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Measuring the Dependency Structure between Yield and Weather Variables for Ratemaking Weather-Based Crop Insurance in Ahar

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Abstract

In Iran, agricultural insurance suffers from asymmetric information, and such problems lead to enormous costs. Weather-Based Crop Insurance scheme as an effective way can solve a number of fundamental problems. Likewise, the designing and pricing of this system is strongly dependent on dependency structure between yield and weather variables. In this paper, we used more flexible approach, so-called "vine copula" to measure joint distribution function of weather variables and rainfed barley yield in Ahar County over the period from 1995 to 2014. We used R-vine to compute premium. The premium was calculated in four levels of coverage (75, 80, 90 and 100 percent) that its amount in 80 percent coverage level is 320058 Rials. The computing premium in WBCI is less than current insurance premium, which is reasonable.

Keywords: Weather-Based Crop Insurance, Vine Copula, Barley, Ahar.

Introduction

Since agriculture sector is dependent on natural factors; therefore, weather variability can critically affect the productivity of agricultural producers. According to FAO (2014), about 70 percent of risk in agriculture sector arises from natural disasters. The strong influence of weather variations on changes in yields, generate high variability in farming household income. This leads to complications in both short-term production and long-term planning. Agricultural producers have to make decisions on whether to expand or reduce production. The ultimate inescapable but very crucial decision by a farmer is whether to stay in farming or to exit. This last resort decision is a great concern to policy maker (Aziznasiri, 2011).

Agricultural producers will increasingly demand effective risk management instruments that allow them to overcome with weather variations (Bokusheva, 2010). There are several ways to reduce weather risk; one of the major policies in the agricultural risk management is insurance scheme. Insurance is an appropriate mechanism to stabilize the income of producers, but traditional insurance systems due to asymmetric information are difficult to perform. Such challenges will lead to increase in premium rate, indemnity; therefore, the insurer will be obliged to accept huge cost to assess the damages. The cost of traditional insurance schemes should be supported by government, while unfortunately government does not have sufficient funds to help such a scheme in developing countries (Ofoghi et al, 2011).

Recently, particular attention has been paid to weather based crop insurance scheme (WBCIS). Such instruments have been introduced as effective programs in several countries. According to the United Nations Department of Economic and Social Affairs (2007), weather-based crop insurance has been implemented in India, Ukraine, Ethiopia, Malawi, Nicaragua, Tanzania, Thailand, Bangladesh and Senegal (Barnett and Mahul, 2007). According to Skees et al (2001), Varangis et al (2002), Zhu et al (2008), Turvey and Belltawn (2009) and Bokusheva (2010), these type of insurance schemes are very useful in reducing the weather risk. In addition, WBCIS can resolve a number of fundamental problems. Unlike traditional insurance, in this insurance system, premium and indemnity determine based on indices and their effect on product losses. This reliance on factors beyond the control of farmers reduces the occurrence of moral hazard. Indemnifications is not linked to the crop survival or failure, hence, the farmers try to make the best decisions for crop survival. The insurance company does not need to visit farmers' field to determine actual losses. If the index amount is less or more than the trigger value, the insurer pays the loss (Turvey and Belltawn, 2009). In relation to the benefits of WBCIS and its successful results in many countries, it is expected that Agricultural insurance in Iran use this kind of system.

Barley is one of the most important crops in Iran. According to "the Ministry of agriculture of Iran Organization" (2012) there are 1.51 million hectares land under barley cultivation, and the share of rainfed land is about 58.92 percent. Agricultural insurance covers 590514 hectares of them. "East-Azerbaijan" province is fifth in the Iran with 5.55 percent of total area under barley cultivation, and Ahar County is one of the greatest producers of barley in this province with 21.27 percent of areas and 23.26 percent of crop.

In insurance risk management, knowledge of the dependency structure between variables is so necessary. There are a variety of ways to measure dependency. The traditional analyses assume that the dependency structure can be captured well by linear correlation. Although linear correlation is very popular in applied economic research, but it is applicable in the scope of multivariate normal distributions However, empirical investigations show that the distributions of the real world are rarely in this class (Bokusheva, 2010). Beside, Karuaihe et al (2006) represented that one index may not adequately explain yield variations. Thus, there is a need to exploit more than one. In this regards, searching for flexible multivariate distributions makes "copula modeling" increasingly popular in many fields of application (Brechmann and Schepsmeier, 2012).

Copula is a powerful tool to create more flexible and more realistic multivariate distribution. In fact, a group of marginal distributions can be connected with copula and create a joint distribution (Nelsen, 2005). Although the simple copula functions are better than other dependency structure measurement methods, Aas et al (2009), Brechmann and Schepsmeier (2012), Dißmann et al (2013) and Czado et al (2014) showed that they are inappropriate models to describe the dependency structure in arbitrary dimension. The multivariate data have often complex dependency patterns, such as non-symmetry and dependence in the extremes. Multivariate copulas lack the flexibility of modeling the dependence among large numbers of variables. Generalizations of these make some improvement, but become rather complex in their structure and provide other limitations such as parameter restrictions (Brechmann and Schepsmeier, 2012). The analysis of high dimensional data requires flexible multivariate stochastic models that can capture the inherent dependency patterns. Considerable efforts have been undertaken to increase the flexibility of multivariate copula models. "Vine copulas" are among the best-received of such efforts (Czado et al, 2014).Vine copulas were proposed by Joe (1996) initially and developed in more detail by Bedford and Cooke (2001, 2002) and Kurowicka and Cooke (2006). Vine copulas let different structural dependencies of pairs of variables to be modeled properly, in particular so with regard to their symmetry, or lack thereof, strength of dependence, and tail dependencies (Czado et al, 2014).

Brechmann and Czado (2011) in the research for risk management of "the Euro Stoxx 50[1]", Dibmann et al (2013) in the study for selecting and estimating regular vine copula for financial

[1] The EURO STOXX 50 is a stock index of Eurozone stocks.

returns, and Goodwin (2012) in modeling for crop insurance and reinsurance contracts showed vine copula models are more flexible and efficient in explanation of dependency structure.

According to successful applications of vine copula for determining dependency between random variables, it seems this method can be particularly suitable to measure the dependency between barley yield and weather variables. Consequently, in this research, weather-based crop insurance for barley in Ahar county as an efficient instrument in risk management is presented with utilization of vine copula.

Materials and methods

The application of copulas for modeling multivariate dependence stems from Sklar's (1959) theorem, which indicates the role that copulas play in the relationship between univariate margins to gain multivariate distribution functions (Nelsen, 2005). A copula, C, is a multivariate distribution function in the unit hypercube [0,1]n with uniform U(0,1) marginal distributions. A unique copula that is associated with the joint distribution, F, can be obtained as:

$$C(u_1,...,u_n) = F(F_1^{-1}(u_1),...,F_n^{-1}(u_n)) \quad (1)$$

Similarly, given a copula, a n-variable joint distribution function with marginal functions F1,…, Fn can be written as:

$$f(x_1,...,x_n) = c(F_1(x_1),...,F_n(x_n))\prod_{i=1}^{n} f_i(x_i) \quad (2)$$

The density function of the copula, c, can be derived using (1) and marginal density functions, f_i (Goodwin, 2012):

$$c(u_1,...,u_n) = \frac{\partial^n C(u_1,...,u_n)}{\partial u_1..\partial u_n} = \frac{f(F_1^{-1}(u_1),...F_n^{-1}(u_n))}{\prod_{i=1}^{n} f_i(F_i^{-1}(u_i))} \quad (3)$$

There are a large number of parametric families of copulas in the literature. Three of the most commonly used of copula families are elliptical, Archimedean and extreme value (EV) copulas. Elliptical copulas are directly gained by inverting "Sklar's theorem" that they are defined as (1). The most famous example, are Gaussian and Student-t copulas, while Archimedean copulas such as Clayton, Gumbel, Frank, Joe and BB, are obtained by generator functions (φ) as:

$$C(u,v) = \varphi^{-1}(\varphi(u) + \varphi(v)) \quad (4)$$

where $\phi : [0,1] \to [0,\infty]$ is continuous strictly decreasing convex function such that $\phi(1) = 0$ and $\phi_{[-1]}$ is the pseudo-inverse (Brechmann and Schepsmeier, 2012).

The EV copulas such as Gumbel, Galambos, Husler and Reiss, Tawn and BB5 are max-stable. It can be shown that EV copulas can be represented in the form:

$$C(u,v) = \exp\{\log(uv)A(\frac{\log(u)}{\log(uv)})\} \quad (5)$$

where $A : [0,1] \to [1/2,1]$ is a convex function such that max (t,1-t) $<$ A(t) $<$ 1 for all $t \in [0,1]$. The function A(t) is called the dependence function (Galambos, 1987).

Vine copulas use bivariate copulas as the so-called "pair copula" construction blocks to describe a multivariate distribution. Vine copula or a set of linked trees factorizes the multivariate probability density function into pair copula (Czado et al, 2014). We can choose each pair copula from arbitrary families. Therefore, vines mix the advantages of multivariate copula modeling, and this allows for more flexibility in dependence modeling. In particular, asymmetries and tail dependence can be taken into account (Brechmann and Schepsmeier, 2012). Following Aas et al (2009), a joint, three-dimensional density function can be factorized as:

$$f(x_1,x_2,x_3) = f_1(x_1).f(x_2 \mid x_1).f(x_3 \mid x_1,x_2) \tag{6}$$

For a given ordering of variables, this density is unique. By Sklar's theorem (2), we know that:

$$f(x_2 \mid x_1) = \frac{f(x_1,x_2)}{f_1(x_1)} = \frac{c_{12}(F_1(x_1),F_2(x_2)).f_1(x_1).f_2(x_2)}{f_1(x_1)} = c_{12}(F_1(x_1),F_2(x_2)).f_2(x_2) \tag{7}$$

and

$$\begin{aligned} f(x_3 \mid x_1,x_2) &= \frac{f(x_2,x_3 \mid x_1)}{f(x_2 \mid x_1)} \\ &= \frac{c_{23|1}(F(x_2 \mid x_1),F(x_3 \mid x_1)).f(x_2 \mid x_1).f(x_3 \mid x_1)}{f(x_2 \mid x_1)} \\ &= c_{23|1}(F(x_2 \mid x_1),F(x_3 \mid x_1)).f(x_3 \mid x_1) \\ &= c_{23|1}(F(x_2 \mid x_1),F(x_3 \mid x_1))c_{13}(F_1(x_1),F_3(x_3)).f_3(x_3) \end{aligned} \tag{8}$$

with

$$h(x \mid \upsilon,\theta) = F(x \mid \upsilon) = \frac{\partial C_{x\upsilon_j|\upsilon_{-j}}(F(x \mid \upsilon_{-j}),F(\upsilon_j \mid \upsilon_{-j}) \mid \theta)}{\partial F(\upsilon_j \mid \upsilon_{-j})} \tag{9}$$

where υ_j is an arbitrary element of υ and υ_{-j} denotes the (n-1)-dimensional vector υ excluding υ_j.

We can rewrite equation (6) as:

$$f(x_1,x_2,x_3) = \overbrace{f_1(x_1).f_2(x_2).f_3(x_3)}^{\text{Marginal}} \times \overbrace{c_{12}(F_1(x_1),F_2(x_2).c_{13}(F_1(x_1),F_3(x_3))}^{\text{Unconditional pairs}} \times \overbrace{c_{23|1}(F(x_2|x_1),F(x_3|x_1))}^{\text{Conditional pairs}} \tag{10}$$

Thus, the joint density (6) can be shown with bivariate copulas densities c12, c13 and c23|1, so-called pair-copulas.

Since the decomposition in (6) is not unique, and there are a lot of pair-copula constructions, Bedford and Cooke (2001, 2002) introduced the graphical model called "Regular vine copula" (R-vine) to classify them. An n-dimensional Regular vine is a sequence of n-1 trees that:

1. T_1 is a tree with nodes N1={1,…,n} and a set of edges E1.
2. Edges in tree j become nodes in tree j+1.
3. Two nodes in tree j+1 can be joined by an edge if the corresponding edges in tree j share a node (Proximity condition). We can identify the edges in an R-vine tree by "conditioned nodes" and "conditioning nodes", i.e., edges are represented by $e=j(e),k(e)|D(e)$ where D(e) is the conditioning set. Consequently, the R-vine density is determined by (Brechmann and Czado ,2011):

$$f_{1\ldots n}(x) = \prod_{k=1}^{n} f_k(x_k) \cdot \prod_{i=1}^{n-1}\prod_{e\in E_i} c_{j(e),k(e)|D(e)}(F(x_{j(e)} \mid x_{D(e)}),F(x_{k(e)} \mid x_{D(e)})) \tag{11}$$

Using the nested set of tree is not a convenient way of representing an R-vine, so, Morales-Napoles (2008) used a matrix to show an R-vine. In fact, he stored the "constraint set[2]" of an R-vine in columns of an n-dimensional lower triangular matrix. Hence the R-vine distribution density in matrix notation is:

[2] The conditioned and conditioning sets of all edges of R-vine are collected in a set called constraint set.

$$f_{1\ldots n}=\prod_{j=1}^{n} f_j \cdot \prod_{k=n-1}^{1}\prod_{i=n}^{k+1} c_{m_{k,k},m_{i,k}|m_{i+1,k},\ldots,m_{n,k}}\left(F_{m_{k,k}|m_{i+1,k},\ldots,m_{n,k}}, F_{m_{i,k}|m_{i+1,k},\ldots,m_{n,k}}\right) \quad (12)$$

where $m_{k,k}$, $m_{i,k}$ and $m_{i+1,k},\ldots,m_{n,k}$ are equal to conditioned set and conditioning set, respectively (Dibmann et al, 2013).

The class of regular vines indicates a large number of possible pair copula decompositions. Therefore, Aas et al (2009), Brechmann et al (2010) and Dibmann et al (2013) suggested that the strongest dependency in the "first tree" to be considered. In general, they can be classified in three main groups, that is, R-vines, C-vines[3] and D-vines[4].

Copula data have uniform margins in [0,1]. Thus, we have to transform data with empirical marginal distribution functions. (v,B,θ) is a regular vine copula specification, where (v) is a n-dimensional regular vine, $B=\{B_e \mid i=1,\ldots,n-1; e\in E_i\}$ is a set of copulas with B_e or bivariate copula or pair copula and the pair copula parameters $\theta=\theta(B(v))$. First, we determine the vine tree structure. Then, for a given vine tree structure, we select pair copula families. Finally, we estimate the parameters of pair copulas.

In this study, we adopt R-vine, and we use selection mechanism suggested by Dibmann et al (2013) to choose the optimal ordering of data to define the vine. In this mechanism:

1. Calculate the empirical Kendall's τ for all possible variable pairs.
2. Select the spanning tree that maximizes the sum of absolute empirical Kendall's τ.
3. For each edge in the selected spanning tree, choose a copula and estimate their parameters by joint maximum likelihood (JML).
4. By using (9), create pseudo-observations.
5. For {T2,…Td}, iterate (1) to (4). We choose the optimal copula with utilization of the minimized value of the AIC and BIC.

There are varieties of ways for pricing, but in general, we can use expected loss. For this purpose, we estimate the joint distribution function of weather variables and barely yield, and then we obtain 10,000 simulated data for yield. To simulate from a chosen vine copula, we use conditional approach (9). Since each simulated data is in [0,1], so we use inverse cumulative distribution function for yield to turn observations into real form. To determine an appropriate marginal distribution function, three goodness of fit tests are used, i.e. “Kolmogorov–Smirnov”, “Anderson–Darling” and “Chi-Squared” tests. We need forecasting yield amount for next year. For this we apply ARIMA model. Afterward, critical value of yield, y_C, in four levels of coverage (100, 90, 80 and 75 percent) is calculated by:

$$y_C = y_{fcast} \times COV \quad (13)$$

Where y_{fcast} is a forecasting yield amount and COV is the level of coverage.

Then, we compare y_C and 10,000 simulated observations of yield, y. The insurer should pay the indemnity, when each of observations is less than y_C. Finally, the expected loss or fair premium is equal to:

$$Fair\ premium = Ave[Max(y_c - y, 0)] * P \quad (14)$$

[3] Canonic al Vine: C-vine trees have a star structure
[4] Drawable Vine: D-vine trees has a path structure

where P is guaranteed price for barley. According to Skees et al (1997), we add loading factor to expected loss to cover the transaction cost, so that the actual premium is as follow as:

$$Actual\ premium = \frac{Fair\ premium}{0.9} \tag{15}$$

In this study, we apply average temperature, cumulative rainfall index, relativity humidity, duration of sunshine days and evaporation in growth period and fasten wind speed in harvest period for rainfed barley in Ahar County. The growth period include three stages, i.e., “Stem extension”, “Heading” and “Ripening”. In Ahar, these stages take, respectively, from March 20th to April 20th, April 21st to May 21st and May 22nd to June 21st, and the harvest period takes from June 22nd to July 22nd. We modify these variables for every year as:

$$\begin{aligned}
T &= w_{st}T_{st} + w_{he}T_{he} + w_{ri}T_{ri}\\
CRI &= w_{st}CRI_{st} + w_{he}CRI_{he} + w_{ri}CRI_{ri}\\
RH &= w_{st}RH_{st} + w_{he}RH_{he} + w_{ri}RH_{ri}\\
N &= w_{st}N_{st} + w_{he}N_{he} + w_{ri}N_{ri}\\
E &= w_{st}E_{st} + w_{he}E_{he} + w_{ri}E_{ri}\\
U &= U_{ha}
\end{aligned} \tag{16}$$

where T is the average temperature (^{0}C), CRI is the cumulative rainfall (mm), RH is the relativity humidity (%), N is duration of sunshine days (days), E is evaporation (mm) and U is the fasten wind speed (knot), w represents a sub-period's weight which is obtained from standard regressions of weather variables on barley yield or y (kg per hectare).

We collect the information of barley yield and weather variables during 1995-2014, respectively, from “the Ministry of Agriculture of Iran” and “Iran Meteorological Organization”.

Results

We intend to determine premium for WBCIS. In addition, we want to highlight the potential consequences associated with a specific representation of the joint distribution by vine copula. First, we investigated the dependency structure of barley yield and weather variables using R-vine. For this, we denoted copula data as:

YECDF=1, TECDF=2, CRIECDF=3, RHECDF=4, NECDF=5, EECDF=6, UECDF=7

Selection of vine tree structure, especially for R-vine, is not simple. The number of possible R-vine on n-dimensions is $\frac{n!}{2} \times 2^{\binom{n-2}{2}}$ as shown by Czado et al (2014). Thus, in seven dimensions there are 2,580,480 different R-vines. As discussed, we considered the strongest dependencies in the first tree. In R-vine, the first tree is a graph on 7 nodes where all nodes are connected to each other by edges. For subsequent trees, it is necessary to consider proximity condition To each edge, we calculated the empirical Kendall's τ as a weight. Then, we found a tree on all nodes as the so-called “spanning tree”, which maximizes the sum of absolute empirical Kendall’s τ. With utilization of this method, the R-vine structure in matrix notation is represented in (17).

$$\begin{bmatrix}
3 & & & & & & \\
7 & 2 & & & & & \\
2 & 7 & 1 & & & & \\
1 & 5 & 7 & 6 & & & \\
6 & 1 & 5 & 7 & 4 & & \\
4 & 4 & 6 & 5 & 7 & 5 & \\
5 & 6 & 4 & 4 & 5 & 7 & 7
\end{bmatrix} \tag{17}$$

With attention to 17, we can represent indices for edges in corresponding R-vine as:

Col1	Col2	Col3	Col4	Col5	Col6
3,7|2,1,6,4,5	2,7|5,1,4,6	1,7|5,6,4	6,7|5,4	4,7|5	5,7
3,2|1,6,4,5	2,5|1,4,6	1,5|6,4	6,5|4	4,5	
3,1|6,4,5	2,1|4,6	1,6|4	6,4		
3,6|4,5	2,4|6	1,4			
3,4|5	2,6				
3,5					

The selection of suitable copula and estimation of corresponding parameters result for R-vine presented in Table 1.

Table 1: The results of R-vine model

Tree Number	Edges	Selected family	Coeff.	Standard error	Lower and upper tail dependence	AIC	BIC
First	3,5	Frank	4.99***	0.35	(0,0)	-7.34	-6.40
	2,6	Frank	4.87***	0.10	(0,0)	-7.67	-6.73
	1,4	Clayton	1.78***	0.14	(0.68,0)	-10.16	-9.21
	6,4	Frank	14.5***	0.32	(0,0)	-31.57	-30.63
	4,5	survival Joe	121.26***	6.38	(0.99,0)	-303.17	-302.23
	5,7	Clayton	1.04***	0.09	(0.51,0)	-2.54	-1.59
Second	3,4|5	rotated Tawn type 1 (90degrees)	-1.19** 0	0.42 0.09	(0,0)	-5.36	-3.47
	2,4|6	rotated Tawn type 1 (180degrees)	20*** 0.06	5.19 0.002	(0.06,0)	0.51	2.40
	1,6|4	Frank	-0.96***	0.25	(0,0)	1.46	2.40
	6,5|4	rotated Tawn type 1 (90degrees)	-1.18*** 0.03	0.20 0.02	(0,0)	-19.20	-17.31
	4,7|5	rotated Joe (270degrees)	-1.01***	0.03	(0,0)	-30.70	-29.76
Third	3,6|4,5	Gaussian	0.06	0.04	(0,0)	1.82	2.76
	2,1|4,6	Frank	-1.76***	0.36	(0,0)	0.32	1.26
	1,5|6,4	rotated Joe (90degrees)	-1.02***	0.07	(0,0)	-31.86	-30.92
	6,7|5,4	rotated Clayton (90degrees)	-0.78***	0.07	(0,0)	-4.24	-3.30
Fourth	3,1|6,4,5	Frank	1.51***	0.31	(0,0)	0.87	1.81
	2,5|1,4,6	Frank	-0.84***	0.35	(0,0)	1.09	2.03
	1,7|5,6,4	rotated Tawn type 2 (270degrees)	-20 0.02	13.11 0.001	(0,0)	-1.54	0.35
Fifth	3,2|1,6,4,5	Frank	-2.76***	0.32	(0,0)	-1.23	-0.29
	2,7|5,1,4,6	rotated Tawn type 2 (270degrees)	-2.41 0.05	1.41 0.02	(0,0)	1.43	3.32
Sixth	3,7|2,16,4,5	Clayton	0.61***	0.10	(0.32,0)	-0.89	0.05
Log-likelihood	250.99						

*For simplicity, they implemented the "Tawn copula" with two parameters in "Vine Copula" packages. Each type has one of the asymmetry parameters fixed to 1.

A large variety of copula functions were investigated for each pair. Based on the minimum amount of AIC and BIC, we chose the optimal copulas. In addition, we measured the tail dependence for each copula. Log-likelihood function value is 250.99, and 85.71 percent of parameters are significant. The R-vine tree structure was displayed in Figure 1. This structure is output of "R 3.2.2" software. In fact, tree structure represents joint density function for barley yield and weather variables. There are two elements as a label for each edge that the first one shows the selected copula family, and the second one is first estimated parameter.

Therefore, the edges sets for tree 1 to 6 are, respectively,

$E_1=\{(3,5),(2,6),(1,4),(6,4),(4,5),(5,7)\}$, $E_2=\{(3,4|5),(2,4|6),(1,6|4),(6,5|4),(4,7|5)\}$,
$E_3=\{(3,6|4,5),(2,1|4,6),(1,5|6,4),(6,7|5,4)\}$, $E_4=\{(3,1|6,4,5),(2,5|1,4,6),(1,7|5,6,4)\}$,
$E_5=\{(3,2|1,6,4,5),(2,7|5,1,4,6)\}$ and $E_6=\{(3,7|2,1,6,4,5)\}$.

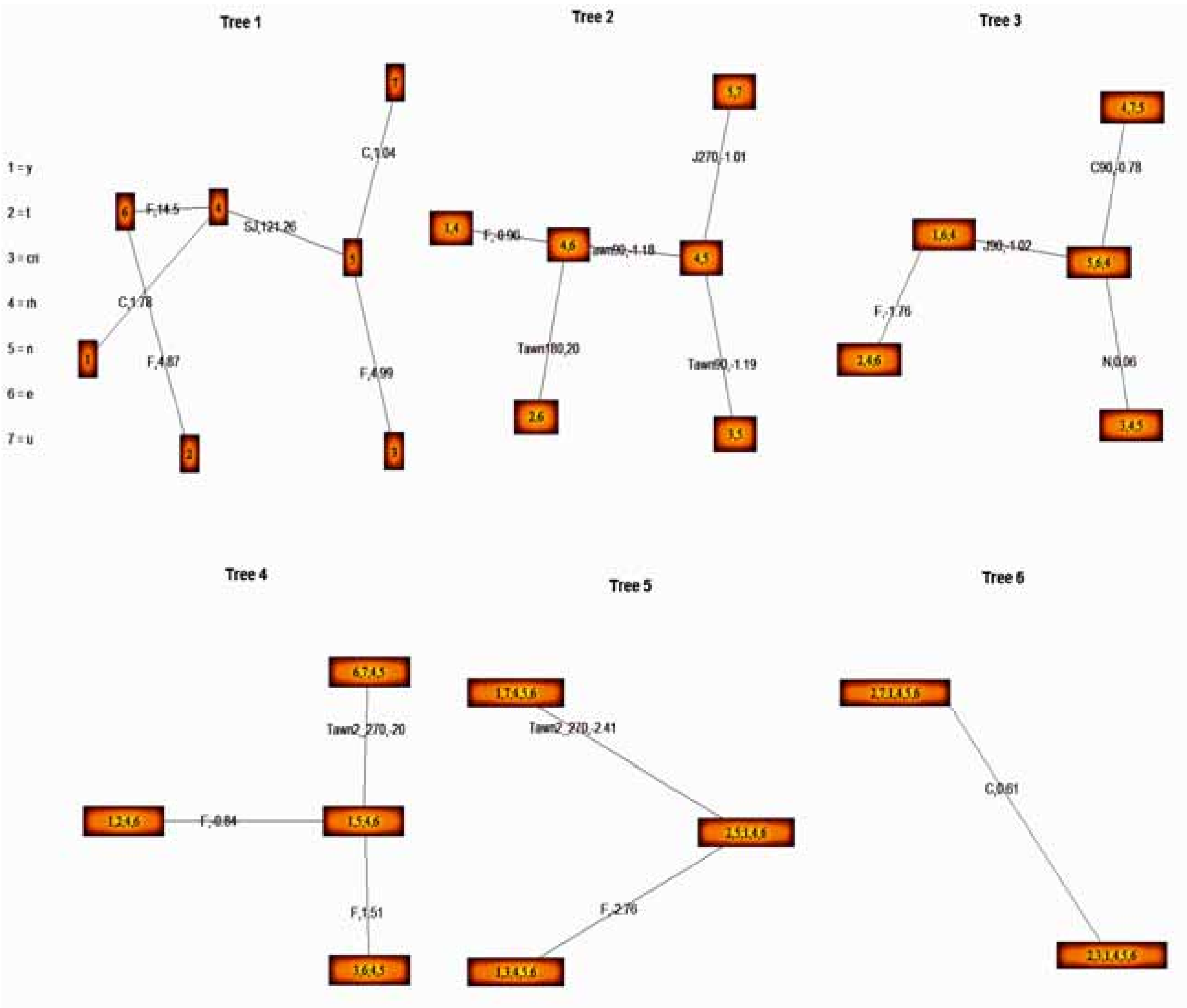

Figure 1: R-vine tree structure

We investigated a large number of parametric distributions (65 in all) to determine barley yield distribution. The fitting and ranking of different distributions to barley yield in "EasyFit 5.5" showed that "Weibull" distribution is mostly appropriate for representing yield empirical distribution. This result is similar to Bokusheva (2010) and Goodwin (2012). The result of three tests for goodness of fit presented, in Table 2. Weibull' feature for yield can be written as:

$$yeild \sim WEB(\alpha=4.1701, \beta=914.11)$$

Where α and β are shape and scale parameters, respectively.

Table 2: Goodness of fit for wheat yield

Suitable distribution		Chi-Squared	Anderson-Darling	Kolmogorov-Smirnov
Weibull	Statistic	0.941	1.042	0.156
	P-value	0.624	---	0.683
	Critical value ($\alpha = \%5$)	5.991	2.501	0.301

With utilization of R-vine copula, we simulated 10,000 observations for yield (and other weather variables). We computed Weibull inverse cumulative distribution to turn yield data into real form. Based on Weibull distribution, the average of simulated yield is 895.77 kg/hec.

The values of the AIC/SBC criteria showed ARIMA(1,0,0) is optimal model for yield, so the forecasting yield amount for next year is 967.414 kg/hec. Then, according to (13), we calculated the critical value of yield based on 4 coverage levels. The guaranteed price is 9200 Rials.

Table 3 presents the amount of premium. The expected loss is 114.66 kg/hec in 100 percent coverage levels. The current insurance system covers 80 percent of expected loss, so that its premium amount is 590,000 Rials. The computing premium amount for this insurance system in 80 percent coverage level is 320058 Rials that is less than current insurance. In addition, the premium amount is reducing with decreasing in coverage level as well as expectation.

Table 3: Computing premium amount for rainfed wheat in Miyaneh (Rials)

Coverage Level (%)	Critical values (kg/hec)	Ave[max(yc-y),0] (kg/hec)	Fair premium	Actual premium
100	967.41	114.66	1054872	1172080
90	870.67	63.55	584660	649622.2
80	773.931	31.31	288052	320057.8
75	725.56	20.98	193016	214462.2

Discussion and conclusions

In Iran, agricultural insurance performs in traditional form, and this type of insurance suffers from asymmetric information. Such challenges will lead to increase in premium rate, indemnity and to decrease incentives for farmers to buy insurance. In addition, the most important risks in agricultural sector is weather risk, especially in dry land farming. Therefore, farmers increasingly expect an effective risk management instrument to cope with these problems. Recently, weather based crop insurance schemes (WBCIS) have been introduced as a successful tool, and the applied results into the feasibility of this system shows that, this type of insurance was very effective in risk reduction.

Barley as an important product has a special position, and East-Azerbaijan province and Ahar County have particular place in Iran's barley, so in this study, we designed the weather based crop insurance for rainfed barley in Ahar. This insurance system can solve traditional insurances' problems.

The literature nearly always assumed that risks are linearly correlated and constant. While in reality, this assumption is wrong and ignoring it-when pricing WBCIS- may lead to an undervaluation of premium, and negatively affect the fairness of this insurance. To cope with this issue, we apply a new innovation in copula modeling—the vine copula. This approach uses a set of pair copulas, and so allows for more flexibility in dependency modeling.

The result showed WBCIS premium is less than current insurance premium, so it can motivate farmer to accept this insurance system. In addition, the government pays 65.6 percent of current insurance premium. Less premium amount can reduce such costs.

Weather indices change in a region over the time, and every region has special climate. Thus, such study should be repeated in future researches, and regions that have similar climate should be selected. Vine copula does not have limitation about high dimension, so many weather indices can be used to make result more reliable. Likewise, it is better to consider and compare other approaches with vine copula in future researches.

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