$$\frac{f(x)=x^{\alpha-1}(1-x)\gamma-1}{B(\alpha,\gamma)} \qquad (3)$$

Logistic distribution: parameters $-\infty<a<\infty,\ b>0$

$$f(x)=\exp[(-x-a)/b]/b\{1+\exp[-(x-a)/b]\}^2 \qquad (4)$$

Lognormal: parameters $\sigma_I>0,\ -\infty<\mu_I<\infty$

$$f(x)=1/x\sigma_I(2\pi)^{1/2}\exp[-(\mathrm{Ln}(x)-\mu_I)^2/2\sigma_I^2\}\} \qquad (5)$$

Normal distribution: parameters $\sigma>0,\ -\infty<\mu<\infty$

$$f(x)=1/x\sigma_I(2\pi)^{1/2}\exp[-(x-\mu)^2/2\sigma^2] \qquad (6)$$

Weibull distribution: parameters $a,\beta>0$

$$f(x)=ax^{\alpha-1}/\beta^{\alpha}\exp[-(x/\beta)^{\alpha}] \qquad (7)$$

The beta and weibull distributions allow a wide range of skewness and kurtosis and are bounded by zero. Also, the weibull can be non-symmetric. The logistic fits well in some specific circumstances especially in cases when excess kurtosis exists. Thus, it is also retained as a fatter-tailed alternative to the normal. The normal distribution is very common in the literature. It is symmetric and covers the entire data and is not bounded below by zero. The lognormal also is used a lot because it is appropriate and can be estimated and understood easily. It is bounded below by zero too (Sherrick et al., 2004; Zanini et al., 2001).

To assess the relative goodness-of-fit of the plausible distributions, the parametric distributions were compared and ranked using the

CDFDEV function in Simetar Software Package. The CDFDEV function can be used to calculate a test scalar to determine which distribution is best for simulating the random variable (Richardson et al., 2010). The CDFDEV measure is programmed to compare a historical series to a simulated series. The function calculates the sum of the squared differences between two CDFs with an added penalty for differences in the tails. The scalar is calculated for two CDFs, F(x) and G(x) as:

$$\mathrm{CDFDEV} = \sum_{i=1}^{N} (F(x_{(i)}) - G(x_{(i)}))^2 + w_i \qquad (8)$$

where w_i is a penalty function that applies more weight to deviations in the tails than values around the mean. If the G(x) distribution is the same as the F(x) distribution, then the CDFDEV value equals zero. The CDFDEV measure is programmed to compare a historical series Nx1 to a simulated series Px1. By comparing two or more distributions as to their goodness-of-fit, the smallest CDFDEV belongs to the "best" distribution (Richardson et al., 2008).

Premium rating

An area yield crop insurance or a GRP insurance contract pays an indemnity if and only if the realized county yield y falls below a critical yield . The critical yield[2] (total liability), $yc = y_{fcast} \times coverage$. The y_{fcast} is insurer's forecast of area yield and a yield coverage level is between 0.7 and 0.9. Following Deng et al. (2008), the county yield forecast (y_{fcast}) is the predicted value from deterministic trend model described above for t = 2014 and if regression analyses represented no statistically significant time trend in county yields data, the in-sample average yield was used as the county yield forecast. Specifically indemnity is calculated by (Deng et al., 2008):

$$Indemnity = max\{0, (y_c - y)/y_c\} \qquad (9)$$

where y is the realized yield and y_c is the critical yield. The expectation of the indemnity function is the actuarially fair premium. Expected insured loss will be given by the product of the probability that a loss will be realized times the expected loss, given that a loss occurs (Goodwin & Ker, 1998). In other words, expected insured loss or the actuarially fair premium is (Goodwin & Ker, 1998):

$$\pi = prob(y < \alpha \hat{Y})[\alpha \hat{Y} - E(y | y < \alpha \hat{Y})] \qquad (10)$$

where π is the actuarially fair premium, α is the coverage level, and $\hat{Y}$ is the predicted yield. The actuarially fair premium rate which is calculated by the ratio of the expectation of the indemnity to total liability with a specific probability density function is calculated (Chen & Miranda, 2008; Goodwin & Ker, 1998; Skees et al., 1997) as:

$$p = \frac{1}{y_c} \int_0^{y_c} (y_c - y) f(y) dy \qquad (11)$$

where P is the actuarially fair premium rate. To calculate the actual GRP rating procedures, a proportional reserve load (1/0.9) is applied to the actuarially fair premium. The area under the density to the left of the guaranteed yield presents the probability of loss and for a contract guaranteeing α×100% of the predicted yield $\hat{Y}$, the integration of the density from 0 to a $\hat{Y}$ will give a measure of the loss probability (Deng et al., 2007; Goodwin & Ker, 1998).

Data

Historical county-level yield data published by Agriculture-Jihad Organization of East Azarbaijan Province in Iran were employed. The data were available for wheat and dry wheat yields in six counties (Ahar, Hashtrud,

Figure 3: East Azarbaijan Province Map

[2] *In practice, a guaranteed price established by the government is used to convert units of production per hectare into monetary units per hectare*

Maragheh, Miyaneh, Sarab and Tabriz) in 1975-2013. The map of the East Azarbaijan Province is presented in Figure 3.

RESULTS AND DISCUSSION

Summary statistics of the data is reported in Table 1. It shows the average amounts of production and yield for wheat and dry wheat during the years 1975 to 2013 in the studied counties. As can be seen, the maximum amount of mean production for wheat belongs to Tabriz (36,002.28 tone) and Hashtrud county has the lowest amount of wheat mean production (7,633.11 tone). The maximum mean production for dry wheat belongs to Hashtrud County (49,387.61 tone) and Tabriz county has the lowest amount of dry wheat mean production (11,644.08 tone). Tabriz has the maximum amount of wheat mean yield (2,676.36 Kg/ha) and Maragheh has the maximum amount of dry wheat mean yield (1,006.16).

The stationary properties of the yield series were investigated using both Elliot et al. (DF-GLS) and KPSS tests for unit roots whose results were reported in Table 2. The DF-GLS test of unit root indicated that the null hypothesis of unit root was rejected for the levels of all yield data series, and the null hypothesis of trend stationary in KPSS test was accepted for all of them. Thus, the yield series were trend stationary.

As mentioned earlier, the common procedure for modeling yield risk is detrending the time-series yield data first. Therefore, the series were detrended whose results are presented in Table 3. Similar to

Table1
Summary Statistics for 1975–2013 County-Level Data

Counties	Wheat (production, tone)			Dry Wheat (production, tone)		
	mean	min	max	mean	min	max
Ahar	16896.6	2355	31282	38841.86	14742	72200
Hashtrud	7633.11	2759	14880	49387.61	18585	92660
Maragheh	23492.69	3890	51400	34734.7	5100	74800
Miyaneh	31365.26	16990	46200	38104.36	10800	75660
Sarab	34193.55	17107	53700	14839.87	2309	27400
Tabriz	36002.28	11947	63760	11644.08	412	32111
Counties	**Wheat (yield, Kg/ha)**			**Dry Wheat (yield, Kg/ha)**		
	mean	**min**	**max**	**mean**	**min**	**max**
Ahar	2353.28	1173.33	4033	754.34	300	1250
Hashtrud	2444.98	1285.71	4271.52	815.35	320.43	1570.51
Maragheh	2782.12	1472.39	4075	1006.16	188.89	2412.9
Miyaneh	2585.78	1435	4200	781.28	193.55	1322
Sarab	2640.31	1425.58	3637.80	762.23	115.45	1284.47
Tabriz	2676.36	1194.7	4677	826.05	103	1420

Table 2
Unit Root Test Result

	DF-GLS:Level		KPSS:Level	
County	Wheat	Dry Wheat	Wheat	Dry Wheat
Ahar	-3.82	-6.30	0.07	0.06
Hashtrud	-4.52	-5.0	0.05	0.05
Maragheh	-3.58	-6.62	0.11	0. 08
Miyaneh	-3.39	-4.59	0.10	0.11
Sarab	-4.04	-5.19	0.09	0.08
Tabriz	-4.38	-5.5	0.09	0.06

Note: for the levels, intercept and trend have been included; the 5% criticalvalue is -3.19 and 0.15 for DF-GLS and KPSS test respectively

Table 3
Summary Statistics for 1975–2013 Detrended County-Level Yields, (Yields Measured in kg per ha)

County	Crop	Mean	SD	Minimum	Maximum	Skewness	Kurtosis
Ahar	Wheat	3647.05	533.44	2196.06	4527.8	-0.83	0.42
	Dry Wheat	1005.75	227.68	366.27	1436.18	-0.92	1.03
Hashtrud	Wheat	3494.05	853.64	2043.78	4749.59	0.01	-1.14
	Dry Wheat	1059.52	333.16	352.39	1673.54	-0.42	-0.51
Maragheh	Wheat	3072.31	718.63	1520.98	4364.56	0.04	-0.47
	Dry Wheat	1085.47	315.92	197.97	1714.92	-0.33	0.41
Miyaneh	Wheat	3580.81	888.97	2142.96	5490.98	0.48	-0.31
	Dry Wheat	772.45	252.08	173.85	1169.08	-0.62	-0.52
Sarab	Wheat	3390.78	668.15	1533.84	4552.99	-0.39	0.04
	Dry Wheat	762.77	235.75	115.03	1284.2	-0.44	0.58
Tabriz	Wheat	4077.07	825.09	1341.34	5547.84	-0.69	2.01
	Dry Wheat	1092.08	276.66	111.57	1663.4	-0.98	3.52

Table 4
CDFDEV Functions Results of Alternative Distributions, Wheat, Dry Wheat

County	Crop	Beta	Weibull	Normal	Lognormal	Logistic
Ahar	Wheat	12132.15*	144926.9	236748.1	574549.5	917134.8
	Dry Wheat	5615.13*	11546.92	38053.83	254617.6	142564.3
Hashtrud	Wheat	8516.48*	564552.6	1096913	2881271	1539376
	Dry Wheat	4733.74*	44636.16	125862.1	1101578	516705
Maragheh	Wheat	27862.11*	333922.4	464258.4	1429754	1950646
	Dry Wheat	16810.5*	26513.5	66609.7	278320.6	302401.2
Miyaneh	Wheat	31595.28*	466608.1	787284.4	1101035	3002966
	Dry Wheat	2162.05*	16859.46	39277.82	414467	132978.2
Sarab	Wheat	50314.7*	172351.2	343458.2	1191694	1526821
	Dry Wheat	8788.95	6690.30*	18034.41	375063.3	72039.48
Tabriz	Wheat	185235.7	182975.3*	433304.1	2737376	1934570
	Dry Wheat	40156.5	16705.03*	40295.43	1755243	138177.3

*indicates the smallest CDFDEV

the findings of Goodwin and Ker (1998), the yields exhibited negative skewness in about 75 % of the cases, although positive skewness is reported, too, in the other researches such as Chen and Miranda (2008). Negative skewness suggests fatter right-hand-side tails with yields close to the maximum yield observed more frequently than very low yields. In order to evaluate the effectiveness of alternative distribution models for the county-level, the parametric distributions were fitted to the all detrended county-level yields.

To evaluate the relative goodness-of-fit of the distributions, we need to compare the CDFDEV function results. Table 4 summarized the results of alternative distributions by CDFDEV functions for both crops in all counties. Results indicated that in most cases, the beta distribution had the smallest CDFDEV and therefore, the beta distribution fitted the data the best except for some series (Sarab dry wheat and Tabriz wheat and dry wheat) for which the weibull distribution fitted the best.

To demonstrate the differences arising from different parametric distribution and to provide a visual illustration, the Cumulative Distribution Function (CDF) and Probability Density Function (PDF) plots of Tabriz wheat yield are presented as an example (see Figure 4). As can be seen, this figure shows differences arising from different parameterizations and similar to the results of CDFDEV functions for Tabriz wheat yield, the CDF plots show that best fitted is the weibull distribution and appears to represent the sample data for this county reasonably well but the distribution domain of the others is

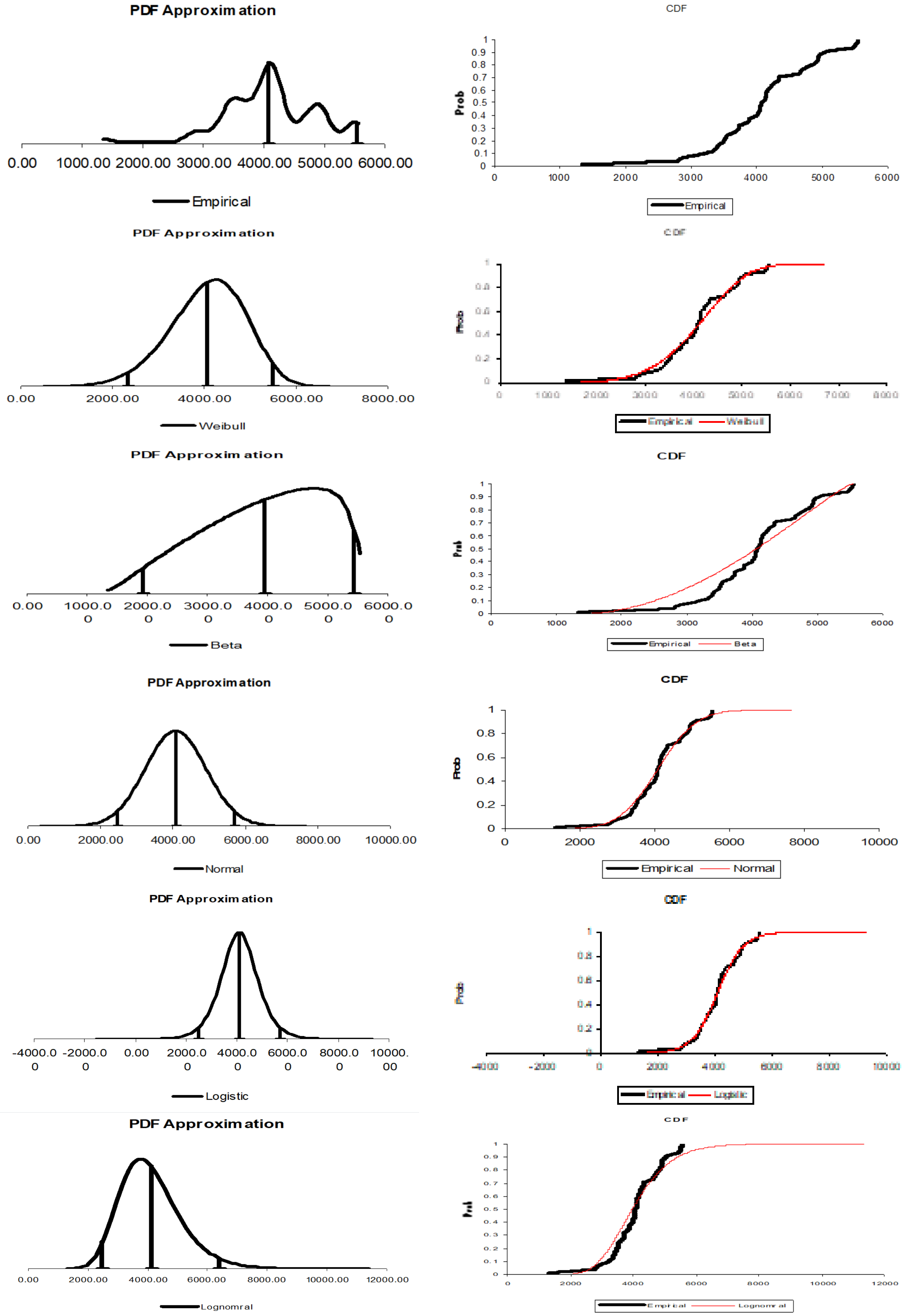

Figure4: Cumulative and probability distribution functions and empirical distribution for wheat yields, Tabriz County

Table 5
Actuarially Fair Premium Rate for Wheat and Dry Wheat at 85% of Coverage Level

County	Crop	Beta	Logistic	Lognormal	Normal	Weibull
Ahar	Wheat	6.7%	4.4%	5.6%	5.2%	4.7%
	Dry Wheat	7.4%	3.4%	5.3%	4.3%	3.9%
Hashtrud	Wheat	6.5%	5.5%	5.6%	5.9%	5.9%
	Dry Wheat	11.1%	7.3%	8.9%	7.9%	7.3%
Maragheh	Wheat	5.1%	4.1%	3.4%	3.8%	4.2%
	Dry Wheat	10.5%	5.5%	4.3%	5.7%	5.6%
Miyaneh	Wheat	5.9%	5.9%	4.9%	5.6%	6.4%
	Dry Wheat	10.9%	6.7%	9%	7.4%	6.6%
Sarab	Wheat	5.2%	3.2%	3.3%	3.3%	3.4%
	Dry Wheat	12.7%	6.4%	9.8%	7.4%	7.3%
Tabriz	Wheat	7.1%	3.1%	4.4%	3.6%	3.8%
	Dry Wheat	12.5%	3.9%	9.9%	5.4%	5.9%

more than the empirical distribution of the sample data.

The fitted beta, logistic, lognormal, normal, and weibull distributions from each county were used alternatively to define f (y) in equation (11) to calculate the corresponding actuarially premium rates on wheat and dry wheat. Following Sherrick et al. (2004) for comparison, only results at the 85% of coverage level are reported in Table 5.

As can be seen, in most cases (11 of 12), the beta rates are larger than other rates, and generally, the symmetric distributions (normal and logistic) give lower premium rates than beta distribution. This finding is consistent with Sherrick et al. (2004) and Ozaki et al. (2008). Following Goodwin and Ker (1998) and Sherrick et al. (2004), the statistical differences between these premium rates with different distributions are evaluated by help of paired t-tests to show the economic significance of the choice of distribution. The results of the paired t-tests are reported in Table 6.

As the results indicate, almost all distributions are significantly different from each other, and just in one case, the difference is not significant, showing the importance of distribution choice. Therefore, given the results which indicate that the differences between premium rates with different distributions are significantly important and the beta and weibull distributions are the best fit for the yield series, we calculate and consider the fair premium rates only with the best distributions. Table 7 contains the actuarially GRP premium rates, for both crops in all counties. These GRP premium rates are reported as a percent of liability. We calculate these premium rates in different GRP coverage levels (65%, 70%, 75%, 80%, 85% and 90%). For wheat, the premium ranges vary from 0.5% in the coverage of 65% for Miyaneh to 9.3% in coverage of 90% for Ahar and for dry wheat, premium rate ranges change from 2.2% in the coverage of 65% for Ahar to 14.3% in the coverage of 90% for Sarab. The comparison of the results with other studies will confirm the accuracy of our estimates. Ozaki et al. (2008) estimated the beta premium rates for corn, soybean and wheat. The beta premium rates for wheat ranged from 2.44 in the coverage of 70% to 4.96 in the coverage of 90%.

Now we can calculate the premiums for considered crops in all counties. Because the traditional premiums are offered in the coverage of 65%, we compare the results in that coverage. Based on the Agricultural Insurance Fund report, the premiums in the year of 2014 in West Azarbaijan Province were 1,100,000 IRR per hectare for wheat and 860,000 IRR per hectare for dry wheat. Our results for wheat and dry wheat premiums in the considered counties are reported in Table 8. The results reported in Table 8 indicate that in all cases, the premiums in the coverage of 65% are less than traditional premiums. The premiums for wheat vary in the range of 246,000 IRR per hectare in the coverage of 65% for Miyaneh to 5,070,000 IRR per hectare in the coverage of 90% for Ahar, and for dry wheat they vary from 265,000 IRR per hectare in the coverage of 65% for Tabriz to

Table 6
Paired t-Tests of Premium Rates

County	Crop		Beta	Logistic	Lognormal	Normal	Weibull
Ahar	Wheat	Beta	-	72.56***	65.49***	76.51***	73.72***
	Dry Wheat	Logistic	-	-	-57.15***	-60.78***	-43.53***
		Lognormal	-	-	-	45.28***	46.42***
		Normal	-	-	-	-	46.44***
	Wheat	Beta	-	59.85***	63.10***	64.66***	64.58***
	Dry Wheat	Logistic	-	-	-46.05***	-43.78***	-32.48***
		Lognormal	-	-	-	43.53***	49.08***
		Normal	-	-	-	-	52.41***
Hashtrud	Wheat	Beta	-	6.75***	6.74***	4.03***	3.72***
	Dry Wheat	Logistic	-	-	-3.08***	-17.55***	-16.38***
		Lognormal	-	-	-	-12.59***	-12.58***
		Normal	-	-	-	-	-6.72***
	Wheat	Beta	-	45.67***	64.39***	55.27***	67.08***
	Dry Wheat	Logistic	-	-	-23.75***	-21.56***	1.64ns
		Lognormal	-	-	-	25.81***	48.31***
		Normal	-	-	-	-	41.44***
Maragheh	Wheat	Beta	-	19.7***	56.79***	36.58***	24.78***
	Dry Wheat	Logistic	-	-	16.42***	12.09***	-8.08***
		Lognormal	-	-	-	-19.74***	-28.07***
		Normal	-	-	-	-	-41.69***
	Wheat	Beta	-	-2.71***	-75.45***	-30.63***	-49.52***
	Dry Wheat	Logistic	-	-	-51.28***	-55.08***	-56.39***
		Lognormal	-	-	-	40.19***	17.06***
		Normal	-	-	-	-	-57.48***
Miyaneh	Wheat	Beta	-	-1.46*	43.69***	5.8***	-9.86***
	Dry Wheat	Logistic	-	-	23.26***	17.68***	-20.31***
		Lognormal	-	-	-	-25.93***	-38.06***
		Normal	-	-	-	-	-54.79***
	Wheat	Beta	-	50.17***	49.93***	59.63***	67.50***
	Dry Wheat	Logistic	-	-	-32.55***	-24.29***	3.39***
		Lognormal	-	-	-	36.04***	60.62***
		Normal	-	-	-	-	42.03***
Sarab	Wheat	Beta	-	46.64***	58.32***	57.62***	53.27***
	Dry Wheat	Logistic	-	-	-1.89*	-1.88*	-16.48***
		Lognormal	-	-	-	1.84*	-6.68***
		Normal	-	-	-	-	-20.00***
	Wheat	Beta	-	65.63***	58.12***	71.11***	73.40***
	Dry Wheat	Logistic	-	-	-50.23***	-36.09***	-24.37***
		Lognormal	-	-	-	55.09***	64.33***
		Normal	-	-	-	-	6.42***
Tabriz	Wheat	Beta	-	60.49***	58.85***	62.98***	63.46***
	Dry Wheat	Logistic	-	-	-39.81***	-30.37***	-43.39***
		Lognormal	-	-	-	45.51***	25.09***
		Normal	-	-	-	-	-26.79***
	Wheat	Beta	-	67.89***	51.14***	69.76***	70.64***
	Dry Wheat	Logistic	-	-	-70.46***	-53.72***	-54.24***
		Lognormal	-	-	-	74.45***	74.59***
		Normal	-	-	-	-	51.02***

***$p < 0.01$ level under paired-t test.*$p < 0.05$ level under paired-t test. ns non-Significant.

1,766,000 IRR per hectare in the coverage of 90% for Hashtrud. Due to the traditional insurance which operates at 65% coverage, we can see that in all cases, the estimated premiums are less than traditional cases, which is acceptable because of lower transaction costs in this kind of insurance.

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Table7
Actuarially Fair Premium Rates (%) for Wheat, Dry Wheat

Crop	county	Crop					
		65%	70%	75%	80%	85%	90%
Wheat	Ahar	0.6%	1.4%	2.7%	4.4%	6.7%	9.3%
Wheat	Hashtrud	0.9%	2%	3.3%	4.9%	6.5%	8.4%
Wheat	Maragheh	0.9%	1.6%	2.6%	3.7%	5.1%	6.6%
Wheat	Miyaneh	0.5%	1.4%	2.7%	4.2%	5.9%	7.8%
Wheat	Sarab	1%	1.7%	2.7%	3.8%	5.2%	6.7%
Wheat	Tabriz	2.3%	3.3%	4.4%	5.7%	7.1%	8.8%
Dry Wheat	Ahar	2.2%	3.3%	4.5%	5.8%	7.4%	9.1%
Dry Wheat	Hashtrud	4.9%	5.8%	7.8%	9.4%	11.1%	12.8%
Dry Wheat	Maragheh	5.1%	6.2%	7.5%	8.8%	10.5%	11.6%
Dry Wheat	Miyaneh	5.6%	6.8%	8%	9.4%	10.9%	12.5%
Dry Wheat	Sarab	6.9%	8.1%	9.7%	11.1%	12.7%	14.3%
Dry Wheat	Tabriz	6.9%	8.2%	9.5%	11.1%	12.5%	14.1%

Table 8
Actual Premium for Wheat and Dry Wheat in the Considered Counties (IRR per Haectar)

		65%	70%	75%	80%	85%	90%
Ahar	Wheat	330000	775000	1480000	2410000	3600000	5070000
	Dry Wheat	290000	435000	590000	760000	970000	1190000
Hashtrud	Wheat	435000	940000	1560000	2300000	3075000	3930000
	Dry Wheat	670000	800000	1080000	1300000	1526000	1766000
Maragheh	Wheat	340000	630000	1000000	1440000	1950000	2520000
	Dry Wheat	680000	826000	990000	1166000	1390000	1550000
Miyaneh	Wheat	246000	675000	1266000	1980000	2800000	3696000
	Dry Wheat	540000	656000	770000	910000	1050000	1200000
Sarab	Wheat	440000	760000	1177000	1675000	2300000	2975000
	Dry Wheat	280000	366000	465000	580000	710000	870000
Tabriz	Wheat	460000	695000	1025000	1470000	2050000	2785000
	Dry Wheat	265000	360000	490000	630000	835000	1040000

CONCLUSION

This study evaluated the alternative parametric yield distribution for area yield crop insurance in East Azarbaijan Province, Iran. Different parametric distributions were estimated for wheat and dry wheat in Ahar, Hashtrud, Maragheh, Miyaneh, Sarab and Tabriz counties. The results showed that, in most cases (9 of 12), the beta distribution fitted the data the best and for the other cases, the weibull distribution was the best. Therefore, the premium rates were estimated with the best distributions and the results were compared with the previous studies for area yield crop insurance in the other countries which confirmed the accuracy of our estimations. Thus, finally, the premiums were calculated, and the results indicated that these premiums were lower than traditional premiums, which would be affordable for insured and insurers. Insured will pay lower premiums and will demand insurance more to manage risk in their farms better and because of less transaction costs in area yield crop insurance contract and the new ways in paying the indemnities (resulting in no need to evaluate the losses in the individual farms), it can be useful for insurers, too. Therefore, given the results of this study and successful experiences in developed and developing countries such as America and India, the Agricultural Insurance Fund is expected to try to use different index-based crop insurance products such as area yield crop insurance instead of current traditional products to help producers to manage agricultural risk better. Also, given the importance of the distribution choice in premium rating, it is recommended that stakeholders should use the advance statistical methods for the accuracy of premium estimates. We propose to use non parametric methods in the future studies because of some benefits of these methods compared to the parametric methods. Also given the importance of the availability of the longer time series data in the accuracy of premium rating, we suggest that the Agricultural Insurance Fund proceed to collect the banking of data in areas smaller than counties because access to long time yield series data in more homogeneous areas causes more accurate premium rating. Now, premiums are determined by the type of crop at the provincial levels. According to the results, in which different values of the premiums are obtained for different counties, we suggest that scales smaller than province (county) be considered for determining the premiums. Also, it is suggested that the premiums be presented in different coverage levels to the insurers.

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