Weather and Climate Extremes 21 (2018) 76–89

Contents lists available at ScienceDirect

Weather and Climate Extremes

journal homepage: www.elsevier.com/locate/wace

Copula-based agricultural conditional value-at-risk modelling for geographical diversifications in wheat farming portfolio management

Thong Nguyen-Huy[a,b,c,d,**], Ravinesh C. Deo[a,b,c,*], Shahbaz Mushtaq[b,c], Jarrod Kath[b,c], Shahjahan Khan[a,b,c]

[a] School of Agricultural, Computational and Environmental Sciences, QLD 4350, Australia
[b] Centre for Applied Climate Sciences, QLD 4350, Australia
[c] University of Southern Queensland, Institute of Agriculture and Environment, QLD 4350, Australia
[d] Vietnam National Space Center (VNSC), Vietnam Academy of Science and Technology (VAST), Australia

ARTICLE INFO

Keywords:
Copula models
Portfolio optimisation
Conditional value-at-risk
Agriculture management
Crop decision
Geographical diversification

ABSTRACT

An agricultural producer's crop yield and the subsequent farming revenues are affected by many complex factors, including price fluctuations, government policy and climate (*e.g.*, rainfall and temperature) extremes. Geographical diversification is identified as a potential farmer adaptation and decision support tool that could assist producers to reduce unfavourable financial impacts due to the variabilities in crop price and yield, associated with climate variations. There has been limited research performed on the effectiveness of this strategy. This paper proposes a new statistical approach to investigate whether the geographical spread of wheat farm portfolios across three climate broad-acre (*i.e.*, rain-fed) zones could potentially reduce financial risks for producers in the Australian agro-ecological zones. A suite of popular and statistically robust tools applied in the financial sector based on the well-established statistical theories, comprised of the Conditional Value-at-Risk (CVaR) and the joint copula models were employed to evaluate the effectiveness geographical diversification. CVaR is utilised to benchmark the losses (*i.e.*, the downside risk), while the copula function is employed to model the joint distribution among marginal returns (*i.e.*, profit in each zone). The mean-CVaR optimisations indicate that geographical diversification could be a feasible agricultural risk management approach for wheat farm portfolio managers in achieving their optimised expected returns while controlling the risks (*i.e.*, target levels of risk). Further, in this study, the copula-based mean-CVaR model is seen to better simulate extreme losses compared to the conventional multivariate-normal models, which underestimate the minimum risk levels at a given target of expected return. Among the suite of tested copula-based models, the vine copula in this study is found to be a superior in capturing the tail dependencies compared to the other multivariate copula models investigated. The present study provides innovative solutions to agricultural risk management with advanced statistical models using Australia as a case study region, also with broader implications to other regions where farming revenues may be optimized through copula-statistical models.

1. Introduction

Climate variability significantly influences agricultural production and the subsequent revenues received from the sale of various crops. However, recent extreme climatic events have been linked to large losses in agricultural production, in both developing and developed nations (Barriopedro et al., 2011; Coumou and Rahmstorf, 2012; Herold et al., 2018). For instance, about one-quarter of the damaged agricultural production in developing nations has been associated with extreme climate-related disasters (FAO, 2015). In addition, the study of Lesk et al. (2016) reported that extreme drought and heat events have also caused a significant decline in cereal production ranging from 9 to 21% in both developed and developing nations. To mitigate and possibly, to reduce agricultural yields and the associated financial losses that could be triggered by extreme climate events, agricultural adaptation strategies are required.

Portfolio theory suggests that the geographical diversification strategy could assist farmers in reducing the impacts of the variabilities faced in respect to the crop yield and prices associated with climate variabilities and the changes in other types of factors (Bradshaw et al.,

* Corresponding author. School of Agricultural, Computational and Environmental Sciences, QLD 4350, Australia.
** Corresponding author. School of Agricultural, Computational and Environmental Sciences, QLD 4350, Australia.
E-mail addresses: thonghuy.nguyen@usq.edu.au (T. Nguyen-Huy), ravinesh.deo@usq.edu.au (R.C. Deo).

https://doi.org/10.1016/j.wace.2018.07.002
Received 22 March 2018; Received in revised form 21 June 2018; Accepted 20 July 2018
Available online 20 July 2018

2004; Mishra et al., 2004). This means that farming systems are diversified over space to reduce the impact of systemic risks. However, the effectiveness of geographical diversification strategies in agriculture is to date poorly studied (see Larsen et al., 2015). To address this need, especially for agricultural reliant nations (*e.g.*, Australia), this study aims to investigate the utility of geographical diversification in portfolio management of wheat farming, an important grain crop for Australia's agricultural sector (Murray and Brennan, 2009).

In classical Markowitz mean-variance (MV) portfolio optimisation, efficient portfolios are optimised to minimise their variances and to reduce overall financial risk (Markowitz, 1952). Hence, each portfolio along the efficient frontier must have a minimum variance for that level of return. However, despite its popularity, the MV method has limitations. For example, the variance metric is a symmetrical measure that does not take into consideration the direction of the co-movement. Minimising the variance penalises the downside risk in a manner appearing the same as the upside risk of the portfolio return distribution. This is an issue since an asset that experiences better than the expected return is deemed to be a risky scenario relative to an asset that is suffering from a lower than expected return. To address this issue, alternative risk-based measures such as the Value-at-Risk (VaR) and the Conditional Value-at-Risk (CVaR) have been introduced to replace the MV method.

Rockafellar and Uryasev (2000) have recommended CVaR as a measure of alternative risk that is preferred to the common VaR concept. A CVaR-based optimised portfolio only penalises for the loss (*i.e.*, the downside risk), and not the gain (*i.e.*, upside risk) in the portfolio return distribution. It is related to but is superior to the VaR for optimisation applications for several reasons. Firstly, the CVaR tends to satisfy the four properties of a coherent risk measure; translation invariance, monotonicity, subadditivity and positive homogeneity (Pflug, 2000). Secondly, the VaR is able to describe a loss of X or greater than this, and thus, this last clause tends to be omitted in most cases when people quote the VaR. CVaR, on the contrary, is an estimate of the size of the tail loss, which gives a more accurate estimate of the associated risk.

In the existing literature, common methods of calculating the CVaR normally consists of the variance-covariance, historical and the Monte Carlo simulation (Chernozhukov and Umantsev, 2001; Zhu and Fukushima, 2009). Calculating CVaR also involves an estimation of the tails of the joint distribution among the marginal returns (*i.e.*, the profit of each farm that is considered in the problem). However, the variance-covariance and historical simulation method have some degree of restrictions, which might not be always reasonable, and necessarily true in practice. For example, the variance-covariance method assumes the returns to be normally distributed, which can be problematic from a practical point of view. This is because many financial returns have elongated and broadened tails in the dataset so a normal distribution assumption can seriously underestimate the size (and the pivotal role) of the tail end of the data (Ang and Chen, 2002; Embrechts et al., 2001; Longin and Solnik, 2001). Simulations based on historical data also assumes that the distributions of the returns in the future are similar to those in the past. Furthermore, in most cases, there are relatively few data points that are present in, for example, the 0–5th percentile or extreme tail of the distribution. The Monte Carlo method is therefore preferred in such circumstances since it is able to calculate the CVaR in a similar fashion to historical simulation, while also being based on the randomly generating scenarios from a model whose parameters are acquired from the historical data.

As mentioned above, the non-linear interdependence at the tails between the marginal returns need to be captured more effectively relative to conventional approaches in order to obtain accurate estimations of CVaR. This requires a robust multivariate prediction model that is capable of fully capturing the joint dependence structure among the related variables. A conventional approach commonly relies on the utilization of a multivariate-normal distribution that assumes a normality of the considered variable(s). However, there is no doubt that the agricultural prices and crop yields have been shown to be non-normally distributed (*e.g.*, Goodwin and Ker, 2002), and therefore, any approach that does not consider this important data limitation aspect can lead to erroneous conclusions. Fortunately, copula functions (that can analyse non-linearity in multivariate data) is able to provide an alternative statistical approach to modelling the joint distribution of multivariate datasets, allowing one to specify the marginal distribution among the tested variable and their dependence structures independently. Due to their distinct merits in modelling multivariate joint distributions, copula-based models have been applied extensively in many fields such as insurance and financial risk modelling (Hu, 2006; Kole et al., 2007), hydrology and water resources (Chowdhary et al., 2011; Favre et al., 2004), drought studies, agricultural and precipitation forecasting (Bessa et al., 2012; Ganguli and Reddy, 2012; Janga Reddy and Ganguli, 2012; Nguyen-Huy et al., 2017; Vergni et al., 2015; Nguyen-Huy et al., 2018).

Although copula method is a popular tool in financial risk literature in general and also in portfolio analysis (Boubaker and Sghaier, 2013; Huang et al., 2009; Kresta and Tichý, 2012), its application in agricultural risk management and crop insurance aspects are relatively recent (Bokusheva, 2014; Goodwin and Hungerford, 2014; Nguyen-Huy et al., 2018; Okhrin et al., 2013; Vedenov, 2008). Furthermore, the published literature in this area shows limited research has been undertaken regarding the application of copulas in geographically diversifying risks in agriculture. In spite of this, some studies are particularly notable, for example, Larsen et al. (2015) proposed a copula-based mean-CVaR model to inspect the potential benefits of risk reduction using a geographical diversification strategy for the case of a US wheat farming scenario. The authors applied multivariate Archimedean copula model and compared it with a traditional multivariate-normal model as a benchmark tool. The mean-CVaR optimisation results indicated the effectiveness of geographical diversification in risk management strategy from a farm's marginal return viewpoint. It was not surprising to note that the multivariate-normal model led to an underestimation of the minimum level of associated risk faced by the wheat farmer at a given level of agricultural profitability. Importantly, the study concluded the copula-based model performed more appropriately for extreme losses of the farm profitability. However, the multivariate Archimedean copulas assume the same dependence parameter among the pair of variables. This sort of assumption is unrealistic in practical scenario (Hao and Singh, 2016; Zhang and Singh, 2014; Nguyen-Huy et al., 2018).

In this paper, we focus on wheat, a primary cereal crop in Australia. However, wheat is mostly grown in drylands in Australia (*i.e.*, as a rainfed crop) that exhibits one of the world's most extreme variable climate conditions (Portmann et al., 2010; Turner, 2004). However, to the best of the authors' knowledge, the effectiveness of geographical diversification including the mean-CVaR optimisation in risk management strategy has not been examined in Australian farming contexts. The present study, therefore, utilises the contemporary vine copula method in Monte Carlo simulation approach for calculating the corresponding value of CVaR. This approach allows to randomly generate the scenarios of the marginal returns of wheat farming based on their joint distribution. The primary merit of vine copula model (Nguyen-Huy et al., 2017, 2018) (in comparison to the other types of multivariate copulas) is that it allows the integration of different bivariate copulas for the modelling of the flexible dependence among the pairwise variable disregarding the marginal selections differences (Bedford and Cooke, 2002).

By extending previous studies in the context of agricultural yield modelling and seasonal precipitation forecasting studies in Australia (Nguyen-Huy et al., 2017, 2018), the aims of the present study are as follows. (1) To investigate the effectiveness of the geographical diversification strategy in reducing risks in agricultural operations. (2) To demonstrate a robust statistical method, the vine copula-based mean-

CVaR model, for quantifying optimum amount of diversification needed for given level of risk. (3) To compare the traditional multivariate-normal, multivariate Archimedean and vine copula model in simulating the extreme losses. The vine copula-based mean-CVaR approach is expected to perform better and provide further insights into improving conventional multivariate-normal models that underestimate the minimum risk levels at a given target of profitability.

2. Materials and method

2.1. Data

In this study, we used aggregated yield and financial data from three of Australia's key wheat producing zones collected from the Department of Agriculture and Water Resources, Australian Government (AgSurf) (http://apps.daff.gov.au/agsurf/) for the period 1990–2016. The three broad-acre wheat zones include Wimmera (Victoria), Eyre Peninsula (South Australia), and the North and East Wheat Belt (Western Australia) where the "()" show the respective wheat growing States. For conciseness and consistency, the study site names henceforth are based on Australian States (*i.e.*, VIC, SA & WA, respectively) for each of the wheat growing zone. These zones, reported in previous studies (Nguyen-Huy et al., 2017, 2018) have been selected as they are geographically distinct spanning across a wide range of climatic and wheat growing conditions and so are expected to expose to different risks at different times (Fig. 1).

The data are as per farm averages, including the wheat receipts ($), the total area sown (ha) and the costs per hectare ($/ha). The total cost consists of the contracts, chemicals, electricity, fertiliser, fuel, interest paid, water charges, repairs, seed, insurance, labour and some of the other related expenses. Marginal returns measured at the farm profitability are expressed as the percentage of the gross revenue exceeds the total cost. The marginal return of the *ith* zone r_i, ($i = 1,2,3$) is calculated as follows (Larsen et al., 2015):

$$gross\ \ revenue = wheat\ \ receipts/toal\ \ area\ \ shown \tag{1}$$

$$r_i = \frac{gross\ \ revenue - total\ \ \text{cost}}{gross\ \ revenue} \tag{2}$$

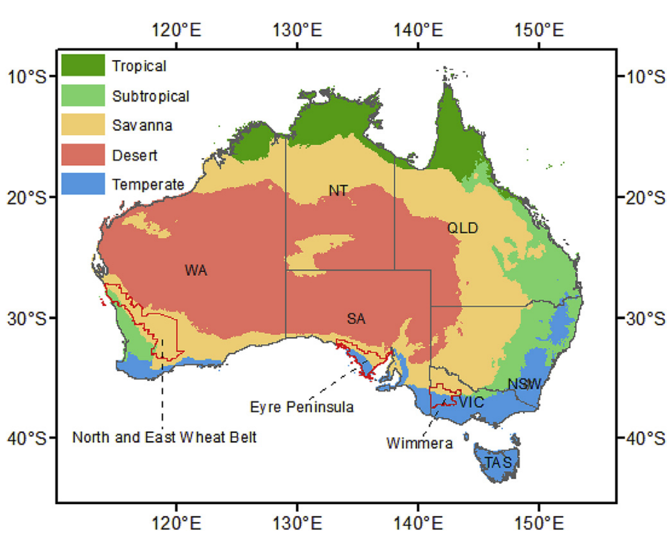

Fig. 1. Location of the broad-acre wheat zones in Australia that spans across different growing conditions. Wheat is grown mostly in temperate climate condition in Wimmera (Victoria, VIC). Eyre Peninsula (South Australia, SA) exhibits a mixture of the temperate and savanna while the entire North and East Wheat Belt (Western Australia, WA) is dominated by savanna.

3. Method

3.1. Conditional Value-at-risk

Suppose that $f(x, y)$ denotes a loss function depending upon the decision x, to be chosen from a feasible set of a realistic portfolio X, and a random vector y. Let $\Psi(x, \alpha)$ be the probability that the loss $f(x, y)$ does not exceed some threshold value α. The VaR function $\alpha_\beta(x)$, which is the percentile of the loss distribution at the confidence level β, is formally defined as (Rockafellar and Uryasev, 2000):

$$\alpha_\beta(x) = \min\{\alpha \in \mathbb{R}|\Psi(x, \alpha) \geq \beta\}. \tag{3}$$

By this definition, *CVaR* is able to measure the conditional expectation of the losses greater than that amount α. Therefore, the CVaR function $\phi_\beta(x)$ is defined mathematically as follows (Rockafellar and Uryasev, 2000):

$$\phi_\beta(x) = (1-\beta)^{-1}\int_{f(x,y) > \alpha_\beta(x)} f(x, y)p(y)dy, \tag{4}$$

Where $p(y)$ is the probability density function of the random vector y. It is clear that the CVaR is a greater bound for the VaR at the same confidence level. Also, with many advantages stated in the previous section, CVaR offers a more consistent risk measure than VaR and generally results more efficient in the context of portfolio optimisation (Mulvey and Erkan, 2006). In addition, CVaR can be expressed as a convex function allowing the construction of the portfolio optimisation problem which can be efficiently solved by linear programming techniques as shown in (Rockafellar and Uryasev, 2000) and will be described in the forthcoming method section. Although VaR plays a role in the optimal portfolio approach, it exposes some inherent restrictions as mentioned above. Therefore, the risk of high losses could be reduced through minimising CVaR rather than minimising VaR since a portfolio with low CVaR will necessary have low VaR as well (Rockafellar and Uryasev, 2000).

3.2. Portfolio optimisation problem

Suppose a portfolio consists of n production zones with a random percentage of the marginal returns $r_1, \ldots, r_n$, the marginal expected return $E[r_i]$ and w_i is a share of the total hectares allocated to the production zone (i.e., the decision vector or weight). The farmer's portfolio optimisation problem, in the context of the agricultural sector, is to maximise the expected returns (sum of all marginal expected returns multiply with the corresponding weights) of the portfolio given a specified risk level β. The portfolio optimisation problem can then be formulated as (Larsen et al., 2015):

$$maximise - - \sum_{i=1}^{n} w_i E[r_i], \tag{5}$$

$$subject, to - - \begin{cases} \phi_\beta(w_i) \leq \phi \\ \sum_{i=1}^{n} w_i = 1 \end{cases}, \tag{6}$$

where ϕ is defined as the target risk (CVaR) levels.

3.3. Calculating Conditional Value-at-Risk

To solve the *subject* function in Eq. (6), the CVaR function in Eq. (4) can be expressed as (Rockafellar and Uryasev, 2000):

$$F_\beta(w, \alpha) = \alpha + (1-\beta)^{-1}\int [f(w, r) - \alpha]^+ p(r)dr, \tag{7}$$

where the indicator function:

$$[I]^+ = \begin{cases} I & when \quad I > 0 \\ 0 & when \quad I \leq 0 \end{cases}. \tag{8}$$

The integral in Eq (7) can be approximated further by sampling the probability distribution of r based on its density $p(r)$ as (Rockafellar and Uryasev, 2000):

$$\widetilde{F}_{\beta}(w, \alpha) = \alpha + \frac{1}{m(1-\beta)} \sum_{j=1}^{m} [f(w, r_j) - \alpha]^{+}. \tag{9}$$

Therefore, the portfolio optimisation problem, as shown in Section 2.2.2, can be alternately formulated as the following linear programming problem:

$$minimise - -\alpha + \frac{1}{m(1-\beta)} \sum_{j=1}^{m} u_k, \tag{10}$$

$$subject, to - -\begin{cases} \sum_{k=1}^{n} w_i E[r_i] \geq R \\ f(w, r_j) - \alpha \leq u_k \\ 0 \leq u_k \\ \sum_{i=1}^{n} w_i = 1 \end{cases}, \tag{11}$$

where $[f(w, r_j) - \alpha]^{+} = u_k$ and R denotes the target expected returns. The sampling of vector r based on the copula methods is introduced in the next section. The linear optimisation problem was solved using the R-package **fPortfolio** (Würtz et al., 2009).

3.4. Copulas

As stipulated above, the calculation of the CVaR using the Monte Carlo simulation method requires a knowledge of the joint distribution of all marginal returns involved in the portfolio. To fulfill this requirement, Sklar (1959) theorem suggests that the joint distribution $F(x_1, ..., x_n)$ can be expressed as:

$$F(x_1, ..., x_n) = C[F_1(x_1), ..., F_n(x_n)], \tag{12}$$

where C: $[0,1]^n \rightarrow [0,1]$ is a unique copula function and $F_i(x_i)$ are marginal distributions (margins) of variables of interest. Note that Eq. (12) implies that the unknown joint distribution can be constructed by two separate parts, including the copula function and the marginal distributions of the historical marginal returns.

Regarding the most suitable copula function, in this study, we have considered several copulas that are commonly classified into different families based on their construction methods, comprising, but not limited to, the elliptical, Archimedean, vine, empirical, extreme value, and the entropy copulas. For more details on the full suite of copula functions, readers are referred to the studies of Joe (1996), Nelsen (2006), and Bedford and Cooke (2002). In this paper, the first three families including the elliptical, Archimedean, and vine copula are tested and compared. The estimation and usage of these functions are described in the next section.

3.5. Construction of the copula-based model

We employ the vine copula approach that was previously utilised in our earlier published work (Nguyen-Huy et al., 2017, 2018) to develop vine copula-based models for this study. Here, we briefly describe the main steps of the vine copula model construction procedure. The first step in constructing the copula model is to select the theoretical distribution functions that are able to approximately describe the historical marginal returns. This study adopts the parametric approach to fit the historical marginal returns since later in the simulating process, the reverse distribution function needs to be used to transform the copula-modelled data back to the real scale values.

A set of twenty-five theoretical probability distributions are fitted to the marginal return data, which follows earlier studies (Nguyen-Huy et al., 2017, 2018). The candidate distribution is selected based on a statistical assessment of the goodness-of-fit test, *i.e.*, the Kolmogorov-Smirnov statistic (KS). If the p-value of the KS test is greater than 0.05, we cannot reject the null hypothesis that the observed data follow that specific distribution. Then, the distribution with a lower Akaike Information Criterion (AIC) is selected for that data. Further, the graphical analysis is also performed to support selecting the most appropriate distribution function as in our previous works (Nguyen-Huy et al., 2017, 2018).

In the second step, the copula parameters are estimated using the maximum pseudo-likelihood method (Chowdhary et al., 2011), requiring the marginal return data to be transformed in the unit hypercube. In general, this transformation can be performed by applying either the fitted distribution (selected in the first step) or the empirical distribution. Here we utilise the empirical method (Genest and Favre, 2007) to ensure that the dependence structure between the pairwise data is independent of the marginal distributions. Thus, the marginal returns are transformed into the pseudo-data using the corresponding empirical distribution function $F(.)$ as $u_i = F(r_i)$. Henceforth, the copula parameters θ are estimated through the maximum pseudo-likelihood estimation method (Chowdhary et al., 2011):

$$\widehat{\theta} = \underset{\theta \in \Theta}{\arg\max} \sum_{t=1}^{T} \ln c(u_{1t}, ..., u_{nt}; \theta), \tag{13}$$

where $c(.)$ is the copula density. The most accurately fitted copula model is selected based on the Akaike Information Criterion $AIC = -2\ln(ll_{\max}) + 2k$ as the function of the maximum log-likelihood value ($ll_{\max}$) and the number of estimated parameters k.

Subsequently, a random vector $(u_1, ..., u_n)$ whose marginal distributions follow a uniform distribution is generated using the selected copulas. The steps in randomly generating the data samples from the fitted copulas are in accordance with the study of Brechmann (2010). Finally, the simulated realizations of the marginal return for each zone are obtained by inverse transformation following $(r_1, ..., r_n) = [F_1^{-1}(u_1), ..., F_n^{-1}(u_n)]$. The six popular copula functions and their rotated functions were employed in this analysis including Gaussian, Student's t (symmetric but heavier tails), Clayton, Gumbel, Frank, and Joe. These copula functions are employed in the construction of both multivariate Archimedian and vine copula models. Readers may refer to the previously published study of Zhang and Singh (2014) for more details on the multivariate elliptical and Archimedean copulas, including vine copulas. The computations are performed using several packages, including: **copula** (Yan, 2007) and **VineCopula** (Schepsmeier et al., 2017) available in **R** software (R Core Team, 2016).

Further applications of a vine copula model in climate extreme event prediction and agricultural yield simulation can be found in our earlier studies (*e.g.* (Nguyen-Huy et al., 2017; Nguyen-Huy et al., 2018)).

4. Results and discussion

In this section, the modelled results generated to solve the problem of farming portfolio-optimisation based on optimal copula-statistical model are provided with a physical interpretation in context of the applied models and the problem of interest. Fluctuations in marginal returns potentially associated with extreme climate conditions are firstly represented. Henceforth, the results of the copula model selection are described using multivariate copulas and vine copula functions. The conventional multivariate-normal model is also developed, for a comparison of the results with multivariate copulas and vine copula models. Finally, we discuss the mean-CVaR optimisations and optimal portfolio allocation results derived from models at different confidence levels.

4.1. Variations in the marginal return

Fig. 2 illustrates the historical marginal returns of each wheat growing zones in Australia. The pattern of marginal return at SA appears to be most stable, except for 2007–8. The extreme losses occurring in all zones for the period 2006–7 may be associated with one of

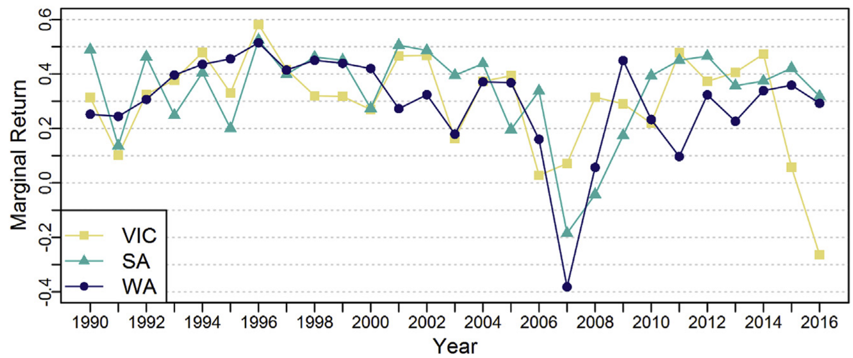

Fig. 2. Historical marginal returns over the period study 1990–2016 at the three wheat production zones in Australia: VIC, SA and WA.

Table 1
The degree of dependence of the farm-level return margins across the different wheat growing study sites across Victoria (VIC), South Australia (SA) and Western Australia (WA) measured by the Pearson's correlation coefficient, Spearman's rho, and the Kendall's τ parameters.

Tested Study Site	VIC	SA	WA
Pearson's correlation coefficient			
VIC	1.0000	0.3643	0.3585
SA		1.0000	0.5770
WA			1.0000
Spearman's rho			
VIC	1.0000	0.4438	0.3358
SA		1.0000	0.1978
WA			1.0000
Kendall's τ			
VIC	1.0000	0.3105	0.2422
SA		1.0000	0.1339
WA			1.0000

Table 2
Summary statistics for the return margins at the three wheat zones: VIC, SA and WA.

Statistical Property	VIC	SA	WA
Mean	0.3018	0.3385	0.2962
Maximum	0.5825	0.5251	0.5150
Minimum	−0.2630	−0.1849	−0.3816
SD	0.1808	0.1699	0.1776
Skewness	−1.2370	−1.5076	−2.1309
Kurtosis	1.7342	1.9601	5.9013
Shapiro-Wilk test	0.8991	0.8436	0.8071
p-value	0.0128	0.0009	0.0002

Table 3
Selected marginal distributions with their parameters, Akaike Information Criterion (*AIC*), and the *p-value* of the Kolmogorov-Smirnov statistic for marginal returns.

Zones	Distribution	Parameters	AIC	p-value
VIC	Generalised Logistic	location = 0.4533 scale = 0.0421 shape = 0.2529	−17.9163	0.9498
SA	Generalised Logistic	location = 0.5047 scale = 0.0130 shape = 0.0775	−30.1221	0.9975
WA	Generalised Logistic	location = 0.4586 scale = 0.0217 shape = 0.1302	−26.0397	0.9942

most severe drought conditions on record, caused by the El Niño event across most of Australia (Bureau of Meteorology). However, it is noted that the marginal return at each zone generally moves in an opposite direction to that in other zones. It can be observed clearly during the El Niño year of 2006–07, while the marginal returns at the SA and the WA farms dropped severely, that at the VIC farm increased considerably. Moreover, the marginal returns at VIC and SA farms are seen to fluctuate during the five consecutive El Niño years of 1991–5 (https://www.longpaddock.qld.gov.au/), however, that of the WA farm during the same period either remained stable or increased. If we study the data further, the opposite co-movement of the marginal returns is also indicated by the generally low correlation coefficients and the different degrees of dependence between the marginal returns of each study zone pair (see Table 1). The stochastic nature of the marginal returns at these study zones clearly suggests that the geographical diversification can be considered as a feasible risk management strategy to possibly assist the wheat farmers in reducing their losses.

In Table 2, we summarize the basic statistics of the historical marginal returns. The difference between the highest (*i.e.*, SA) and the lowest (*i.e.*, WA) average marginal return is found to be approximately 14%. Notably, VIC is seen to have the widest range of marginal return that varies from −26% (loss) to 58% (gain), while the marginal return at SA is seen to be the smallest, ranging from −19% to 53%. The highest marginal return at WA is approximately 52%, whereas the lowest is approximate −38%. It is worth pointing out that the maximum and the minimum values of the marginal returns at the VIC and WA study sites suggest that these farming zones might potentially yield a high profitability but they may also potentially have an extremely low profitability. Both of these zones have the highest standard deviation, as expected. Conversely, the SA farming region does not exhibit extreme values of marginal return accompanying the lowest standard deviation. Therefore, a visual conclusion derived from the analysis of the summary statistics is that the growing of wheat in SA is likely to gain a more stable benefit and a reduction in some risks. However, the skewness and kurtosis also expose VIC has the lowest outliers in the lower tail (extreme losses).

Table 2 also provides information regarding the higher moments of the marginal return data indicating the unreality of the normal assumption of marginal returns. It can be seen that WA study site has the highest absolute values of the skewness (2.13) and the kurtosis (5.90) factors, following by SA (1.5 and 1.9, respectively), meanwhile those are the lowest at VIC (1.24 and 1.73, respectively). According to Curran et al. (1996), a normal distribution has the skewness equal to 0 and the kurtosis equal to 3. It is clear that the skewness and kurtosis of all the three zones are significantly different to those of normal distribution. Therefore, it is suggested that the distributions of the marginal returns at three zones are non-normal and asymmetric. The results from the Shapiro-Wilk normality test also reject the hypothesis that the marginal return data are normally distributed with *p*-values less than 0.1. These results, therefore, question the practice of the linear correlation analysis and normal assumptions in previous studies, to justify the use of the non-linear copula approach that is pursued in this study.

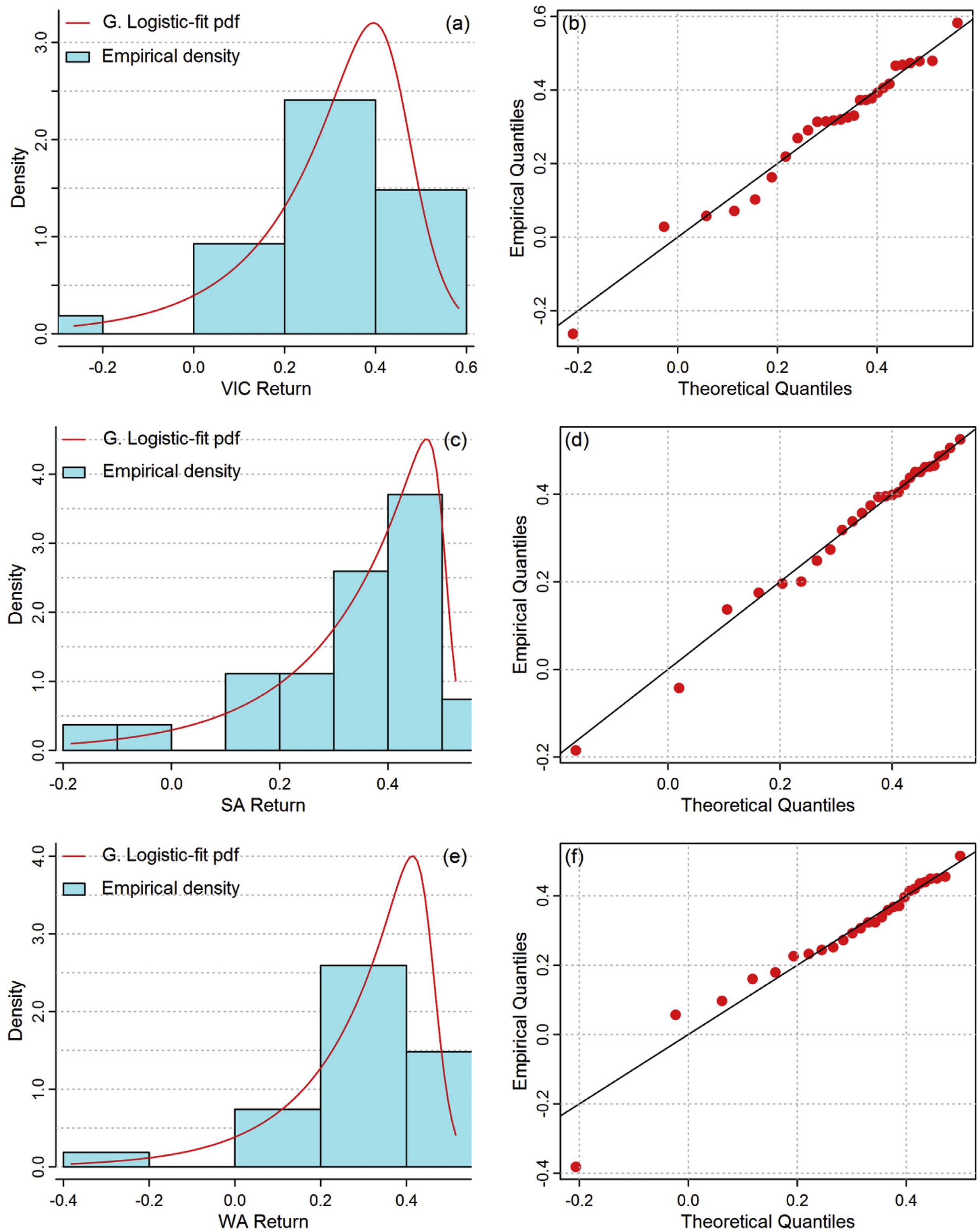

Fig. 3. Graphical analysis of goodness-of-fit for selecting marginal distributions approximate to VIC (a–b), SA (c–d), and WA (e–f) returns with density and quantile-quantile plots.

4.2. Copula model

As the first step of the model construction, the historical marginal returns are fitted to the theoretical distribution curves (Nguyen-Huy et al., 2017, 2018). All of the three historical marginal return data can be appropriately described by the generalised logistic distribution with the estimated parameters shown in Table 3. The graphical assessment involves the density, cumulative distribution function, quantile-quantile, and probability-probability plots, which are analysed to confirm the marginal distribution results. Fig. 3 displays the density and

Table 4
Copula parameters, maximum log-likelihood (ll_{max}), and the Akaike Information Criterion (*AIC)*.

Copula function	Parameters	ll_{max}	AIC
Gaussian	ρ_1 = 5526, ρ_2 = 0.453, ρ_3 = 0.395	6.060	−6.121
Student's t	ρ_1 = 0.417, ρ_2 = 0.371, ρ_3 = 0.282, ν = 4.000	5.526	−5.052
Clayton	θ = 0.655	4.980	−7.959
Gumbel	θ = 1.365	5.688	−9.376
Frank	θ = 2.189	3.679	−5.358
Joe	θ = 1.512	4.827	−7.653
Survival Clayton	θ = 0.654	4.722	−7.444
Survival Gumbel	θ = 1.342	4.980	−7.960
Survival Joe	θ = 1.482	4.379	−6.759

Table 5
Structure of vine copula model with parameters, maximum log-likelihood (ll_{max}), and Akaike Information Criterion (*AIC*).

Tree level	Edge	Copula function	Parameter	ll_{max}	AIC
SA as center: VIC – SA – WA					
T_1	VIC, SA	Survival Clayton	θ = 0.949	8.389	−8.779
	WA, SA	Student's *t*	ρ = 1.604, ν = 2.000		
T_2	VIC|SA, WA|SA	Survival Joe	θ = 1.560		
VIC as center: SA – VIC – WA					
T_1	SA, VIC	Survival Clayton	θ = 0.949	6.040	−6.079
	WA, VIC	Gumbel	θ = 1.370		
T_2	SA|VIC, WA|VIC	Gumbel	θ = 1.082		
WA as center: SA – WA – VIC					
T_1	SA, WA	Student's *t*	ρ = 1.604, ν = 2.000	7.330	−6.660
	VIC, WA	Gumbel	θ = 1.370		
T_2	SA|WA, VIC|WA	Survival Clayton	θ = 0.547		

quantile-quantile plots (as for example), while graphical analysis of goodness-of-fit in conjunction with statistical test in Table 3 support the selection of the generalised logistic distribution for fitting the returns in VIC, SA, and WA.

Table 4 represents the summary results of the multivariate copula functions with the corresponding parameters, maximum log-likelihood ($ll_{\max}$), and AIC. Based on the AIC, the results show that the Gumbel copula is the most appropriate copula model regarding the case of multivariate copulas. The same set of copula functions are employed for the vine copula development and the selected vine copula model is illustrated in Table 5. Similar to the procedure adopted for fitting the marginal distributions, in this study we also applied graphical tools to support the selection of the most suitable copula. Fig. 4 plots the contours of the selected bivariate copulas for each pairs of the returns, superimposed on empirical observations and simulated data derived from the corresponding copulas.

Since there are three zones in this study it is pertinent to construct three unique drawable D- and canonical C-vine copulas (Aas et al., 2009). The vine copula with the construction data of VIC – SA – WA combinations is selected among the three cases since this construction yields the lowest AIC. It is noteworthy that the zone names imply the nodes of the copula model with the corresponding and the respective order whereas the dashed symbols denote the edges of the first tree of the vine copula model construction.

Following the construction of optimal copula-statistical models, we apply the copula-based Monte Carlo simulation and obtain 2700 simulations (*i.e.*, simulation is repeated in 100 times for the sample size of 27 points) of the marginal returns for each zone from the chosen Gumbel and the vine copula models (Nguyen-Huy et al., 2017, 2018). For the purpose of comparison, the traditional multivariate-normal distribution is also used in this study to generate another a set of simulated data using the Monte Carlo simulation technique. In this case, the marginal returns are assumed to follow a multivariate-normal distribution (*i.e.*, the individual marginal return distributions and their dependences are assumed to be normal). These three sets of randomly simulated data (have been transformed back to the real values) are finally employed in the following geographical diversification analysis and interpretation.

4.3. Mean-CVaR efficient frontiers

This section describes the mean-CVaR optimisations where the expected return of wheat farmer's portfolio are maximised subject to the target risk (CVaR) constraint. Table 6 displays the examples of optimal portfolios at three common confidence levels (*i.e.*, 90%, 95%, and 99%) from copula-based and conventional multivariate normal models. It is noticed that, by definition, the CVaR risk measure evaluates the outcomes versus the zero and, consequently, it is likely to have positive and negative values. The reported values of the positive or greater than zero CVaR (similar to the positive VaR) refers to the certain negative outcomes (i.e., losses), and the negative CVaR correspond to certain positive outcomes (i.e., the gains or the returns). For example, a value of 95% CVaR of 0.10 (a positive value) refers to the scenario that the expected return of the 135 worst scenarios (*i.e.*, 5%*2700) is equal to −10%, and conversely, a value of 95% CVaR of −0.10 (a negative value) refers to the scenarios that the expected return of the 135 worst

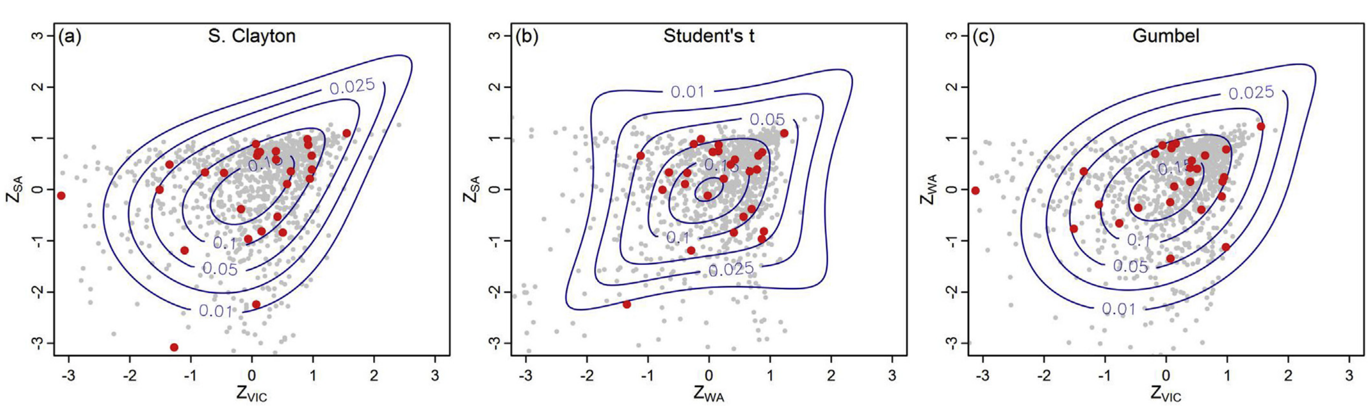

Fig. 4. Contour plots of selected bivariate copulas for each pairs of returns superimposed with standardized empirical observations (red points) and 1000 simulated data (smaller grey points) derived from the corresponding survival Clayton, Student's t, and Gumbel copulas. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 6
Three examples of the optimal portfolios with the conditional value-at-risk (*CVaR*) and the target returns at 90%, 95%, and 99% confidence levels for the case of the vine, Gumbel, and multivariate-normal (M-Normal) portfolios.

Copula Type	90%		95%		99%	
	Target Return	Mean-CVaR	Target Return	Mean-CVaR	Target Return	Mean-CVaR
C-Vine	0.332	−0.0177	0.332	0.0680	0.332	0.2628
Gumbel	0.332	−0.0029	0.332	−0.0090	0.332	0.2611
M-Normal	0.332	−0.0651	0.332	−0.0229	0.332	0.0520

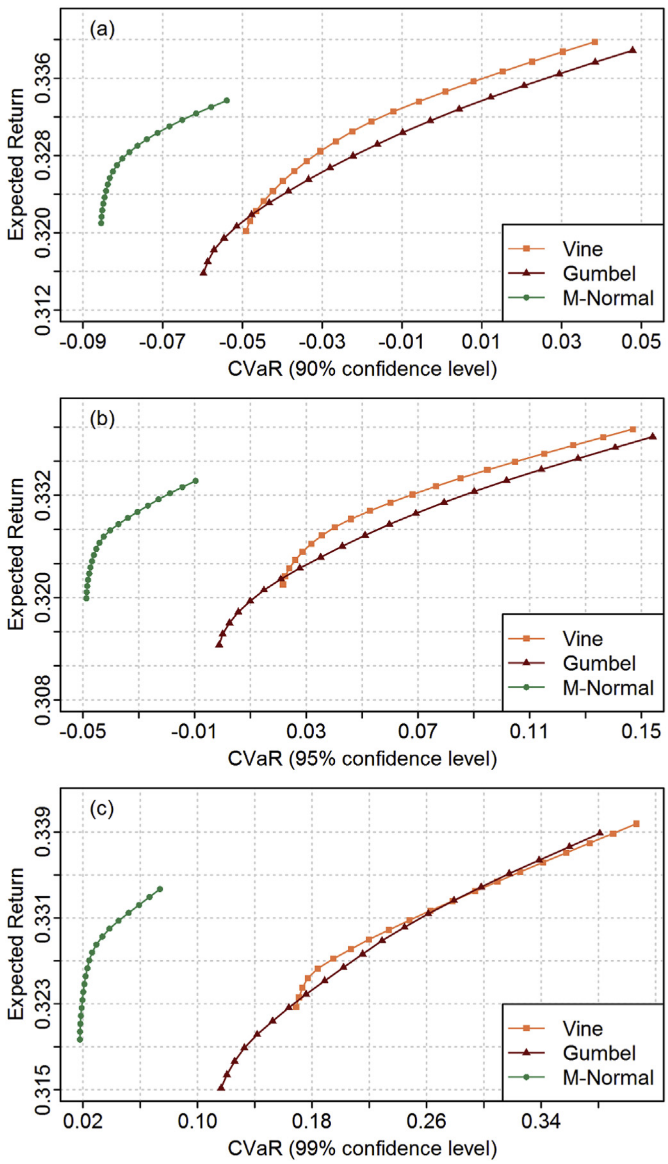

Fig. 5. Mean-CVaR efficient frontiers from the vine, Gumbel, and multivariate-normal (*i.e.*, M-Normal) model at confidence levels of 90%, 95% and 99%.

scenarios is equal to 10%.

In order to compare the optimised values of mean-CVaR under different distribution assumptions, the same targets of the expected returns are selected for each confidence level. The two copula-based portfolios produce a higher mean-CVaR value than the conventional multivariate-normal portfolio. Thus, the results in Table 6 indicate that if the joint distribution of the marginal returns is followed properly by a non-normal distribution modelled as by the copulas, the wheat farmers are likely to underestimate the minimum level of the risk measured by mean-CVaR for a given expected return using the multivariate-normal method. Since the marginal returns clearly do not follow the normal distribution as shown in section 3.1 and Table 3, the risk level should be measured based on the copula model.

The underestimation of risk under the assumption of a multivariate-normal distribution is displayed clearly in Fig. 5. The mean-CVaR efficient frontier acquired from the traditional multivariate-normal portfolio is plotted against those from the copula-based portfolios for different confidence levels. As it can be seen from Fig. 5, the significantly higher values of the frontiers can be observed from the copula-based models compared to the multivariate-normal model. This is because the copula-based models are able to account for the tails dependences whereas the multivariate-normal distribution assumes the coefficient of the tail dependence is zero, and therefore, it ignores the co-movement in the tail of the joint distributions. As such, the portfolio optimisation method relying on the conventional multivariate-normal assumption might be less protective, whereas copula-based models are more appropriate for farmers who are concerned with the extreme losses of their farm profitability.

Regarding the copula-based portfolios, we can infer that the vine copula is able to measure the risk much better than the Gumbel copula for all considered confidence levels. It is because, by the construction method, the vine copula models the dependences of each variable pairs more flexible than the multivariate Archimedean copula (Bedford and Cooke, 2002; Zhang and Singh, 2014). To examine this, we also inspect the preservative capacity of the three model for modelling the dependences among variable pairs. Fig. 6 displays a comparison of simulated and observed rank-based correlation coefficients (Kendall's τ) for the three models. It is clear that the vine approach is able to reserve the dependences of all variable pairs compared to the multivariate Gumbel and multivariate-normal model. Therefore, the Gumbel model may overestimate the risks given the same target expected returns in comparison to the vine model.

The single portfolios of each zone relative to the vine copula-based frontiers are shown in Fig. 7. This figure reveals how risk reduction can be achieved by a geographical diversification strategy. It can be seen that the farmer's profitability currently growing wheat at VIC and WA zones is below the efficient frontiers level whereas those for SA are on the frontier curve. Geographical diversification is likely to improve the profitability in both the VIC and the WA zones, but not in the SA farming area for a given level of downside risk. Growing wheat in SA could, therefore, face the maximum risk since it is located at the highest point of the frontier curve, however, it has the possibility of reaching the highest profitability as well. In addition, in the circumstances, the producers could decide to be slightly less profitability by geographically diversifying in order to reduce a relatively large downside risk. For example, by allocating about 10% of their production area to VIC, wheat producers in the SA region can adjust their expected profitability in the worst 5% of the cases from approximately 33.98%–33.69% (*i.e.*, a reduction of 0.29%), which in turn can reduce the downside risk from approximately 14.70%–11.51% (i.e., a risk reduction of 3.19%). This is because the average marginal return (and the standard deviation) in SA is just 3.67% higher (and 1.09% lower) than in VIC. The kurtosis (and skewness) in the SA region is also 22.59% higher (and 27.06% lower) than that in the VIC region (Table 3). By definition, the kurtosis factor is able to measure whether the data are heavy-tailed or light-tailed

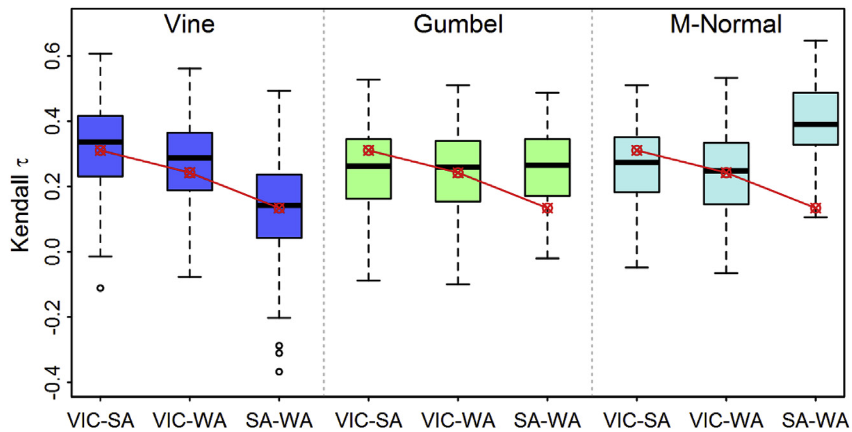

Fig. 6. Comparison of the simulated (in box plots) and the observed (as red points) values of the Kendall's τ for the vine, Gumbel, and multivariate-normal (M-Normal) model. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

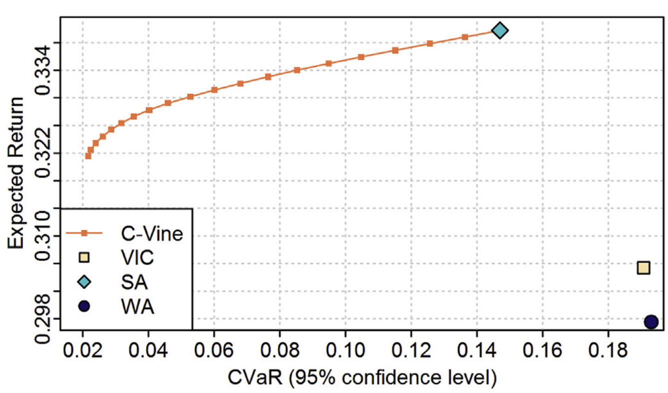

Fig. 7. Mean-CVaR efficient frontiers at the 95% confidence level for the vine copula model and single portfolios.

Table 7
Comparison of equal weight feasible and efficient CVaR portfolios (at 95% confidence level).

Allocation and Risk Level	VIC	SA	WA	Expected return	CVaR
Equal weight feasible portfolio					
Hectare allocation	0.3333	0.3333	0.3333	0.3142	0.0345
Covariance risk budget	0.3702	0.2962	0.3336		
Efficient CVaR portfolio					
Hectare allocation	0.3978	0.3214	0.2808	0.3142	0.0337
Covariance risk budget	0.4603	0.2768	0.2630		

relative to a normal distribution. Thus, we deduce that the SA region is likely to have higher heavy tails or outliers in the lower tail (extreme losses) since the high negative skewness implies the asymmetry to the left of its marginal return distribution.

In accordance with the results, the ratios of the trade-off between target risks and expected returns changes along the efficient frontiers. In contrast to the high targets of the expected returns, the wheat producers can increase their expected returns without exposing themselves to higher risk through the geographical spread of wheat farms at the lower levels of expected profitability. This is possible by balancing the hectares allocated to the SA and VIC regions, and allocating a small part to the WA region. This result is expected in terms of the reasons mentioned above between the SA and VIC zones. Importantly, WA has the lowest average marginal return and the highest kurtosis and (absolute) skewness. Therefore, the major benefits from growing in WA are derived mostly from the low relationship (or opposite co-movement) of the marginal returns with VIC and SA (see Table 1 and Fig. 2).

4.4. Optimal portfolio allocation

In this section, we analyse the optimal percentage allocation among three growing zones. Firstly, we investigate the differences between a feasible portfolio with equal weight (*i.e.*, the total hectare is divided equally into three zones) and an efficient CVaR portfolio. This comparison is performed by specifying the target expected return and then optimising the portfolio which has the lowest risk for both cases. The results illustrated in Table 7 indicate that the risk of the optimised efficient CVaR portfolio has been lowered from 3.45% to 3.37% for the same target return.

We further explore on the optimal hectare allocation with the mean-CVaR efficient frontiers. Fig. 8 represents the efficient allocation (*i.e.*, optimal weight) (a), weighted returns (b), and the covariance risk budgets (c) corresponding to different targets of the mean-CVaR efficient frontiers (for 95% confidence level) for the vine copula-based portfolios. Since the weighted return is the product of the optimal weight (*i.e.*, the hectare allocated) and corresponding marginal return, its value illustrates the proportion of each zone contributing to the expected marginal return. Thus, these figures appear to show a similar pattern to figure (a).

It is clear that the optimal share allocated to each growing zone varies depending on the different expected marginal returns and risk levels. As expected, the optimal decision is to allocate all production to the zone with the highest expected marginal return, *i.e.*, SA in this case, resulting in the maximum risk level. The optimal choice for the minimum CVaR portfolio is to operate in all the three zones with the highest proportion of growing land allocated to SA (50%), followed by VIC (40%) and WA (10%). In order to achieve a medium to high level of expected profitability, wheat should be grown mostly in SA and not at all in WA. It is also optimal to allocate the majority of the land to SA and VIC, and less than 10% to WA when targeting low to medium levels of profitability and risk.

Figs. 9 and 10 are similar to Fig. 8, however, for the confidence levels of 90% and 99%, respectively. It can be seen clearly that the patterns of hectare allocation are different corresponding to the interested confidence levels. For the very worst cases (*i.e.*, at the confidence level of 99%), to optimize the minimum risk, the total hectare should be allocated more in SA (55%) and lesser in WA (5%) since SA has the lowest standard deviation.

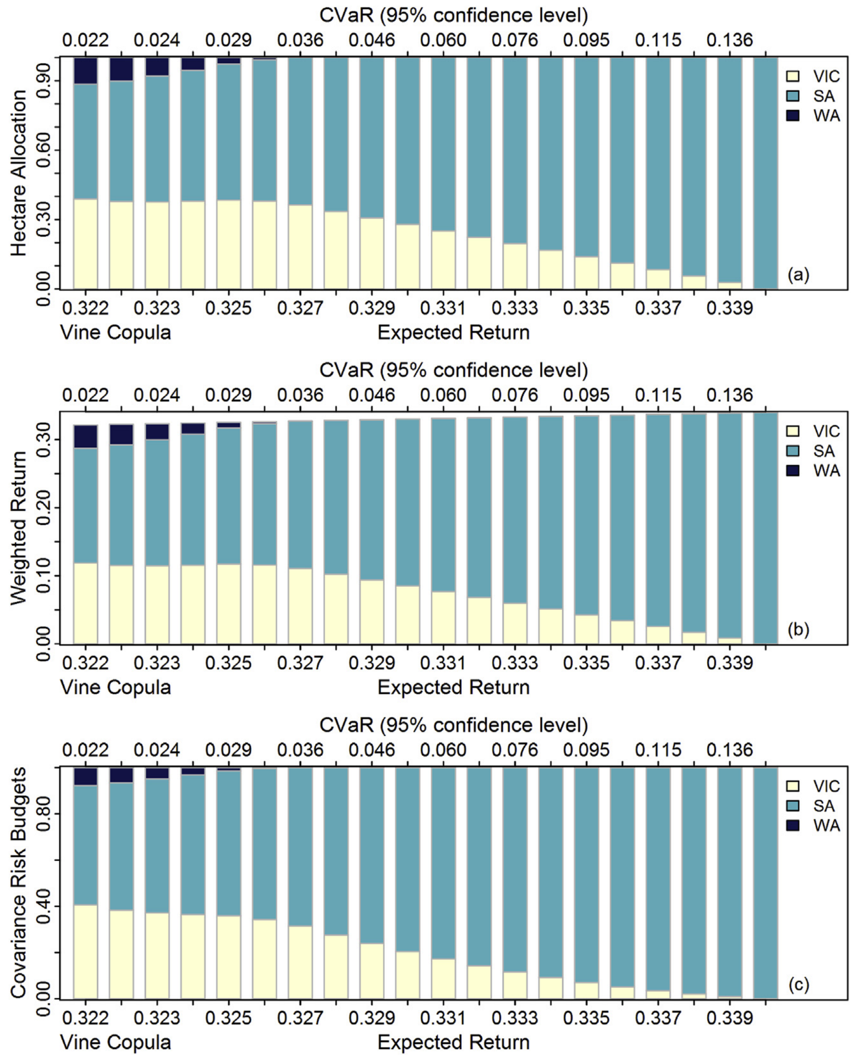

Fig. 8. The percentage of hectare allocation among the three wheat zones at the 95% confidence level for the vine copula-based portfolios.

5. Discussion

It is not surprising that there is an argument on improving the efficiency of diversification strategies in agriculture. In the worst case when a series of weather events are highly correlated, it is obvious there may be no benefit of diversification. According to Mahul (1999), we cannot diversify systemic risk if natural disasters occur concurrently among a large number of farming systems. Some relevance may be drawn from the study of Xu et al. (2010) in Germany, stating that systemic weather risks are not possible to be diversified a regional scale. Based on a study in the United States, Holly Wang and Zhang (2003) stated that a wheat-cropping system can be geographically diversified at the county level. Accordingly, the behavior of systemic weather risks may be different over a global scale because of the differences in geographical topography and climatic conditions (Odening and Shen, 2014). In this study, geographical diversification has been examined as a potentially effective strategy for risk reduction in an Australian farming system. This study is important since portfolio managers can achieve an optimal portfolio with specifically required target risks and expected returns through the proposed copula-based mean-CVaR approach. This can be performed by adjusting the proportion of the total growing hectare to acquire an optimal return-risk trade-off.

In regards to the methodology, the copula-based model is found to be superior to the conventional multivariate-normal approach. It is expected since the distribution of the marginal returns is not normal and our results are in agreement with the study of Larsen et al. (2015). However, while that author applied only the multivariate copulas with lower tail, our study is employed copula functions that have either lower tail or upper tail for more flexible and appropriate description of data dependences. Furthermore, the vine copula is found to be better than the multivariate copula (as used in the study of Larsen et al., 2013) in modelling the dependence structures of the joint distribution by reserving the dependences among variable pairs. This finding reconfirms the advantages of the vine copulas stated in Brechmann (2010) and found by Zhang and Singh (2014).

This study points out several challenges in copula model development that could form the subject of further investigation to address these limitations. One such challenge is that underlying uncertainties in the model that could influence of result when estimating the copula parameters, including the potential sources of error that are derived from data management and model structures generated by a purely statistical approach. This could lead to major issues, where some of the copula parameters may equally fit the statistical goodness-of-fit test (Sadegh et al., 2018; Vrugt et al., 2003) but may in fact carry errors within them to confound the overall accuracy of the simulated data. This problem could also affect the process of finding a unique combination of copula parameters that are considerably superior to the others. Furthermore, one combination of copula parameters may be either be better than the others based on the goodness-of-fit measure or it may be worse in respect to another parameter. For example, if a

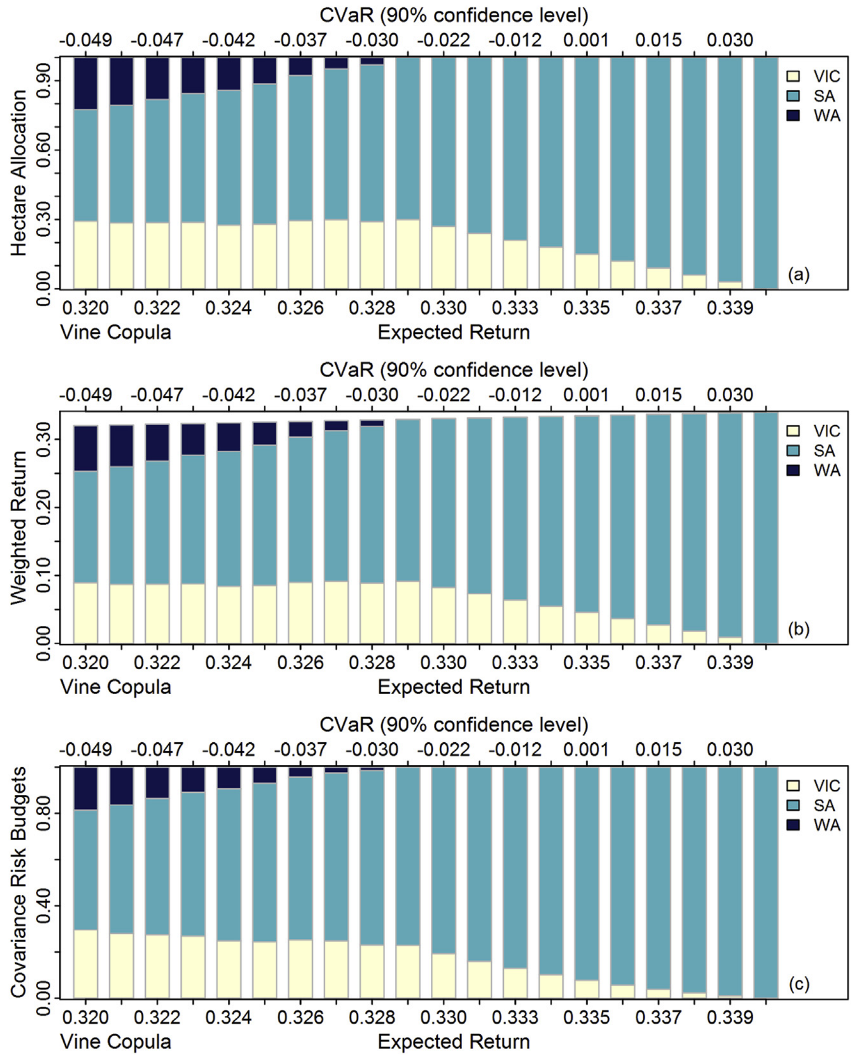

Fig. 9. The percentage of hectare allocation among the three wheat zones at the 90% confidence level for the vine copula-based portfolios.

copula family is selected according to the Bayesian Information Criteria (BIC), the penalty for a two-parameter copula (*e.g.*, Student's t, BB1, BB6, etc.) could be greater than that based on the AIC value (Schepsmeier et al., 2017).

It is also worth noting that the estimation of copula parameters relies on the period of observed data (Nguyen-Huy et al., 2018; Sadegh et al., 2018). This means that the dependence structure between any observations could vary with the time factor, resulting in different selection of copulas for modelling the relationship between the same objects. For example, in our previous study (Nguyen-Huy et al., 2018), the copula combination was different in each *k*-fold cross-validation process where the dataset was split into different training and testing subsamples. Therefore, the use of an acceptable group of samples to reflect more information about the system behavior is encouraged rather than finding the best parameter combination which is implied as the true representative of the system (Sadegh et al., 2018). In addition, according to Sadegh and Vrugt (2014), choosing the best copula parameter combination may lead to an underestimation of the uncertainties of the entire system. Finally, the limited length of the data can plausibly affect the accuracy of the parameter estimation by increasing the uncertainties (Bevacqua et al., 2017). All these reasons, and others, warrant a further investigation to mitigate the complications in selecting the best copula model as well as the best parameters of the optimal copula function.

The present study also comes with common assumptions that have been reported in published literature. First, this study does not account for the cost of growing crops in different zones (Larsen et al., 2015). Second, it is assumed that the marginal distribution does not change over the passage of time (Sadegh et al., 2018; Sadegh and Vrugt, 2014). Finally, since the statistical model was developed using historical data, this data is not able to account for the scenarios which have not been occurred before. This means the model cannot be easily adjusted to accommodate for the changes in factors such as climate, technology, and cultivation practices. Therefore, in order to achieve more robustness diversification benefits, it is important to incorporate the impacts of all the costs that may occur in geographical distributing the farm system as well as performing the model with under many projected scenarios.

6. Conclusion

In this study, we have demonstrated the effectiveness of applying a geographical diversification strategy to agricultural risk management. The mean-CVaR, the most popular and appropriate measure of downside risk, was calculated using the copula-based approach. Compared to the traditional multivariate-normal model, the copula-statistical approach was able to flexibly model the joint distribution of different types of marginal datasets including those of the non-normal distributions. Furthermore, the study revealed that the vine copula-statistical models were able to capture the full range of different dependence

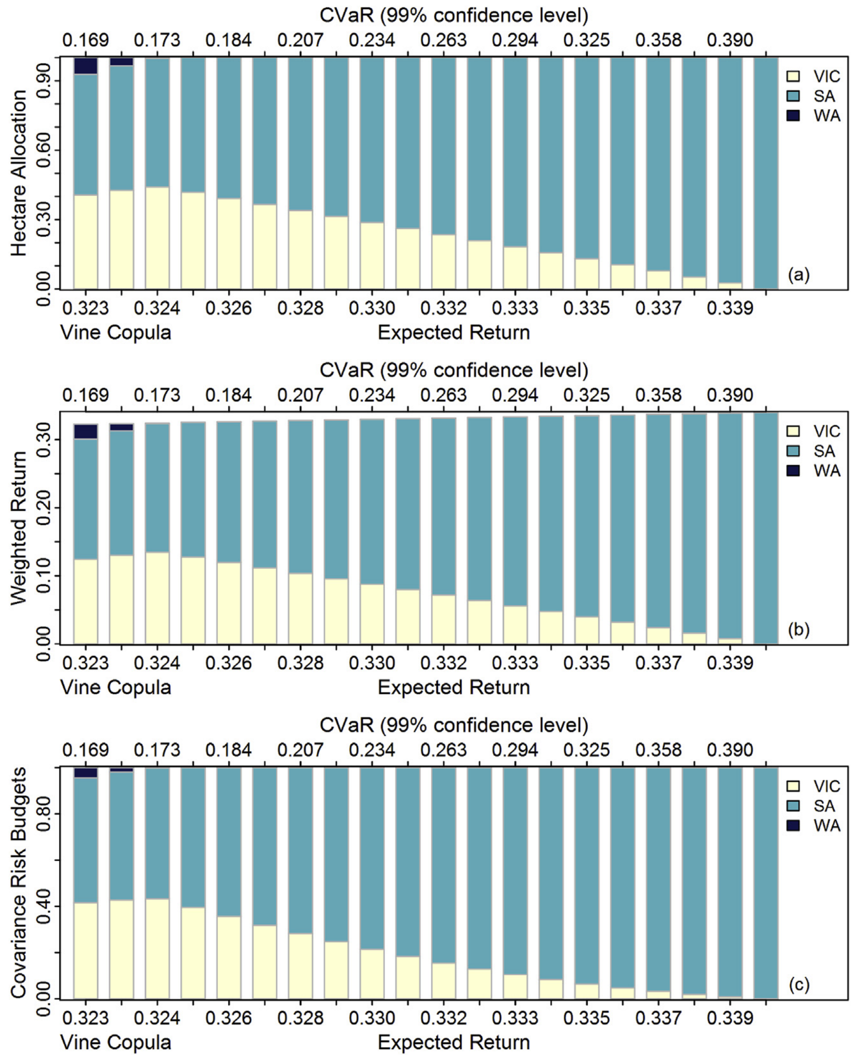

Fig. 10. The percentage of hectare allocation among the three wheat zones at the 99% confidence level for the vine copula-based portfolios.

structures and in particular the case where the joint distribution of marginal returns exhibits the tail dependence, as also revealed in earlier studies on precipitation and wheat yield forecasting (Nguyen-Huy et al., 2017, 2018).

Although the results have useful implications for three major wheat growing zones in Australia including VIC Mallee, SA Eyre Peninsula, and WA North and East Wheat Belt, the approach is applicable to other agricultural regions and crops outside of Australia. This is because the models have a good ability to analyse joint dependences, and able to examine the potential assistance that can be offered to the farmers as part of the optimised geographical strategy in agricultural risk reduction. The approach is fairly justified to be used as a broad method for modelling such problems since the multivariate joint distribution of the marginal returns was constructed by the copula function and then evaluated against the multivariate-normal approach for comparison purposes. To optimize the method, the CVaR criteria were calculated using scenarios from Monte Carlo simulation methods and the portfolio optimisation was attained by maximising the expected marginal return for given target levels of CVaR.

The optimised mean-CVaR results, as described by the corresponding efficient frontier and optimal hectare allocation, indicated that using geographical diversification to downside risk is viable. To be more specific, the risk can be reduced for wheat producers in VIC and WA region since both regions are located below the efficient frontiers. To explain this, we consider SA, which was located on the frontier curve, and therefore meant that zone was able to obtain the least benefit from geographical diversification. Nevertheless, it was also evident that SA was able to gain a relatively large risk reduction by reducing the marginal return in a subtle way from the geographical diversification since it was located at the riskiest point of the frontier curve. In general, three optimal portfolio models in this study showed that the geographical diversification strategy was an achievable tool for agricultural risk modelling and management. However, the optimal share of the hectares allocated to each zone varied depending on the target risk and the profitability that the wheat producers expect.

The results in this paper also indicate the advantages of the copula method in addressing the lower tail dependence of the joint return distribution. That is, if the marginal returns are not normally distributed (as it is the case in this study), the multivariate-normal model is likely to underestimate the minimum level of the downside risk at a given target of expected marginal return by discounting the existence of the lower tail dependence in the model. In this case, the copula approach developed in this paper is more appropriate and can be used to analyse the benefits of the geographical diversification strategy. It was evident that the vine copula performed better than the Gumbel copula since it allowed each variable pairs to be modelled by different copula functions.

Considering the results and their interpretation it is concluded that wheat producers could possibly achieve a higher expected return given the same level of downside risk by dividing the crops among the three zones. While the results are at a regional scale, the method can be extended to a farm level as well as to the other crops. This study, however, was unable to account for the costs that could possibly occur when growing in different places, a dataset that could add value to the modelling strategy followed in this paper. Thus, a follow-up study could take into account the cost-related components in the performance of geographical diversification strategy. Finally, a potential avenue of future research could also be to consider the spatio-temporal impact of climate conditions on the marginal returns across the different zones.

Acknowledgment

The project was financed by University of Southern Queensland Post Graduate Research Scholarship [USQPRS 2015-2018]; School of Agricultural, Computational and Environmental Sciences and Drought and Climate Adaptation [DCAP] Projects (Producing Enhanced Crop Insurance Systems and Associated Financial Decision Support Tools). The authors would like to acknowledge all constructive comments from the reviewers and the journal Editor-in-Chief.

Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.wace.2018.07.002.

References

Aas, K., Czado, C., Frigessi, A., Bakken, H., 2009. Pair-copula constructions of multiple dependence. Insur. Math. Econ. 44, 182–198. https://doi.org/https://doi.org/10.1016/j.insmatheco.2007.02.001.
Ang, A., Chen, J., 2002. Asymmetric correlations of equity portfolios. J. Financ. Econ. 63, 443–494. https://doi.org/10.1016/S0304-405X(02)00068-5.
Barriopedro, D., Fischer, E.M., Luterbacher, J., Trigo, R.M., García-Herrera, R., 2011. The hot summer of 2010: redrawing the temperature record map of Europe. Science. https://doi.org/10.1126/science.1201224.
Bedford, T., Cooke, R.M., 2002. Vines: a new graphical model for dependent random variables. Ann. Stat. 1031–1068. https://doi.org/https://doi.org/10.1214/aos/1031689016.
Bessa, R.J., Miranda, V., Botterud, A., Zhou, Z., Wang, J., 2012. Time-adaptive quantile-copula for wind power probabilistic forecasting. Renew. Energy 40, 29–39. https://doi.org/https://doi.org/10.1016/j.renene.2011.08.015.
Bevacqua, E., Maraun, D., Haff, I.H., Widmann, M., Vrac, M., 2017. Multivariate statistical modelling of compound events via pair-copula constructions: analysis of floods in Ravenna (Italy). Hydrol. Earth Syst. Sci. 21, 2701.
Bokusheva, R., 2014. Improving the Effectiveness of Weather-based Insurance: an Application of Copula Approach. University Library of Munich, Germany.
Boubaker, H., Sghaier, N., 2013. Portfolio optimization in the presence of dependent financial returns with long memory: a copula based approach. J. Bank. Finance 37, 361–377.
Bradshaw, B., Dolan, H., Smit, B., 2004. Farm-level adaptation to climatic variability and change: crop diversification in the Canadian prairies. Climatic Change 67, 119–141. https://doi.org/10.1007/s10584-004-0710-z.
Brechmann, E.C., 2010. Truncated and Simplified Regular Vines and Their Applications. Diploma.
Chernozhukov, V., Umantsev, L., 2001. Conditional value-at-risk: aspects of modeling and estimation. Empir. Econ. 26, 271–292. https://doi.org/10.1007/s001810000062.
Chowdhary, H., Escobar, L.A., Singh, V.P., 2011. Identification of suitable copulas for bivariate frequency analysis of flood peak and flood volume data. Nord. Hydrol 42, 193–216. https://doi.org/https://doi.org/10.2166/nh.2011.065.
Coumou, D., Rahmstorf, S., 2012. A decade of weather extremes. Nat. Clim. Chang. https://doi.org/10.1038/nclimate1452.
Curran, P.J., West, S.G., Finch, J.F., 1996. The robustness of test statistics to nonnormality and specification error in confirmatory factor analysis. Psychol. Methods 1, 16.
Embrechts, P., Lindskog, F., McNeil, A., 2001. Modelling Dependence with Copulas. Rapp. Tech. Département mathématiques, Inst. Fédéral Technol, Zurich, Zurich.
FAO, 2015. The Impact of Natural Hazards and Disasters on Agriculture and Food and Nutrition Security – a Call for Action to Build Resilient Livelihoods.
Favre, A.-C., El Adlouni, S., Perreault, L., Thiémonge, N., Bobée, B., 2004. Multivariate hydrological frequency analysis using copulas. Water Resour. Res. 40. https://doi.org/10.1029/2003WR002456.
Ganguli, P., Reddy, M.J., 2012. Risk assessment of droughts in Gujarat using bivariate copulas. Water Resour. Manag. https://doi.org/10.1007/s11269-012-0073-6.
Genest, C., Favre, A.-C., 2007. Everything you always wanted to know about Copula modeling but were afraid to ask. J. Hydrol. Eng. 12, 347–368. https://doi.org/https://doi.org/10.1061/(ASCE)1084-0699(2007)12:4(347).
Goodwin, B.K., Hungerford, A., 2014. Copula-based models of systemic risk in US agriculture: implications for crop insurance and reinsurance contracts. Am. J. Agric. Econ. 97, 879–896.
Goodwin, B.K., Ker, A.P., 2002. Modeling price and yield risk. A Comprehensive Assessment of the Role of Risk in US Agriculture. Springer, pp. 289–323.
Hao, Z., Singh, V.P., 2016. Review of dependence modeling in hydrology and water resources. Prog. Phys. Geogr 0309133316632460.
Herold, N., Ekström, M., Kala, J., Goldie, J., Evans, J.P., 2018. Australian climate extremes in the 21st century according to a regional climate model ensemble: implications for health and agriculture. Weather Clim. Extrem 20, 54–68.
Holly Wang, H., Zhang, H., 2003. On the possibility of a private crop insurance market: a spatial statistics approach. J. Risk Insur. https://doi.org/10.1111/1539-6975.00051.
Hu, L., 2006. Dependence patterns across financial markets: a mixed copula approach. Appl. Financ. Econ. 16, 717–729.
Huang, J.-J., Lee, K.-J., Liang, H., Lin, W.-F., 2009. Estimating value at risk of portfolio by conditional copula-GARCH method. Insur. Math. Econ. 45, 315–324. https://doi.org/https://doi.org/10.1016/j.insmatheco.2009.09.009.
Janga Reddy, M., Ganguli, P., 2012. Application of copulas for derivation of drought severity-duration-frequency curves. Hydrol. Process. https://doi.org/10.1002/hyp.8287.
Joe, H., 1996. Families of m-variate distributions with given margins and m (m-1)/2 bivariate dependence parameters. Lect. notes-monograph Ser 120–141. https://doi.org/https://doi.org/10.1214/lnms/1215452614.
Kole, E., Koedijk, K., Verbeek, M., 2007. Selecting copulas for risk management. J. Bank. Finance 31, 2405–2423.
Kresta, A., Tichý, T., 2012. International Equity Portfolio Risk Modeling: the Case of the NIG Model and Ordinary Copula Functions.
Larsen, R., Leatham, D., Sukcharoen, K., 2015. Geographical diversification in wheat farming: a copula-based CVaR framework. Agric. Finance Rev. 75, 368–384.
Larsen, R., Mjelde, W., Klinefelter, D., Wolfley, J., 2013. The use of copulas in explaining crop yield dependence structures for use in geographic diversification. Agric. Finance Rev. 73, 469–492.
Lesk, C., Rowhani, P., Ramankutty, N., 2016. Influence of extreme weather disasters on global crop production. Nature. https://doi.org/10.1038/nature16467.
Longin, F., Solnik, B., 2001. Extreme correlation of international equity markets. J. Finance 56, 649–676. https://doi.org/10.1111/0022-1082.00340.
Mahul, O., 1999. Optimum area yield crop insurance. Am. J. Agric. Econ. https://doi.org/10.1111/j.l467-8276.2009.01368.x.
Markowitz, H., 1952. Portfolio selection. J. Finance 7, 77–91.
Mishra, A.K., El-Osta, H.S., Sandretto, C.L., 2004. Factors affecting farm enterprise diversification. Agric. Finance Rev. 64, 151–166. https://doi.org/10.1108/00214660480001160.
Mulvey, J.M., Erkan, H.G., 2006. Applying CVaR for decentralized risk management of financial companies. J. Bank. Finance 30, 627–644.
Murray, G.M., Brennan, J.P., 2009. Estimating disease losses to the Australian wheat industry. Australas. Plant Pathol. 38, 558–570.
Nelsen, R.B., 2006. An Introduction to Copulas, second ed. Springer.
Nguyen-Huy, T., Deo, R.C., An-Vo, D.-A., Mushtaq, S., Khan, S., 2017. Copula-statistical precipitation forecasting model in Australia's agro-ecological zones. Agric. Water Manag. 191. https://doi.org/10.1016/j.agwat.2017.06.010.
Nguyen-Huy, T., Deo, R.C., Mushtaq, S., An-Vo, D.-A., Khan, S., 2018. Modeling the joint influence of multiple synoptic-scale, climate mode indices on Australian wheat yield using a vine copula-based approach. Eur. J. Agron. 98. https://doi.org/10.1016/j.eja.2018.05.006.
Odening, M., Shen, Z., 2014. Challenges of insuring weather risk in agriculture. Agric. Finance Rev. 74, 188–199.
Okhrin, O., Odening, M., Xu, W., 2013. Systemic weather risk and crop insurance: the case of China. J. Risk Insur. 80, 351–372.
Pflug, G.C., 2000. Some remarks on the value-at-risk and the conditional value-at-risk. Probabilistic constrained Optim. Methodol. Appl 272–281. https://doi.org/10.1007/978-1-4757-3150-7_15.
Portmann, F.T., Siebert, S., Döll, P., 2010. MIRCA2000-Global monthly irrigated and rainfed crop areas around the year 2000: a new high-resolution data set for agricultural and hydrological modeling. Global Biogeochem. Cycles 24 n/a-n/a. https://doi.org/10.1029/2008GB003435.
R Core Team, 2016. R development Core Team. R A Lang. Environ. Stat. Comput. https://doi.org/http://www.R-project.org.
Rockafellar, R.T., Uryasev, S., 2000. Optimization of conditional value-at-risk. J. Risk 2, 21–42.
Sadegh, M., Moftakhari, H., Gupta, H.V., Ragno, E., Mazdiyasni, O., Sanders, B., Matthew, R., AghaKouchak, A., 2018. Multi-hazard scenarios for analysis of compound extreme events. Geophys. Res. Lett.
Sadegh, M., Vrugt, J.A., 2014. Approximate bayesian computation using Markov chain Monte Carlo simulation. Water Resour. Res. https://doi.org/10.1002/2014WR015386.Received.
Schepsmeier, U., Stoeber, J., Brechmann, E.C., Graeler, B., Nagler, T., Erhardt, T., Almeida, C., Min, A., Czado, C., Hofmann, M., 2017. Package 'VineCopula.'.
Sklar, M., 1959. Fonctions de répartition à n dimensions et leurs marges. Université Paris, pp. 8.
Turner, N.C., 2004. Agronomic options for improving rainfall-use efficiency of crops in dryland farming systems. J. Exp. Bot. 55, 2413–2425. https://doi.org/https://doi.org/10.1093/jxb/erh154.
Vedenov, D., 2008. Application of copulas to estimation of joint crop yield distributions. In: American Agricultural Economics Association Annual Meeting, pp. 27–29 Orlando, FL.
Vergni, L., Todisco, F., Mannocchi, F., 2015. Analysis of agricultural drought characteristics through a two-dimensional copula. Water Resour. Manag. https://doi.org/10.1007/s11269-015-0972-4.

Vrugt, J.A., Gupta, H.V., Bouten, W., Sorooshian, S., 2003. A Shuffled Complex Evolution Metropolis algorithm for optimization and uncertainty assessment of hydrologic model parameters. Water Resour. Res. https://doi.org/10.1029/2002WR001642.
Würtz, D., Chalabi, Y., Chen, W., Ellis, A., 2009. Portfolio Optimization with R/Rmetrics. Rmetrics.
Xu, W., Filler, G., Odening, M., Okhrin, O., 2010. On the systemic nature of weather risk. Agric. Finance Rev. 70, 267–284.
Yan, J., 2007. Enjoy the joy of copulas: with a package copula. J. Stat. Software 21, 1–21.
Zhang, L., Singh, V.P., 2014. Trivariate flood frequency analysis using discharge time series with possible different lengths: cuyahoga river case study. J. Hydrol. Eng. 19, 5014012. https://doi.org/https://doi.org/10.1061/(ASCE)HE.1943-5584.0001003.
Zhu, S., Fukushima, M., 2009. Worst-case conditional value-at-risk with application to robust portfolio management. Oper. Res. 57, 1155–1168. https://doi.org/10.1287/opre.1080.0684.