Copula-based probabilistic assessment of intensity and duration of cold episodes: A case study of Malayer vineyard region

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Abstract

Frost, particularly during the spring, is one of the most damaging weather phenomena for vineyards, causing significant economic losses to vineyards around the world each year. The risk of tardive frost damage in vineyards due to changing climate is considered as an important threat to the sustainable production of grapes. Therefore, the cold monitoring strategies is one of the criteria with significant impacts on the yields and prosperity of horticulture and raisin factories. Frost events can be characterized by duration and severity. This paper investigates the risk and impacts of frost phenomenon in the vineyards by modeling the joint distribution of duration and severity factors and analyzing the influential parameter's dependency structure using capabilities of copula functions. A novel mathematical framework is developed within this study to understand the risk and uncertainties associate

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with frost events and the impacts on yields of vineyards by analyzing the non-linear dependency structure using copula functions as an efficient tool. The developed model was successfully validated for the case study of vineyard in Malayer city of Iran. The copula model developed in this study was shown to be a robust tool for predicting the return period of the frost events.
Keywords: Copula model; Extreme climatic event; Frost; Probabilistic risk assessment; Return period; Vineyard.

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1. Introduction

Grapes (*Vitis vinifera L.*) are one of the most economically valuable fruit crops in the world, planted in over 90 countries, and consumed as fresh fruit, or processed as raisins and wine. The widespread geographical distribution of grapes tree makes the production of this fruit more vulnerable to various environmental stresses (Keller, 2015). Cold stress, due to prolonged periods of freezing in autumn, winter and spring, damages permanent tissues, growing organs and reproductive organs of the vines (Karimi, 2017; Karimi, 2019b). The damage due to frost and freezing events either at the onset or after bud break result in significant economic losses each year (Karimi, 2019a).

Iran is one of the important regions for grape production with over 290,000 hectares of vineyards and approximately 2.3 million tons production of grapes, ranked as the 8th in the world in terms of vineyard area and 10th largest producer of grapes (FAO, 2018). With over 10,000 ha of vineyards, the province of Hamadan in western Iran is a major hub of grape and raisin production in Iran. In recent years, the grape production system in Iran has been recognized as Globally Important Agricultural Heritage Systems (GI-

AHS) by FAO (FAO, 2018). Malayer is located in Zagros mountain-range with extreme winter climate and temperature which sometimes drop to -23 $^{\circ}C$. Moreover, temperatures in the region can fall to as low as -4 $^{\circ}C$ during the spring (Karimi, 2019b). Under these harsh climatic conditions, cold injury is expected in mid-winter, but it also often occurs in late fall or early spring, due to unexpected cold weather fronts in mountain regions. Therefore, strategies to reduce cold stress damage is one of the key requirements of vineyard management and sustainable production of grapes in the regions prone to extreme climatic conditions, such as Malayer. The decision on what strategies are the best for a specific vineyard are mainly based on the results of the different region-specific climate projections.

Previous studies confirm that changes in climate, including changes in the duration and severity of frost, are widely expected to have significant impacts in vineyards (e.g. Webb et al., 2007; Keller, 2010; Fraga et al., 2013). Sgubin et al. (2018) assessed the risk of tarvide frosts, i.e. frost events which occur after grapevine budburst, for the French vineyards throughout the 21st century by analyzing temperature projections from eight climate models. Gobbett et al. (2018) adopted multivariate adaptive regression splines technique to produce a high-resolution model of minimum temperatures for southeastern Australia. Gobbett et al. (2018) analyzed minimum night-time temperatures to investigate the impact of current and future frost risks. However, this study develops a copula-based model to evaluate the risks and predict the frost based on the intensity and duration of cold episodes by modeling the joint distribution of duration and severity factors as a robust multivariate technique.

A thorough review of the literature in the field suggests that the best way to evaluate and manage frost damages in vineyards is to have a detailed understanding of the frequency of frost events characterized by duration and severity. The frost risk assessment of the vineyards using the univariate frequency analysis approach is based on considering one of the variables affecting frost at the time which does not capture the complexity of the problem and the non-linear dependence structure between the climatic parameters contributing to a frost event. Hence, the univariate models are not appropriate measures for understanding and predicting frost events. An alternative and more efficient method to evaluate the risk of frost is to use the multivariate approaches (e.g. Laughlin and Kalma, 1987; Lindkvist et al., 2000; Chung et al., 2006; Wang et al., 2008; Neteler, 2010; Zhu et al., 2013; Farsi et al., 2017; Tait and Zheng, 2003; Pouteau et al., 2011; Webb et al., 2018; Esmaeilbeigi et al., 2020; Borzooei et al., 2019a) by jointly modelling all uncertain climatic factors contributing to the occurrence of the frost. Given the high degree of linear/non-linear dependency between duration and severity of frost events, the model with capability to reveal the impact of these two factors in frost risk assessment analysis should be used. However, the applicability of many traditional multivariate distributions is limited by constraints such as the need for the quantities of interest to share the same type of marginal distribution (see Kurowicka and Cooke, 2006; Bedford et al., 2014; Chatrabgoun et al., 2018; Chatrabgoun et al., 2020; Joe and Kurowicka, 2011; and Bedford et al. (2016) for further details).

To overcome the difficulties associate with the methods described above, this paper develops a novel frost risk assessment methodology based on cop-

ula function models described by Sklar et al. (1959). Copulas are efficient mathematical tools, capable of combining several univariate marginal cumulative distribution functions into their joint cumulative distribution function. Copula models are becoming increasingly popular for those problems which a need flexible bivariate distribution (Joe, 1997; Nelsen, 2007). In recent years, the application of copula functions in earth and environmental sciences, including hydrology, flood modelling and characterization(Grimaldi and Serinaldi, 2006; Dupuis, 2007; Karmakar and Simonovic, 2009; Chowdhary et al., 2011; Daneshkhah et al., 2016; Borzooei et al., 2020; Salarijazi et al., 2013; Salarijazi et al., 2015) and drought modelling (Liu et al., 2011; Liu et al., 2016; Ganguli and Reddy, 2012; Chen et al., 2013; Shiau and Modarres, 2009; Zhang et al., 2013; Rauf and Zeephongsekul, 2014; Tosunoglu and Can, 2016; Sina et al., 2019) have been successfully investigated.

The main aim of this paper is thus to develop a novel modelling framework for better understanding and evaluating the risk and impacts of frost event characterized by the frost severity and duration of the vineyards using the copula model. This modelling approach enables us to efficiently computing the joint distribution of the uncertain factors causing the frost events with complex and non-linear dependency structure, and probabilistically predict the next returning periods of these events. This study will first examine the robustness of copula function model to assess probabilistic frost risk through modeling the joint distribution and obtaining dependency structure between severity and duration parameters as the main frost characteristic variables. The frost risk is probabilistically assessed by selecting the most appropriate copula function from known copula families to construct joint distribution

between severity and duration of frost events and then their parameter(s) is estimated. Also, this study for the first time, adopts the copula functions for probabilistic evaluation of frost in vineyards. The joint distribution function of duration and severity series of frost is constructed using copula model for two purposes: 1) Construction of bivariate distribution between severity and duration of frost events, 2) Assessment of non-linear correlation between severity and duration parameters characterising the frost. Following these steps, the return-period of frost event is predicted. The probabilistic frost assessment framework of this paper can then be used for deriving site-specific adaptation-mitigation strategies to reduce the damage due to frost. For example, the likelihood of frost damage can be reduced by pruning in late spring (after budburst) to delay bud break into a period when frosts are less likely to occur (Friend et al., 2011).

2. Modeling multivariate data using copulas

Copula functions are predominantly characterized by their uniform univariate marginal distributions. For the problems with bivariate data, the distribution of the data of interest can be decomposed into its copula, containing the dependence information and its marginal densities. This is characterized by Sklar's theorem, described in Eq. (1):

$$F(x_1, x_2) = C(u_1, u_2; \boldsymbol{\theta}), \tag{1}$$

where $C : [0,\ 1]^2 \rightarrow [0,\ 1]$ is a copula distribution function, $\boldsymbol{\theta}$ denotes to the association parameters, $u_i = F_i(x_i),\ i = 1, 2$ and F_1, F_2 are marginal distribution functions. The joint density $f(x_1, x_2)$ can be easily concluded

from (1) as follows:

$$f(x_1, x_2) = f_1(x_1) \times f_2(x_2) \times c(F_1(x_1), F_n(x_2)) \tag{2}$$

where $f_i(x_i)$ is the density function corresponding to $F_i(x_i)$, $i = 1, 2$, and $c = \partial^2 C(\cdot, \cdot)/(\partial F_1 \times \partial F_2)$ describes the copula density (Nelson, 2006). The practical implication of Sklar's theorem is that the modeling of the marginal distributions can be conveniently separated from the dependence modeling. The method for identifying the copula functions remains the main issue for practical applications of Sklar's theorem. For the problems with bivariate data, a rich variety of copula families are available and well-investigated, especially the two major classes of elliptical and Archimedean copulas (Joe, 1997; Nelsen, 2007). Elliptical copulas are directly derived by inverting Sklar's theorem. Considering a bivariate distribution function F with invertible margins F_1 and F_2, then

$$C(u_1, u_2) = F(F_1^{-1}(u_1), F_1^{-1}(u_2)),$$

is a bivariate copula for $u_1, u_2 \in [0, 1]$. C is called elliptical if F is elliptical. The bivariate Gaussian copula is the most famous example of elliptical copula classes which reads as follows:

$$C(u_1, u_2) = \Phi_\rho(\Phi^{-1}(u_1), \Phi^{-1}(u_2)),$$

and the bivariate *Student-t* copula

$$C(u_1, u_2) = t_{\rho,\upsilon}(t_\upsilon^{-1}(u_1), t_\upsilon^{-1}(u_2)),$$

with dependence parameter $\rho \in (-1, 1)$ and degrees of freedom parameter $\upsilon > 1$ for the Student-t copula. Φ_ρ denotes the bivariate standard normal

distribution function with correlation parameter ρ and Φ^{-1} is the inverse of the univariate standard normal distribution function. Similarly, $t_{\rho,\upsilon}$ is the bivariate Student-t distribution function with correlation parameter ρ and υ degrees of freedom, while t_{υ}^{-1} denotes the inverse univariate Student-t distribution function with υ degrees of freedom. Both copulas described above are symmetric and hence lower and upper tail dependence coefficients are the same.

On the other hand, bivariate Archimedean copulas, are defined as:

$$C(u_1, u_2) = \varphi^{[-1]}(\varphi(u_1), \varphi(u_2)),$$

where $\varphi : [0, 1] \to [0, \infty]$, is a continuous strictly decreasing convex function such that $\varphi(1) = 0$ and $\varphi^{[-1]}$ is the pseudo-inverse

$$\varphi^{[-1]}(t) = \begin{cases} \varphi^{-1}(t) & 0 \leq t \leq \varphi(0), \\ 0 & \varphi(0) \leq t \leq \infty, \end{cases}$$

φ is the generator function of the copula C (see Nelsen (2007) for further details). Clayton, Gumbel and Frank are the most common single parameter members of the Archimedean copula families (Joe, 1997; Nelsen, 2007). The more flexible structure of Archimedean copula allows for different non-zero lower and upper tail dependence coefficients. Table 1 summaries the bivariate elliptical and bivariate Archimedean copulas notions used in this paper and their associated properties. The details of relationship of the parameter(s) presented in Table 1 to Kendall's τ, and dependence coefficients can be found in Joe (1997); Nelsen (2007).

Table 1: Properties and notation of bivariate Elliptical and Archimedean copula families

Family	Name	Generator function, $\varphi(t)$	Parameter range	Kendall's τ range	Tail dependence (lower, upper)
Eliptical	Gaussian	$-$	$\theta > 0$	$\frac{\theta}{\theta+2}$	$(0, 0)$
	t	$-$	$\theta \geq 1$	$1 - \frac{1}{\theta}$	$(0, 2 - 2^{\frac{1}{\theta}})$
Archimedean	Clayton	$\frac{1}{\theta}(t^{-\theta} - 1)$	$\theta > 0$	$\frac{\theta}{\theta+2}$	$(2^{-\frac{1}{\theta}}, 0)$
	Gumbel	$(-\log(t))^{\theta}$	$\theta \geq 1$	$1 - \frac{1}{\theta}$	$(0, 2 - 2^{\frac{1}{\theta}})$
	Frank	$-\log(\frac{e^{-t\theta}-1}{e^{-\theta}-1})$	$\theta \in \mathcal{R} \setminus \{0\}$	$1 - \frac{4}{\theta} + 4\frac{\int_0^{\theta} \frac{c/\theta}{\exp(t)-1} dt}{\theta}$	(0,0)

One of the key features of dependence modeling is that every copula function has a unique behaviour influenced by the tail dependence. Using the tail dependence measures, enables capturing the dependence more locally, rather than globally, in the tails (lower and/or upper) of distributions. The upper and lower tail dependency measures are denoted by λ_U and λ_L, respectively, defined as:

$$\lambda_U = \lim_{\alpha \to 1^-} \frac{1 - 2\alpha + C(\alpha, \alpha)}{1 - \alpha}, \qquad \lambda_L = \lim_{\alpha \to 1} \frac{C(\alpha, \alpha)}{\alpha}. \tag{3}$$

When dealing with bivariate data, such as the problem described in this paper, namely duration and severity of frost, the true copula describing the dependence is always unknown. Hence, tools are required to determine an appropriate bivariate copula family to describe the observed dependence pattern. There are various graphical and analytical methods available to select an appropriate copula for the underlying data. The standard scatter and contour plots are the most common graphical tools which could be useful to perform preliminary investigation on the dependence characterisations between two variables. However, they are not useful to detect tail depen-

dency (Nelsen, 2007). Amongst other graphical methods, Kendall's plot (K-plot) and the chi-plot are more appropriate tool for detecting dependence and to select the best bivariate copula models directly (Genest and Favre, 2007). Genest and Rivest (1993) propose the λ-function method as an alternative graphical tool for understanding bivariate copula dependence. The λ-function is characteristic for each copula family and defined as

$$\lambda(\nu, \theta) = \nu - K(\nu, \theta),$$

where $K(\nu, \theta) = P(C(U_1, U_2|\theta) \leq \nu)$ is Kendall's distribution function for a copula C with parameter(s) $\nu, \theta \in [0, 1]$ and (U_1, U_2) distributed according to C with uniform margins. In addition to the graphical tools, the numerical output of Kendall-τ which is used for K-plot, can be considered as a useful analytical tool. The implementation of these tools will be illustrated in the next section.

For the bivariate data analysis, the independence test is usually the first step, if the strength of dependence, initially realized from the scatter and contour plots appears to be rather small. In this regard, Genest and Favre (2007) propose the use of a simple bivariate independence test based on Kendall's τ. This copula goodness-of-fit test based on Kendall's process for bivariate data are further developed in Genest and Rivest (1993); Clarke (2007) and Belgorodski (2010).

Having selected an appropriate bivariate copula family for given observations, by using the graphical and analytical tools described above, the corresponding copula parameter(s) has/have to be estimated. This can be established by either a method of moments (inversion of Kendall's τ) or maximum likelihood estimation (MLE) (Kojadinovic and Yan, 2011; Joe,

1997). Here and in the sequel, bivariate copula was fitted by use of maximum likelihood (ML) method. When u_i contains data transformed to the unit hypercube by parametric estimates of their marginal cumulative distribution functions, this is known as the Inference Functions for Margins (IFM) method. Through IFM method the estimation procedure is split into two steps. First, the marginal parameters are estimated and second, given the estimates of the marginal parameters, the copula parameters are inferred using the ML method as fully described in the next section. Alternatively, when u contains data transformed by the empirical cdf, this is known as Canonical Maximum Likelihood (CML) and considered as a semi-parametric approach. By utilizing CML the univariate marginals are transformed to uniform distributions using the empirical cdf before estimating the parameters of the copula model using the ML method (Bouyé et al., 2000).

3. Application

3.1. Study area and Datasets

Malayer County with the area of 3210 km^2 is located in Hamadan Province of Iran (Latitude: 34° 17' 48.84" N Longitude: 48° 49' 24.60" E; Figure 1). The area covered by vineyards in Malayer is approximately 10000 hectare and annual grape production in the region is around 180000 tons. High grape yields (22.5 thousand ton/hectare under non trellised training system) is one of the special features of this region in comparison with other parts of the country. Based on published data, 3.5% of Iran's grape production occurs in Malayer County. With 61 raisin production factories, Malayer is one of the most important hubs for raisin production and trade. In fact

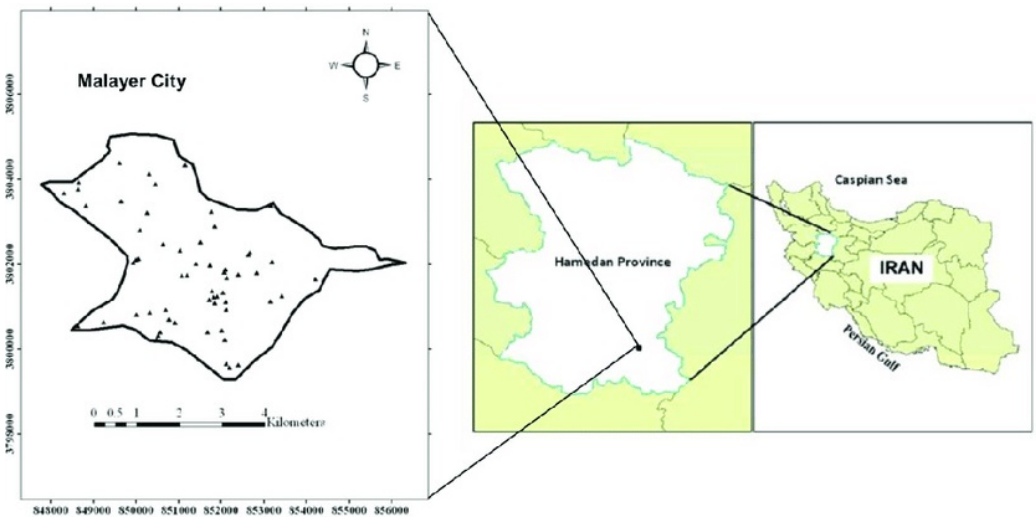

Figure 1: The location of Malayer in Iran.

Malayer produces about 3.86% (28000 ton) of the total raisins export of Iran. 'Sultana' or 'Kishmish Sefid' is one of the most important grape cultivar in Malayer vineyards which cultivated for its valuable raisin and other grape by-products. Malayer has cool and temperate climate. In this area, winter minimal temperatures drops to -23 $°C$ and exceptionally -28 $°C$ for several hours, causing serious damage to vineyards (Karimi, 2019b). Grape growers in Malayer prevent or reduce frost damage in winter and spring by soil covering operation. The postharvest operation in vineyard at which the vines are covered with intra-furrow soil (with moisture around field capacity) in mid-autumn and then brought out in mid-spring (Poling, 2008; Karimi et al., 2014). However, this strategy often increases annual costs of vineyards management and also results in irregular budburst, canes breaking and crown gall disease (grapevine cancer) which subsequently reduced

crop productivity (Karimi, 2017; Karimi et al., 2014). Despite protecting the vines by preventing early budbreak in this way, the new vines taken out from the soil could fall back into the late spring frost which could last over several years. Sometimes these aforementioned methods can be good options to avoid spring frost in the vineyards. Therefore, to facilitate the adoption of the best approach to tackle the common frost problem, probabilistic frost risk assessment and predicting cold return period is crucial for sustainable production of grapes. This paper will investigate frost risk through severity and duration of cold periods as highly influential indicators. Determining and predicting the return period of frost based on these two factors and their dependency structure using the copula function will be considered in the following.

The severity and duration of cold (frost) period is studied using 20 years of meteorological data including 187 data points, recorded by Malayer weather station database, and 188 records of daily minimum temperatures from January 1998 to December 2018, (Figure 2). The definition of chilling and freezing injuries varies in each season for the vineyards. Hence, different temperature thresholds are set depending on the seasons as follows (Karimi, 2019b):

1) 22 October to 5 December (-8°C);

2) 6 December to 1 January (-15°C);

3) 2 January to 4 February ($< -15°C$);

4) 5 February to 20 March ($< -8°C$);

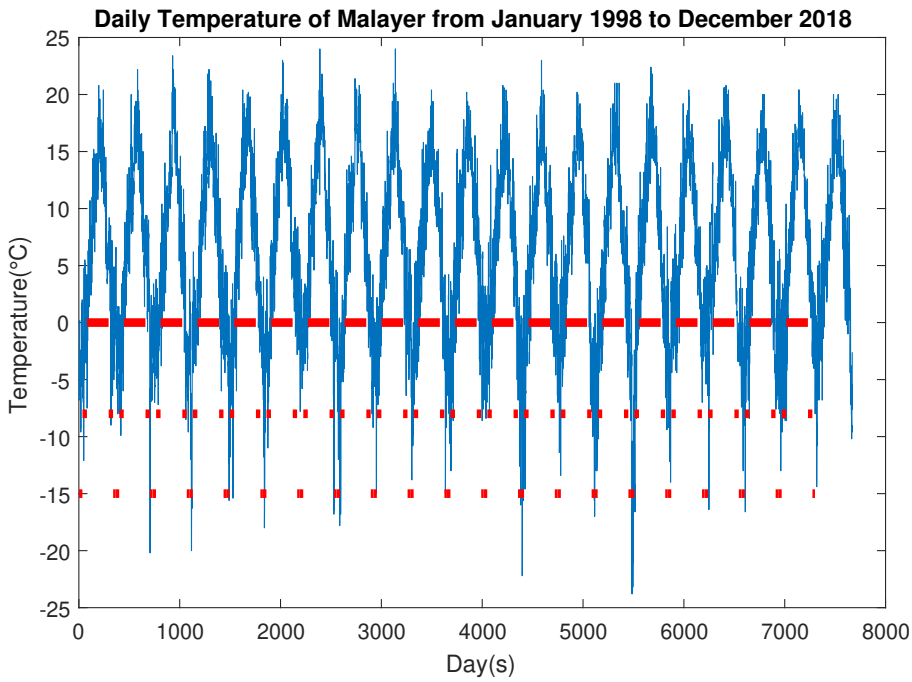

Figure 2: Malayer daily temperature from January 1998 to December 2018. The red lines indicate different temperature thresholds which are set depending on the seasons as suggested in Karimi (2019b).

5) 21 March to 5 May (0 $°C$).

The above classification is key for determining the lethal temperature threshold for different vegetative and reproductive tissues of grapevine plants at different phonological stages from starting to cold acclimation in autumn, entering to full cold acclimation in winter and deacclimation in spring (Karimi, 2019b; Karimi, 2019a). It should be noted that the plant does not complete cold acclimation phase (i.e. failure in periderm formation and also osmoregulant accumulation in buds and permanent tissues) in October to November. At this stage and the Spring, even temperatures near -8$°C$ could be lethal for canes and bud reproductive tissues. However, when plants experienced full cold acclimation during January to February, lower than freezing temperatures such as -15$°C$ to -20$°C$ (depending to grape cultivars) are not damaging and the vines can tolerance such cold episodes without freezing injury.

- The temperature thresholds for each time interval are specified (in red colour) in Figure 2. The number of days in which the daily temperature was below these threshold values at each time interval is defined as Duration (D variable, Figure 3). The absolute value of minimum temperature for each duration is considered as the frost severity (S variable) during that period (Figure 4), given the severity of the cold condition. The absolute value of minimum temperature for each frost event is considered as the frost severity (S variable) during that period. Also, the number of consecutive days that this frost has occurred is defined as D variable. For example, suppose that a cold episode with duration of 10 consecutive days occurred within the period of 21 of March to 5 May (last category), with daily temperatures over this

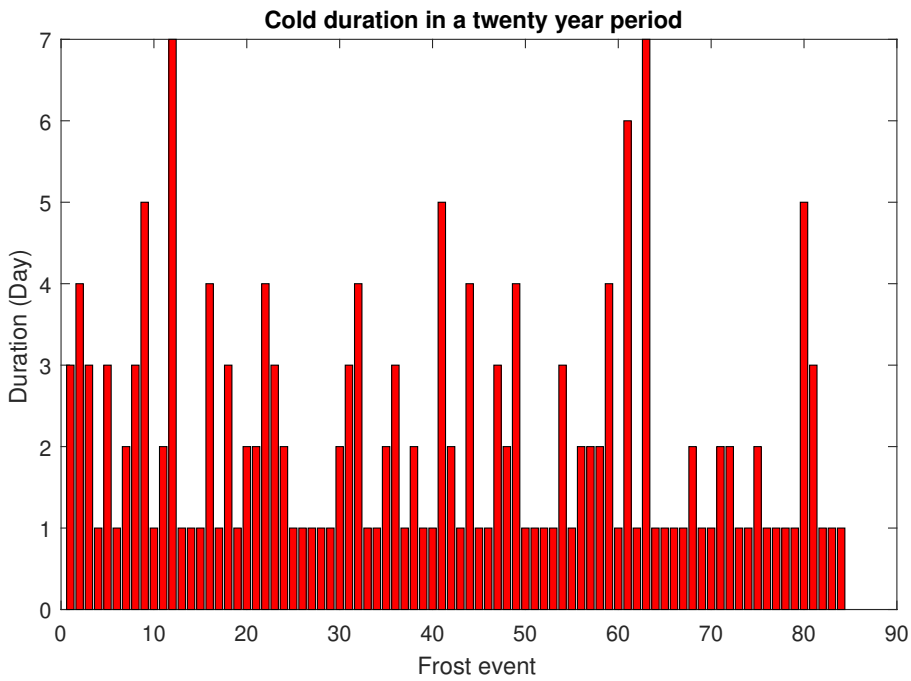

Figure 3: Cold duration from January 1998 to December 2018

cold episode recorded as

$$-2^{\circ}C, -1^{\circ}C, 1^{\circ}C, 1^{\circ}C, 3^{\circ}C, 4^{\circ}C, -4^{\circ}C, -2^{\circ}C, -1^{\circ}C, 2^{\circ}C.$$

According to these recorded daily minimum temperatures, there exist two period of frost based on the pre-specified cold threshold ($0^{\circ}C$). For the first cold period, S and D are 2 (absolute value of minimum temperature) and 2 (number of consecutive days), respectively. For the second cod period in the series above, S and D are 4 and 3, respectively.

Table 2 provides descriptive statistics of the frost event variables (Severity, S; and Duration, D) during the study period. Regardless of the positive or negative sign, the kurtosis coefficients are high. Also, their skewness coef-

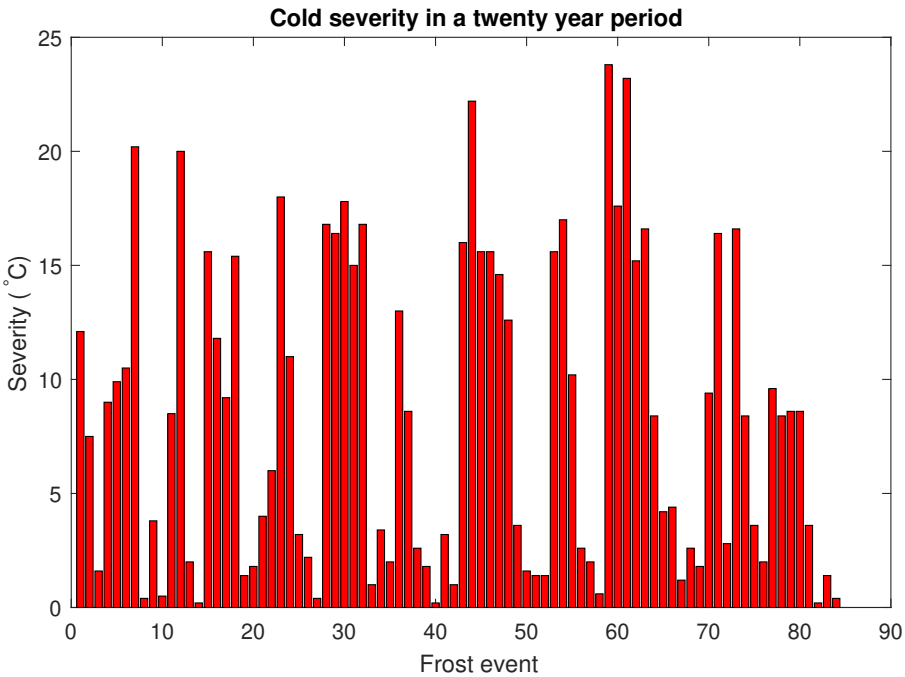

Figure 4: Cold severity from January 1998 to December 2018

Table 2: Summary statistics of the frost event variables.

Variables	Max	Min	Mean	Std	Skewness Cof.	Kurtosis Cof.
Severity	23.8	0.2	8.3	6.8	0.48	-1.05
Duration	7	1	2.05	1.45	1.56	2.2

ficients are positive indicating that these frost variables can be best modeled by non-symmetric heavy tailed distributions. The magnitude of the skewness in the D variable is greater than the S variable.

The numbers of frost events recorded by meteorological data are extracted from the database. In total, 87 frost events are highlighted in the 20 years of the climatic data available for the case study region in Iran. Considering the nature of frost events, the available size of data is usually small which could increase the uncertainty of the statistical models. However, as evidenced by previous studies (Daneshkhah et al. (2016); Bedford et al. (2016)), the multivariate copula model, used in this study, is capable of robust predictions for the cases of data scarcity. For instance, Gaál et al. (2015) successfully conducted bivariate dependence analysis for a relatively small sample size (between 10 to 31 events) of environmental events. Genest et al. (2007) showed meta-elliptical copulas is capable of robust analysis of spring flow hydrology based on a small database consisted of 47 observations. Favre et al. (2004) used a total of 66 observations (consisted of 42 observations of annual peak flow at Chute-des-Passes recorded from 1960 to 2001, and 24 data points from intermediate watershed during 1979 to 2002) for multivariate hydrological frequency analysis using copula models.

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3.2. Modeling marginal distributions

In order to find the best marginal distributions fitted to the frost event variables, we evaluate many non-symmetric heavy tailed distributions as candidate distributions. The best fitted distribution were selected based on the calculated Akaike information criterion (AIC), and the parameters of the fitted marginal distributions are estimated using the maximum likelihood approach. The Nakagami distribution which has the smallest AIC (=513.4) with estimated parameters $\hat{\mu} = 0.4$ and $\hat{\omega} = 114.76$ is the best distribution

fitted to the severity which is defined as follow

$$f(x;\mu,\omega) = \frac{2\mu^{\mu}}{\Gamma(\mu)\omega^{\mu}} x^{2\mu-1} \exp\left(-\frac{\mu}{\omega}x^2\right), \quad \forall x \geq 0.$$

The Nakagami distribution is a probability distribution related to the gamma distribution. The family of Nakagami distributions has two parameters: a shape parameter $\mu \geq 1/2$, and a second parameter controlling spread $\omega > 0$.

The best distribution fitted to the frost duration is Inverse Gaussian with AIC 233.33 and estimated parameters $\hat{\mu} = 2.05$ and $\hat{\lambda} = 4.88$. In probability theory, the Inverse Gaussian distribution is a two-parameter family of continuous probability distribution with probability density function given by:

$$f(x;\mu,\lambda) = \sqrt{\frac{\lambda}{2\pi x^3}} \exp\left(-\frac{\lambda(x-\mu)^2}{2\mu^2 x}\right),$$

for $x > 0$, where $\mu > 0$ is the mean and $\lambda > 0$ is the shape parameter. Figure 5 shows the cumulative distribution functions (CDFs), probability distribution functions (PDFs) and Q-Q plots of the fitted distributions to the data which supports our choices of distributions reported in Table 3.

Table 3: Fitting marginal probability distributions for frost variables

frost variables	Distributions	Estimated parameter	AIC
Severity	**Nakagami**	$\hat{\mu} = 0.4, \hat{\omega} = 114.76$	**513.4**
Duration	**Inverse Gaussian**	$\hat{\mu} = 2.05, \hat{\lambda} = 4.88$	**233.33**

3.3. Bivariate copula models

In this section, the dependencies between the frost event variables with the marginal distributions, derived in the previous section, is modeled by

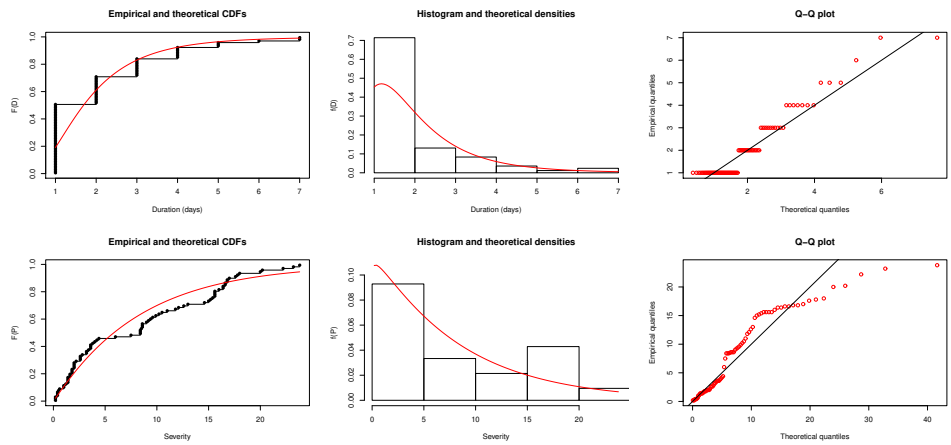

Figure 5: Fitted distributions to the frost variables, Severity (S) and Duration (D). The 1st to 3rd columns illustrate CDFs, PDFs and Q-Q plots for the frost variables, respectively.

fitting a bivariate copula model. The first impression of the dependency structure for the frost event data is given in Figure 6. The figure on the left shows scatter plot, and figure on the right shows the contour plot of D versus S. However, these plots suggest that there could be some degree of association between $(S,\ D)$, but the strength of this association/dependence should be evaluated further using proper statistics and hypothesis testing.

Table 4 shows the estimated Pearson, Kendall-τ and Spearman correlation coefficients between frost event variables (i.e, severity and duration), and their corresponding p-values. These coefficients and p-values indicate that there is a significant association between these two frost event variables. The next step will be thus to fit a proper joint density distribution to these variables, appropriate for risk assessment of frost due to extreme climatic events.

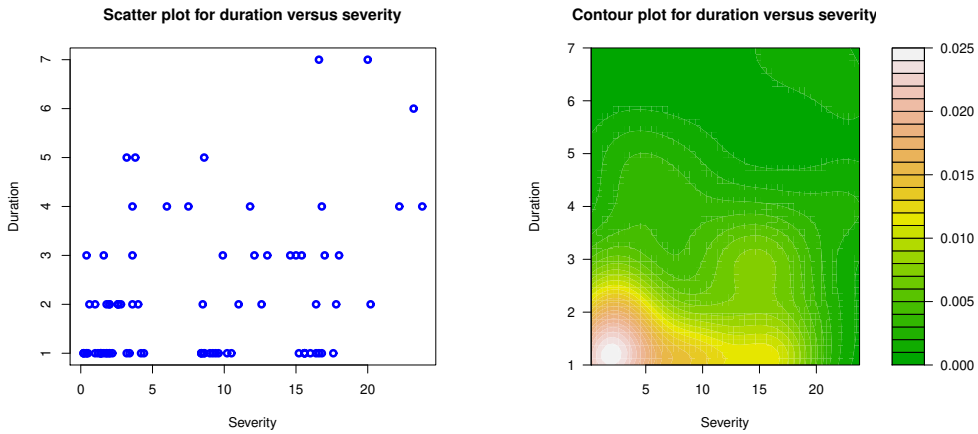

Figure 6: The scatter plot (Left) and contour plot (Right) of the frost data.

Table 4: The correlation coefficients between frost event variables severity and duration.

	Pearson	kendall τ	Spearman
Correlation	0.351	0.241	0.311
Sig.	0.001**	0.004**	0.004**

In this paper, the best fitted bivariate copula model are chosen from the well-known Archimedean and Elliptical family (described in Section 2), using the log-likelihood value and AIC. The values of log-likelihood and AIC associated with the selected copula models are reported in Table 5.

Based on the the lowest AIC value as a goodness of fit metric (Table 5), the Frank Archimedean copula is the most suited of the copulas tested to model the dependencies of the frost variables with the estimated parameter $\hat{\theta}_{SD} = 3.79$. However, while the Frank copula, which has been used for modeling a wide range of data including hydrological data (Chowdhary et al., 2011; Chen et al., 2013;), is generally superior to the other models, it has

Table 5: The results of fitting different bivariate copula functions to the frost data.

Copula Function	Parameter(s)	Log-Likelihood	AIC
Gaussian	0.3155	9.39	-17.86
t-student	0.262 (1.638)	6.52	-9.04
Frank	**3.79**	**102.93**	**-203.86**
Gumbel	1.611	7.53	-13.06
Clayton	1.55	10.23	-18.46

only one parameter and zero tail dependence. The Frank copula is defined as a copula with symmetric tail dependence. The tail dependence measures enable us to capture the dependence more locally, rather than globally, in the tails (lower and/or upper) of distributions. Zero tail dependence, as measures of extremal dependence for estimated Frank copula, means that the variables are asymptotically independent.

The results presented in Table 5 can be further investigated graphically. Figure 7 shows the Kendall's plots (Left panel) and chi-plots (Middle panel) of the variables (S, D) which indicate strong positive dependencies between this pair of variables. Symmetric tail dependence between the frost variables is evident in Figure 7. Based on the properties of the different copula candidates and their corresponding chi and Kendall's plots, we can conclude that Frank copula is the most appropriate for this pair of variables. In addition to these plots, by comparing empirical and theoretical λ-functions, an indication can be given as to which copula family is more suitable to describe the observed dependencies. Figure 7 (right panel), compares the empirical

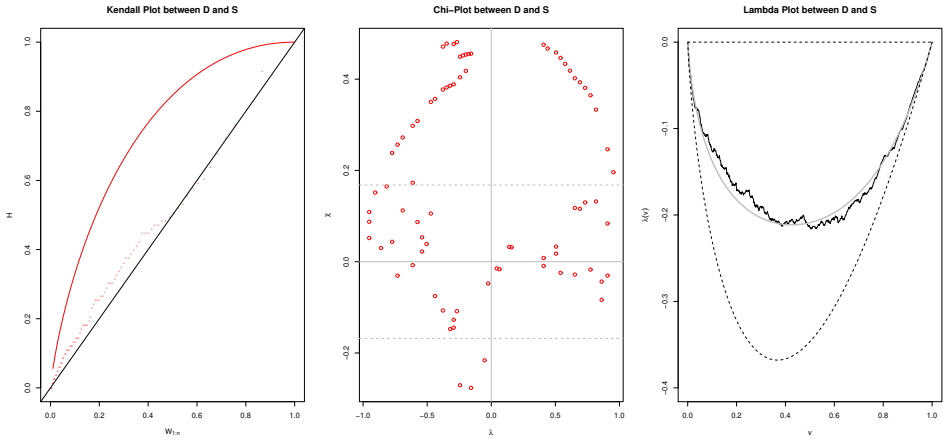

Figure 7: Graphical representation of the Frank copula as the best fitted copula to the data. The left panel shows K-plot, middle panel illustrates the chi-plot, and right panel exhibits the empirical λ-function.

λ-function (black line) and theoretical λ-function of a Frank copula fitted to the pair of variables (S, D) with the estimated parameters (grey line) as well as independence and comonotonicity limits (dashed lines). The similarity of the theoretical λ-function of the suggested copula with the empirical λ-function confirms the robustness of results yielded by using the chi and Kendall's plots.

Furthermore, the scoring test based on the Vuong and Clarke method (Vuong, 1989; Clarke, 2007) strongly tends to select a Frank copula for the pair of variables, (S, D) with the estimated parameter, $\hat{\theta}_{SD} = 3.79$. The same copula models will be chosen if the AIC, log-likelihood, Cramer-von Misses or Kolmogorov-Smirnov test statistics are applied as the goodness-of-fit measures. Frank copula CDF and Frank copula PDF between frost variables S and D can be seen in Figure 8 left and right hand side, respectively.

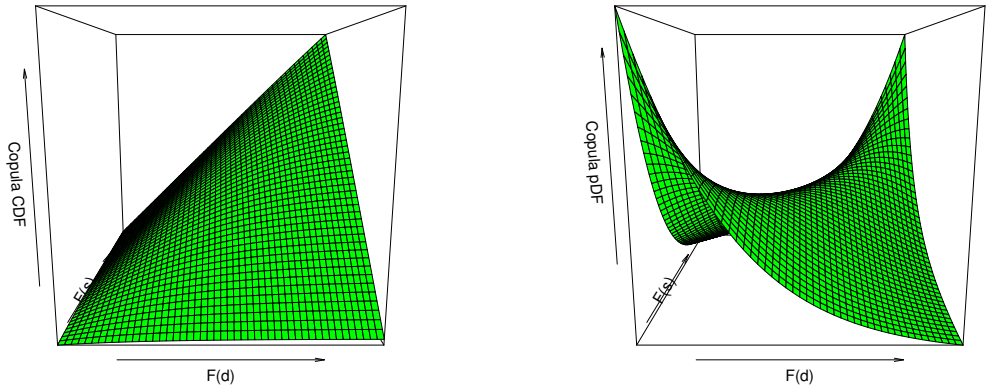

Figure 8: Frank copula CDF (Left) and Frank copula PDF (Right) between frost variables S and D. $F(d)$ and $F(s)$ stand for the CDF of D and S, respectively.

3.4. Validation by Simulation

The simulation of data from the proposed copula model, and comparison between correlations in the simulated data versus the observed data are discussed in this section. The simulation are performed based on sampling from the cumulative distributions. The sampling strategy is as follows: sample two independent variables, distributed uniformly on intervals $[0, 1]$, denoted by U_1, U_2, and calculate values of the original variables using the following equations:

$$x_1 = u_1, \quad x_2 = F_{2|1}^{-1}(u_2 \mid x_1),$$

where x_i is realization values of X_i, and u_i is realization values of U_i.

Figure 9 illustrates the scatter plot of the transformed observed data (+) versus simulated samples of the CDFs of frost variables taken from the fitted

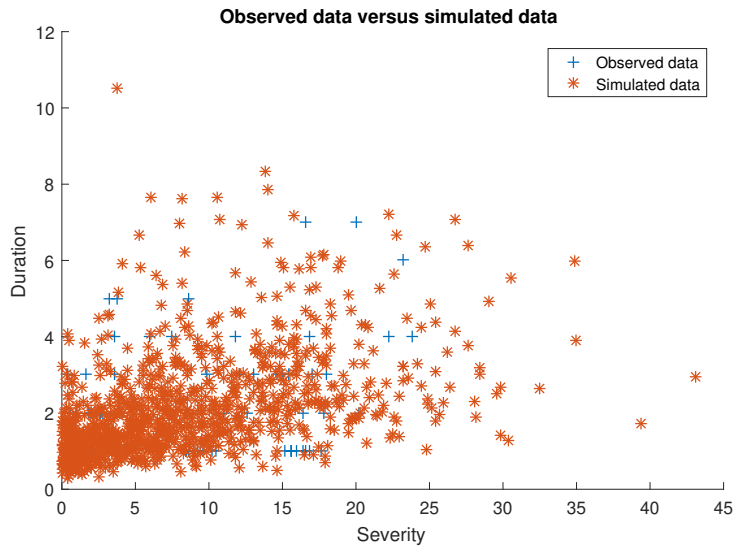

Figure 9: Scatter plots of the transformed observed values versus simulated samples of frost variables from the Frank copula

copula model (∗). The figure shows that the simulated data and the original data have similar dependence patterns. The rank correlations between the pair of the frost variables calculated from the original observed data is 0.311, and based on the simulated data of size 1000 taken from the fitted bivariate Frank copula is 0.303. By comparing these two correlations, it can be concluded that the results show strong consistency and the estimated correlation based on the copula model is closely approximating the observed data.

4. Probabilistic analysis of frost variables

In Malayer vineyards, depending on grapevine cultivars and air temperature means, buds commonly break between late March and early April in the spring. During this period due to cold deacclimation and re-hydration in buds, the newly growing shoot and leaves are very prone to injury due to

cold (Trought et al., 1999; Sgubin et al., 2018; Karimi, 2019b). Therefore, predicting the time of budbreak by using meteorological data can help to improve vineyard management and identify mitigation strategies. Accurate prediction of lethal freezing temperatures during winter is key for protection of vine's permanent tissues (i.e. trunk and 2 year-old canes). Prediction of spring chills are also vital for new growing tissues and reproductive organs of vines, and for prioritizing effective methods for reducing the risk of crop loss and sustainable production in vineyards (Cittadini et al., 2006; Sgubin et al., 2018; Vitasse et al., 2018).

The frequency analysis method is adopted in this study for robust prediction of frost events. The analysis involves understanding the relationship between the magnitude of extreme events to their frequency of occurrence through probability distributions. Traditional statistical approaches deal with such problems using univariate techniques, where the frost return period in the vineyards based on the severity series is determined by:

$$T_S = \frac{1}{1 - F_S(s)} \ ,$$

where $F_S(s)$ is cumulative distribution function. A similar univariate technique for calculating frost return period in the vineyards based on the duration can be described by the following equation:

$$T_D = \frac{1}{1 - F_D(d)} \ ,$$

where $F_D(d)$ is cumulative distribution function of frost duration variable.

While traditional statistical methods can deal with this problem using a univariate technique, the copula method described in this study use multivariate distribution, and evaluate the risk of frost by taking into account

both frost duration and severity as follows

$$T_{D,S} = \frac{1}{1 - F_{D,S}(d,s)} \ ,$$

where $F_{(D,S)}(d,s)$ is joint cumulative distribution function for the frost duration and severity. However, for the bivariate case, in which the $D > d^*$, variables, S, D exceeds their respective thresholds ($S > s^*, D > d^*$), the joint return period is computed using inclusive probability ("OR" and "AND" cases) of all two events, known as primary return periods (Salvadori, 2004). The quantities d^* and s^* denote assumptive and respective thresholds for variables D and S, respectively. The joint primary return period in "OR" case $T^{OR}_{(D,S)}$ (for annual $D > d^*$, analysis) is given by,

$$T^{OR}_{(D,S)}(d^*, s^*) = \frac{1}{P(D \geq d^*, \vee \ \ S \geq s^*)} = \frac{1}{1 - P(D \leq d^*, S \leq s^*)}$$

$$= \frac{1}{1 - F_{D,S}(d^*, s^*)} = \frac{1}{1 - C(u_1, u_2)}$$

where $u_1 = F_D(d^*)$, $u_2 = F_S(s^*)$ and $C(u_1, u_2)$ is a bivariate Frank copula.

The joint primary return period in "AND" case $T^{AND}_{D,S}$ (for annual frost analysis) is defined by,

$$T^{AND}_{(D,S)}(d^*, s^*) = \frac{1}{P(D \geq d^*, S \geq s^*)} =$$

$$\frac{1}{1 - F_D(d^*) - F_V(s^*) + F_{D,S}(d^*, s^*)}$$

$$= \frac{1}{1 - F_D(d^*) - F_S(s^*) + C(u_1, u_2)}$$

where $C(u_1, u_2)$ is bivariate Frank copulas between the CDFs of the $D > d^*$, variables.

This study obtained the frost event return period using univariate marginal distributions of severity and duration; and joint return periods for "AND" and "OR" cases for the proposed fitted Frank copula. Hence, it infers that the occurrence of bivariate frost characteristics simultaneously is less frequent in "AND" case and more frequent in "OR" case.

Figure 10 shows the joint bivariate return periods for the OR and AND cases for the pairs of frost variables. In this figure, the risk of occurrence of high severity and duration for frost event are predicted according to the different years. Ganguli and Reddy (2012) concluded that the joint bivariate return period in "AND" case is greater than the joint bivariate return period in "OR" case. The results shown in Figure 10, reaffirm the findings of Ganguli and Reddy (2012). From the joint bivariate return period in "AND"case illustrated in Figure 10, it can be concluded that if the frost's severity was at -8°C and lasted for 4.5 days, this frost event would be more likely to return in 3 years time. However, from the return period plot for "OR" case, it can be concluded that if the frost's severity was at -25°C or its duration was for 9 days, the similar frost event would be more likely to return in 50 years time.

Furthermore, as discussed in the introduction, spring is one of the seasons where the probabilistic frost risk assessment and predicting frost return period is very important to the vineyard managers, since most frost damage occurs during the spring. This issue is specifically investigated and highlighted in Figure 11. The figure illustrates that the joint bivariate return period in "AND" case is greater than the joint bivariate return period in "OR" case. By the same argument, from the joint bivariate return period in "AND"case illustrated in Figure 11, it can be concluded that if the frost's

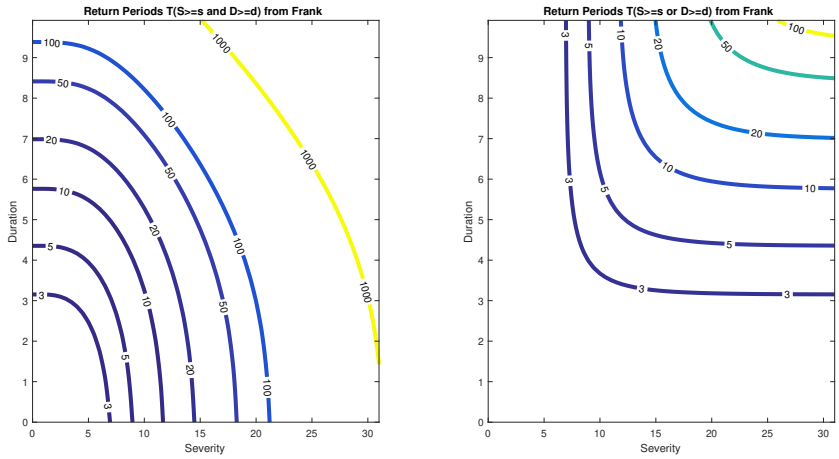

Figure 10: Contour plots for joint return period values (in years) for OR and AND cases for the pairs of frost event variables.

severity was at -7°C and lasted for 1 day in spring, a similar frost event would be more likely to return in 3 years time. However, from the return period plot for "OR" case, it can be concluded that if the frost's severity was at -20°C or its duration was at least 3 days, the similar frost event would be more likely to return in 50 years time in spring time.

The applicability of using 20 years of historical records to make conclusions on the frost return periods of 100 years or even 1,000 years can be argued, given that climate data have non-stationary pattern. However, the copula model described and developed in this paper does not directly rely on the climate data and instead, the model uses produced indicators including 'Severity' and 'Duration' and, computes their non-linear complex interactions and effects on the extreme event (frost for the case of this study) to determine the return periods of 100 or even 1,000 years. Hence, the copula model

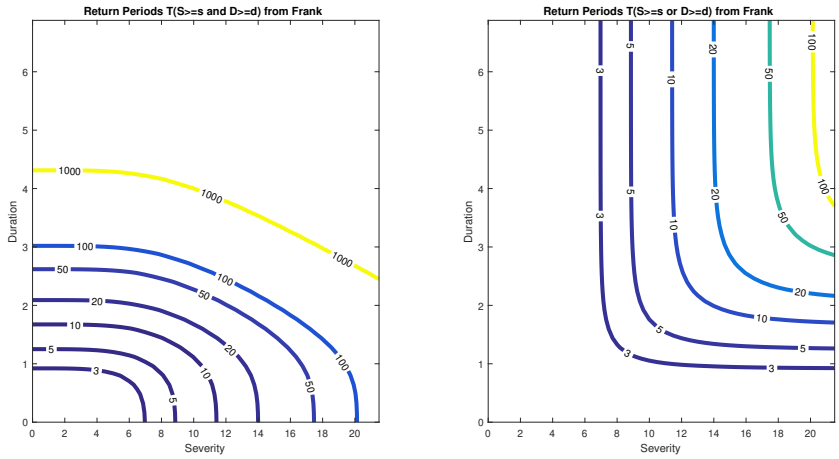

Figure 11: Contour plots for joint return period values (in years) for OR and AND cases for the pairs of frost event variables in spring season.

is an indirect use of climate data according to the yielded indicators which are stationary. The modified Q-statistic and the Lagrange multiplier test was previously done to confirm the appropriateness of the proposed model for limited climatic datasets (see Aas et al. (2009) for further details).

5. Conclusions

This paper developed a probabilistic frost risk assessment and predictive model to facilitate and support design and planning of appropriate mitigation-adaptation strategies to minimize cold damages to vineyards from frost, with a specific focus towards extreme cold events in the spring seasons. The modeling framework described in the paper is applied to over 20 years of meteorological data from Malayer in Iran. Malayer is an internationally recognized hub for sustainable production of grapes and raisins and therefore,

protecting over 10000 hectare vineyards in this region from cold damages is of major socioeconomic importance.

A novel probabilistic frost risk assessment is presented in this study, through modeling the joint distribution between duration and severity of frost; and analyzing their dependency structure using capabilities of copula functions. The dependency structure from meteorological data of frost in Malayer was analyzed. The results of the dependency structure analysis were then used to develop a probabilistic predictive model for determining the return period of frost events in the vineyards of Malayer.

The best bivariate copula to model the joint density of the frost variables was selected. Using a combination of graphical and analytical goodness-of-fit criterion's, the Frank copula model was chosen as the best bivariate copula. The Frank copula model was then employed to analyze the return period of cold in the vineyards. The primary return periods of the frost event data was computed using Frank copulas. Detailed analysis of the results obtained from the model showed robustness of the proposed model in predicting the return period of frost events. The results from predictive model can be used to reduce the likelihood of frost damage by strategies such as pruning in late spring (after budburst) to delay bud break into a period when frosts are less likely to occur.

In addition to assessment of climate-related variables for prediction of vineyards frost, the copula model can be used for evaluating other climate-based risks and hazards such as drought hazard on agricultural systems due to the climate change effects, enabling appropriate mitigating measures to be developed for tackling drought-related crop losses. The copula model can be

used to estimate joint probability distributions between climatic conditions (e.g. drought) and crop yield anomalies of the rainfed crops, such as wheat and barley (see Ribeiro et al. (2019) for further details).

It is evident that the vineyards, in the years with abnormal and harsh freezing temperatures, would experience devastating damages in permanent tissues (i.e. canes, trunks and even root injuries) in winter and reproductive organs damaging in spring in which resulted in significant economic loss to the grapes production industry (Karimi, 2017; Karimi, 2019b). Due to lack of grapes health and yields data, it was not possible to numerically evaluate and connect the grapes health and yields of the vineyards exposed to the frost events over these long-term periods with the meteorological data. The proposed methodology can be easily expanded to construct a model (as proposed in Bedford et al. (2016), and Daneshkhah et al., 2016) by including grapes health and yields to provide the farmers and decision makers with the valid evaluation of association between frost events and grapes health and yields.

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