Copula-based model for rainfall and El-Niño in Banyuwangi, Indonesia

R E Caraka¹², Supari³, M Tahmid³
¹ Department of Statistics, Universitas Padjadjaran, Bandung, Indonesia
² School of Mathematical Sciences, Faculty of Science and Technology, The National University of Malaysia, Bangi, Malaysia
³ Indonesia Agency for Meteorology Climatology and Geophysics (BMKG), Indonesia

E-mail: Rezzyekocaraka@gmail.com

Abstract. Modelling, describing and measuring the structure dependences between different random events is at the very heart of statistics. Therefore, a broad variety of varying dependence concepts has been developed in the past. Most often, practitioners rely only on the linear correlation to describe the degree of dependence between two or more variables; an approach that can lead to quite misleading conclusions as this measure is only capable of capturing linear relationships. Copulas go beyond dependence measures and provide a sound framework for general dependence modelling. This paper will introduce an application of Copula to estimate, understand, and interpret the dependence structure in a given set of data El-Niño in Banyuwangi, Indonesia. In a nutshell, we proved the flexibility of Copulas Archimedean in rainfall modelling and catching phenomena of El Niño in Banyuwangi, East Java, Indonesia. Also, it was found that SST of nino3, nino4, and nino3.4 are most appropriate ENSO indicators in identifying the relationship of El Nino and rainfall.

1. Introduction

Climate is a paradigm of a complex system. Analysing climate data is an exciting challenge. Analysis connects the two other fields climate measurements and climate models. Statistical methods can be used to learn about the evolution of climate See [9]. What’s more, we have a limited amount of data, but we want to know the truth about the climate evolution influenced by noises. Similarly, we can not expect estimate based on data to equal the truth. Alternatively, we can justify the typical size of derivation. Related concepts are confidence intervals or bias. Error bars help to assess estimation results critically, they prevent us from making overstatements, they guide us on our way to enhance the knowledge about the climate. Estimates without error bars are useless. Copulas is a methods of formalizing dependence structures of random Vectors. Although they have been known about for a long time [11] they have been rediscovered relatively and recently in applied sciences (biostatistics, reliability, biology, etc.). Although the concept of copulas is well understood, it is now recognized that their empirical estimation is a harder and trickier task. Many traps and technical difficulties are present, and these are, most of the time, ignored or underestimated by practitioners. The problem is...
that the estimation of copulas usually implies that every marginal distribution of the underlying random vectors must be evaluated and plugged into an estimated multivariate distribution. Such a procedure produces unexpected and unusual effects concerning the usual statistical procedures: non-standard limiting behaviours, noisy estimations, etc.

Copulas is one of robust multivariate statistics methods. Researcher using copula function for modelling between random variables. The word copula appears for the first time (Sklar 1959), Introduced to financial applications [5], widely used in insurance, finance, energy, hydrology, survival analysis, etc. The copula is used to describe the relationship between random variables. Multivariate Copula is the probability distribution for the marginal probability distribution of each variable with a uniform distribution [10]. Theorem Sklar [11] stated that some joint multivariate distribution could be expressed in univariate marginal distribution functions and Copula can describe the structure of connection or relationship multivariate distribution function with marginal distributions. To estimate copula functions, the first issue consists in specifying how to estimate the margins and the common law separately. Moreover, some of these functions can be fully known. Depending on the assumptions made, some quantities have to be estimated parametrically, or semi or even non-parametrically. In the latter case, the practitioner has to choose between the usual statistical methodology of using "empirical counterparts" and invoking smoothing methods well-known in statistics: kernels, wavelets, orthogonal polynomials, nearest neighbors, etc.

Let $F$ represent the joint distribution function (df) of a continuous random vector $X = (X_1, \ldots, X_d) \in \mathbb{R}^d$. Let $F_1, \ldots, F_d$ be their marginal df s and let $X_i \rightarrow F_i(X_i), i = 1, \ldots, d$, be their probability integral transformation to the standard uniform distribution. Then the copula $C$ pertaining to $F$ is defined as

$$C(u_1, \ldots, u_d) = F(F_1^{-1}(u_1), \ldots, F_d^{-1}(u_d)), \forall (u_1, \ldots, u_d) \in (0,1)^d$$

where $F_i^{-1}$ is the quantile function of $F_i, i = 1, \ldots, d$. Thus, the copula is a multivariate distribution with uniform (0,1) margins. The copula $C$ completely specified the distribution $F$ as much as

$$\forall (x_1, \ldots, x_d) = F(x_1, \ldots, x_d) = C(F_1(x_1), \ldots, F_n(x_d))$$

When $F$ is not continuous, there still exists the copula representation of $F$, but it may not be unique anymore. The copula of any $F$ captures and summarizes the dependence between the $X_i$ variables and is invariant under strictly increasing transformation of the $X_i$. By taking partial derivate one, obtains the multivariate density function

$$f(x_1, \ldots, x_d) = c(F_1(x_1), \ldots, F_d(x_d)) \prod_{i=1}^d f_i(x_i)$$

Where $c$ denotes a d-dimensional copula density. Decomposition equation above simplifies the specification of the data underlying multivariate distribution and suggest estimating the marginal distributions $f_i$ separated from the dependence structure given by the d-variate copula. Dependence measures defined only through $C(.)$ or $c(.)$ whose expressions do not involve the margins of $F_i$ or $f_i$ are known as copula based dependence measures.

In this paper, we focus on the practical issues in modeling rainfall and El-Niño southern oscillation (ENSO). El Niño is defined by sea-surface temperature SST in the eastern tropical Pacific, while the Southern Oscillation Index is a measure of the atmospheric circulation response in the Pacific–Indian Ocean region.

2. Literature Preview

2.1 Sklar’s Theorem

Sklar’s theorem elucidates the role that copulas play in the relationship between multivariate distribution functions and their univariate margins.

A distribution function is a function $F$ with domain $\mathbb{R}$ such that

1. $F$ is non-decreasing,
2. $F(-\infty) = 0$ and $F(\infty) = 1$

A joint distribution function is a function $H$ with domain $\mathbb{R}^2$ such that

1. $H$ is 2-increasing.
2. \( H(x, -\infty) = H(-\infty, y) = 0 \) and \( H(\infty, -\infty) = 1 \)

Thus \( H \) is grounded, and because \( \text{Dom } H = \mathbb{R}^2 \), \( H \) has margin \( F \) and \( G \) given by \( F(x) = H(x, \infty) \) and \( G(y) = H(\infty, y) \). \( F \) and \( G \) are distribution functions. Let \( H \) be a joint distribution function with margins \( F \) and \( G \). Then there exists a copula \( C \) such that for all \( x, y \) in \( \mathbb{R}^2 \)

\[
H(x, y) = C(F(x), G(y))
\]

If \( F \) and \( G \) are continuous, then \( C \) is unique. Let \( F \) be a distribution function. Then a quasi-inverse of \( F \) is any function \( F^{(-1)} \) with domain \( I \) such that. If \( t \) is \( \text{Ran} F \), then \( F^{(-1)}(t) \) is any number \( x \) in \( \mathbb{R} \) such that

\[
F(x) = t, \text{ for all } t \text{ in } \text{Ran} F
\]

(5)

If \( F \) is strictly increasing, then it has but a single quasi-inverse, which is of course the ordinary inverse, for which we use the customary notation \( F^{(-1)} \)

and let \( F^{(-1)} \) and \( G^{(-1)} \) be quasi-inverses of \( F \) and \( G \), respectively. Then for any \( (u, v) \) in \( \text{Dom } C' \)

\[
C'(u, v) = H(F^{(-1)}(u), G^{(-1)}(v))
\]

(7)

\[
C(u, v) = \frac{u^v}{u^v + v^v}
\]

(8)

2.2 Families of Copula

There are many families of Copula, some of which are family Copula Archimedean, Copula Ellipse, Copula Bivariate Extreme Value, and Copula Marshall-Olkin. The univariate exponential distribution plays a central role in mathematical statistics because it is the distribution of waiting time in a standard Poisson process. The following bivariate exponential distribution, first described by Marshall and Olkin in [8] plays a similar role in a two-dimensional Poisson process the characteristics of copulas can be seen in Table 1 and Table 2.

The most popular Copula is Archimedean and Ellipse. Among Archimedean copulas, we are going to consider in particular the one parameter ones, choosing the generator, one obtains a subclass or family of Archimedean copulas. Table 1 describes some well-known families and their generators (for a more exhaustive list see [10]. The Gumbel family has been introduced by Gumbel in [7] it is also known as the Gumbel–Hougaard family. The Clayton family was first proposed by [4], and studied by [9]. To end up with, the Frank family, which appeared in [6]. We can see in Table 1 the explanation of each Copulas

| Family | Type | Parameters | \( \lambda_L \) | \( \lambda_U \) | \( C \) | \( C' \) |
|--------|------|------------|-----------------|----------------|--------|--------|
| Gaussian | Elliptical | \(-1 \leq \rho \leq 1\) | 0.0 | 0.0 | \( \rho = -1 \) | \( \rho = 0 \) | \( \rho = +1 \) |
| t-copula | Elliptical | \(-1 \leq \rho \leq +1, v\) | \( \checkmark \) | \( \checkmark \) | \( \rho = -1 \) | - | \( \rho = +1 \) |
| Frank | Archimedean | \(-\infty < \theta < +\infty\) | 0.0 | 0.0 | \( \theta \rightarrow -\infty \) | \( \theta = 0 \) | \( \theta \rightarrow +\infty \) |
| Surv.Clayton | Archim./EV | \( \theta \geq 0\) | 0.0 | \( \checkmark \) | - | \( \theta = 1 \) | \( \theta \rightarrow +\infty \) |
| Gumbel | Archim./EV | \( \theta \geq 1\) | 0.0 | \( \checkmark \) | - | \( \theta = 1 \) | \( \theta \rightarrow +\infty \) |
| BB7 | Archimedean | \( \theta \geq 1, \delta > 0\) | \( \checkmark \) | \( \checkmark \) | - | - | \( \theta \text{ or } \delta \rightarrow \infty \) |

Table 1. Summary characteristics of selected copulas. For the t-copula, \( \lambda_L = \lambda_U = 2t_{\nu+1}(-\sqrt{\nu + 1} - \sqrt{1 - \rho} / \sqrt{1 + \rho} \). The Gumbel copula has \( \lambda_U = 2 - 2^{1/\theta} \). Clayton copula possess \( \lambda_L = 2^{-1/\theta} \). For the BB7 copula, \( \lambda_U = 2 - 2^{1/\theta} \) may be different from \( \lambda_L = 2^{1/\theta} \)

| Copula | Generator \( \phi(u) \) | Copula Bivariante \( C(u_1,u_2) \) |
|--------|----------------|----------------|
| Clayton | \( \frac{u^\theta - 1}{\theta}, \theta \in (0, \infty) \) | \( \left( \frac{1}{u_1^{-\theta} + u_2^{-\theta} - 1} \right)^{\frac{1}{\theta}} \) |
Gumbel \[ (-\log(u))^\theta, \theta \in [1, \infty) \]
\[ \exp\left\{-\left(\frac{(-\log(u))^\theta + (-\log(u_z))^\theta}{\theta}\right)^\frac{1}{\theta}\right\} \]

Frank \[ \log\left(\frac{e^{\theta u} - 1}{e^{\theta z} - 1}\right), \theta \in R \setminus \{0\} \]
\[ \frac{1}{\theta} \log\left(1 + \frac{(e^{\theta u} - 1)(e^{\theta z} - 1)}{(e^{\theta z} - 1)}\right) \]

Every copulas has a different tail-dependencies [1]. Clayton copulas bottom-tail dependencies, Copula Frank, does not have a tail dependencies, while Copula Gumbel has a top-tail dependencies [2]. The Copula each pattern is shown in Figure. 1.

![Copula Patterns](image1.png)

**Figure. 1** Copula (a) Clayton, (b) Frank, and (c) Gumbel

From a statistical point of view, a copula function is a straightforward expression of a multivariate model and, as for most multivariate statistical models, much of the classical statistical inference theory is not applicable. The only theory that can be applied is the asymptotic maximum likelihood estimation (MLE) [3]

\[ f(x_1, x_2, ..., x_n) = c(F_1(x_1), F_2(x_2), ..., F_n(x_n)) \prod_{j=1}^n f_j(x_j) \]  

(9)

where

\[ c(F_1(x_1), F_2(x_2), ..., F_n(x_n)) = \frac{\partial^n c(F_1(x_1), F_2(x_2), ..., F_n(x_n))}{\partial (F_1(x_1)) \partial (F_2(x_2)) ... \partial (F_n(x_n))} \]  

(10)

Is the n th mixed partial derivative of the copula C, c is the copula density and f is the standard univariate probability density function. This canonical representation for the multivariate density function permits us to say that, in general, a statistical modeling problem for copulas could be decomposed into two steps:

- identification of the marginal distributions;
- definition of the appropriate copula function.

This is an important point, to begin with, for estimation issues as we will see below.

Let \( \mathbf{X} = \{x_{1t}, x_{2t}, ..., x_{nt}\} \) be the sample data matrix. Thus, the expression for the log-likelihood function is

\[ l(\theta) = \sum_{t=1}^T \ln c(F_1(x_{1t}), F_2(x_{2t}), ..., F_n(x_{nt})) + \sum_{t=1}^T \ln f_j(x_{jt}) \]  

(11)

Where \( \theta \) is the set of all parameters of both the marginal and the copula. Hence, given a set of marginal probability discrete functions and a copula the previous log-likelihood may be written and by maximization I obtain the MLE estimator

\[ \hat{\theta}_{\text{MLE}} = \max_{\theta \in \Theta} l(\theta) \]  

(12)

Throughout this section, we assume that the usual regularity conditions for asymptotic maximum likelihood theory hold for the multivariate model (i.e., the copula) as well as for all of its margins (i.e., the univariate p.d.f.s). After doing parameter estimation using MLE, then testing Copula parameter estimates to determine the significant parameters. Can be defined as
With $H_0: C = C_0$ and $H_1: C \neq C_0$, follow Archimedean family and $H_1: C_0$ follow another model. Moreover, the distribution becomes $\sqrt{n}Z_n \rightarrow N(0,1)$ standard normal distribution.

Hypotheses used can be defined as follows.

$$H_0: \theta = \theta_0$$
$$H_1: \theta \neq \theta_0$$

Statistical test:

$$z = \frac{\hat{\theta} - \theta_0}{SE(\hat{\theta})}$$

(13)

The null hypothesis is rejected if $|z| > z_{\alpha}$ or $p$-value $< \alpha$

### 3. Simulation and Results

The data used in this research obtained from the Meteorology, Climatology and Geophysics (BMKG Indonesia) and the NOAA National Weather Service, which can be accessed [http://www.cpc.ncep.noaa.gov/](http://www.cpc.ncep.noaa.gov/). Data obtained from BMKG is the rainfall data in Banyuwangi, East Java, Indonesia from 1982-2013. Data from NOAA's National Weather Service is the ENSO indicators data, SST Niño 1+2, SST Niño 3, SST Niño 4 dan SST Niño 3.4. El Niño refers to the periodic warming of the eastern equatorial Pacific Ocean that brings sea surface temperatures above average. Also, El Niño conditions, which can last for a year or two, develop concurrently with atmospheric changes leading to a variety of global effects. Including drier than normal weather in Indonesia and the Philippines, wetter than normal weather for Peru and Ecuador, a warmer than usual winter for much of the United States and above normal precipitation for the southern tier of the United States.

![El Niño Simulation](http://www.cpc.ncep.noaa.gov)

**Figure. 2** El Niño Simulation ([www.cpc.ncep.noaa.gov](http://www.cpc.ncep.noaa.gov))

The formation of an El Niño is linked with the cycling of a Pacific Ocean circulation pattern known as the southern oscillation. In a typical year, a surface low pressure develops in the region of northern Australia and Indonesia and a high-pressure system over the coast of Peru. As a result, the trade winds over the Pacific Ocean move actively from east to west. The easterly flow of the trade winds carries warm surface waters westward, bringing convective storms to Indonesia and coastal Australia. Along the coast of Peru, cold bottom water wells up to the surface to replace the warm water that is pulled to the west. Before analysing must be known the pattern data of rainfall in Banyuwangi. In Figure 31 we can see that the rainfall in Banyuwangi experiencing fluctuating
Rainfall in Banyuwangi showed a high variation in each month and each year. The extreme climate often calls it, the climate is very low to cause flooding until the climate is very high and cause dryness. Based on descriptive statistics found that the maximum value of 1040.00 mm rain in Banyuwangi that occurred in January 1994 and obtained a mean value over 31 years amounted to 203.9 mm.

Indonesia experiences ENSO influences from April on both El Niño (warm phase) and La Niña (cold phase). Although some indications of La Niña impacts exist as soon as March, the signal in March is too weak. The influences of ENSO reach their peaks in August and September by both types of events and decay afterward. By the end of the year, as the Asian monsoon comes, there is no clear signal that ENSO influences still exist. This is in agreement to what is found by Kirono (1999). The global climate during 1997 was affected by one of the most influential Pacific warm episodes on record. These warm episode conditions developed rapidly in March, with high ENSO conditions persisting from May through the end of the year (and subsequently well into 1998). Before the 1980s and 1990s, intense El Niño events occurred on average every 10 to 20 years. In the early 1980s, the first of a series of intense events developed. The El Niño of 1982-83 brought extreme warming to the equatorial Pacific. Surface sea temperatures in some regions of the Pacific Ocean rose 6° Celsius above average. The equatorial Walker circulation is characterized by ascending motion over Indonesia and the western tropical Pacific, and descending motion over the east-central equatorial Pacific, with upper-level westerly (low-level easterly), flow completing the "direct" circulation cell.

| Variable | N      | Mean  | StDev | Variance | Minimum | Median | Maximum | Range  |
|----------|--------|-------|-------|----------|---------|--------|---------|--------|
| SST 1+2  | 384    | 0.0168| 1.1838| 1.4014   | -2.1    | -0.23  | 4.62    | 6.72   |
| SST 3    | 384    | -0.0137| 0.9596| 0.9207   | -2.07   | -0.155| 3.62    | 5.69   |
| SST 4    | 384    | -0.0154| 0.7057| 0.498    | -1.87   | 0.115 | 1.25    | 3.12   |
| SST 3,4  | 384    | -0.021 | 0.9439| 0.8909   | -2.38   | -0.065| 2.79    | 5.17   |
Based on the above table it can be seen that the maximum value of ENSO SST 1+2 was 4.62 which occurred in June 1983 and a minimum of -2.1 which occurred in November 2007. In the variable SST 3 maximum value of 3.62 that occurred in December 1997 and a minimum of -2.07 that occurred in December 1988. Thus, SST 4 maximum value of 1.25 that occurred in November 2009 and a minimum value of -1.87 in November 1988.

SST 3.4 variable maximum value amounted to 2.79 which occurred in January 1983 and a minimum of -2.38 that occurred in November 1988. Analyses were performed with Archimedean Copula approach, using Copula Frank, Clayton and Gumbel for variables that were analysed did not follow a normal distribution. However, for SST 3.4 also use the Gaussian Copula approach, because in testing the normal distribution cannot be concluded whether or not normal based on test Kolmogorov-Smirnov and Anderson-Darling.

| Variables                  | Frank | Clayton | Gumbel | Gaussian |
|----------------------------|-------|---------|--------|----------|
| RF Banyuwangi and SST 1+2 | -0.009| -0.019  | 0.991  | -        |
| P-value                    | 0.723 | 0.721   | -      | -        |
| RF Banyuwangi and SST 3   | -0.104| -0.188  | 0.906  | -        |
| P-value                    | 0.01  | 0.000   | -      | -        |
| RF Banyuwangi and SST 4   | -0.087| -0.160  | 0.920  | -        |
| p-value                    | 0.010 | 0.005   | -      | -        |
| RF Banyuwangi and SST 3.4 | -0.115| -0.206  | 0.897  | -0.116   |
| p-value                    | 0.000 | 0.000   | -0.000 |          |

Description: (·) = do not use the Gaussian Copula
*RF = Rain Fall

Table 5 shows the structure of dependencies between rainfall and ENSO indicators in Banyuwangi. The significant parameters for rainfall and SST Niño 3, SST Niño in Bayuwangi is Frank and Clayton Copula because it has a p-value<α. Parameter Copula Frank, Clayton, and Gaussian rainfall and SST Niño 3.4 in Banyuwangi significantly, the structure of dependencies of each variable follow Copula elected, whereas for rainfall and SST Niño 1 + 2 in Banyuwangi not follow Copula anything, because of p-value>α. Copula Gumbel in Banyuwangi cannot be estimated because of the value of the parameter calculations in Table 3 for Copula Gumbel less than 1. Should the value θ of the Copula Gumbel is θ ∈ [1, ∞).

| Table 5 Fitting Copula using MLE |
|--------------------------|----------------|----------------|
| RF Banyuwangi and SST 3 | Frank | -0.935 | 4,262   |
|                         | Clayton| -0.170 | 5,042   |
| RF Banyuwangi and SST 4 | Clayton| -0.323 | 17,556  |
|                         | Frank  | -0.913 | 4,071   |
| RF Banyuwangi and SST 3.4| Clayton| -0.276 | 14,381  |
|                         | Gaussian| -0.154| 3,542   |

Description: Value in Bold indicates significant at α=0.05 and log-lkelihood italic values showed significant on a α=0.10

Fitting Copula with the MLE (Maximum Likelihood Estimation) is performed for each Copula significant. We are using R software to anlaysis. Moreover, the best model for each pair of variables selected based on the fitting with the largest log-likelihood value and p-value is significant. Estimation shows that the parameter that indicates the close relationship between rainfalls in
Banyuwangi with 3.4 SST follow Clayton Copula. Some points indicate an outlier observation that is far from other observations. Scatterplot analysis in other districts is presented in more detail in Figure 5, Figure 6 and Figure 7.

Figure 5 Scatterplot and Histogram between Lag 1 Rainfall indicator and ENSO in Banyuwangi 1982-2013

Figure 6 Scatterplot and Histogram of Transformation to Uniform [0,1] between Lag 1 Rainfall indicator and ENSO in Banyuwangi 1982-2013

Figure 7 Scatterplot Copula Rank between Lag 1 and Rainfall indicator and ENSO in Banyuwangi 1982-2013

In lag 1 does not form a symmetrical pattern, the distribution pattern has a skewness, especially in rainfall data. The rainfall distribution pattern has the right skewness, indicating that much data (mode) of rainfall is of little value.
Figure. 8 Scatterplot Copula of Random Data (n=5000) between Lag 1 and Rainfall indicator and ENSO in Banyuwangi 1982-2013

Analysis of the relationship rainfall and ENSO indicators have been conducted on rainfall data and indicators of ENSO lag 0, lag 1 and lag 2. It aims to determine whether there are differences in the pattern of the relationship between rainfall and ENSO indicators of the time difference in the two variables. In addition to knowing there may be other factors that influence on the occurrence of rainfall in Banyuwangi, for example, there is the influence of wind, distance, and other factors that may affect the relationship of ENSO and rainfall in Banyuwangi. The results of the identification of patterns of relationships on 0 lag, lag 1 and lag two are shown in Table 4. Identification of relationship rainfall patterns with different time lags in Table 4 shows the difference Copula parameter and log-likelihood value in Banyuwangi. It shows the relationship between the two variables follows different Copula. Then relationship rainfall and SST El Niño 1 + 2 does not follow any Copula, which means SST El Niño 1 + 2 does not have a relationship with rainfall in Banyuwangi. However, for the relationship rainfall and Niño 3.4 SST based on the difference in a time lag, showed the same results on the relationship both follow Clayton Copula. Comparison of the three analyses is also to know at what time lag rainfall in Banyuwangi is closely related to ENSO indicators.

Table 6. Comparison of Parameters Copula on Lag 0, Lag 1 and Lag 2

| Regional  | SST 1+2 | SST 3 | Log-likelihood | SST 4 | Log-likelihood | SST 3.4 | Log-likelihood |
|-----------|---------|-------|----------------|-------|----------------|---------|----------------|
|           |         |       | Estimation     |       | Estimation     |         | Estimation     |
| Banyuwangi| -       | -0.915 | 4,183          | -0.299| 14,769         | -0.247  | 10,547         |
|           |         |        | Lag 0          |       | Lag 1          |         | Lag 2          |
| Banyuwangi| -       | -0.170 | 5,042          | -0.323| 17,556         | -0.276  | 14,381         |
| Banyuwangi| -       | -0.189 | 6,297          | -      | 10,387         | -0.265  | 13,425         |

Description: A = Following Copula Frank (Not Having a Tail Dependency)
B = Following Clayton Copula (Having Tail Dependency)
- = Not Following Copula

Parameter estimation results with the difference in time lag which on lag 0, lag 1 and lags 2 between rainfall and ENSO indicators produces negative parameter values. It shows the relationship between rainfall and indicators of ENSO is reversed, i.e. in case of El Niño in the Pacific Ocean, the rainfall in Banyuwangi will decline could even lead to the occurrence of drought, and vice versa in case of La Nina, the rainfall will increase and could lead to flooding. Table 4 shows the relationship most strictly based on the lag time 1. This means that the ENSO events in the Pacific Ocean will affect rainfall next month. Also, scatterplot copula rank among lag 1 rainfall and ENSO indicators more amorphous than scatterplot Copula another rank. In addition, it can be concluded that the El Niño 3.4 SST is most
appropriately used in identifying the relationship of precipitation and ENSO indicators the lag 1 because it has the largest log-likelihood.

4. Conclusion
In this paper the possibility of analysing the copula family of the rainfall and El Niño has been demonstrated. Copulas Archimedean has already proven their flexibility in rainfall modeling and catching phenomena of El Niño in Banyuwangi, East Java, Indonesia. It can be concluded that 1997-98 El Niño is among the most reliable recorded and low rainfall in Indonesia. The relationship rainfall and SST El Niño 1 + 2 does not follow any Copula, which means SST El Niño 1 + 2 does not have a relationship with rainfall in Banyuwangi. ENSO indicators are most appropriate in identifying the relationship with rainfall is El Niño SST 3.4, SST 3 and SST 4. In general, the drought caused by climate anomalies and human activities. Prolonged drought that caused frequent droughts due to climate anomalies such as El Niño.

Acknowledgments
This research was supported by Department of Statistics, Universitas Padjadjaran, School of Mathematical Sciences, Faculty of Science and Technology, The National University of Malaysia, Bangi, Malaysia, Indonesia Agency for Meteorology Climatology and Geophysics (BMKG), Indonesia.

References
[1] Caraka R E, Haryono S, Hasbi Y, and Brilian W U 2018 Exploratory MATLAB Software The Step Construction of Copula Gaussian Multivariate (America: Institute of Physics)
[2] Caraka R E, Hasbi Y, Sugiyarto W, Sugiaro, and Ismail K M 2016 Time Series Analysis Using Copula Gauss And Ar(1)-N.Garch(1,1) MEDIA STATISTIKA 01–13
[3] Cherubini, Umberto, Luciano E, and Vecchiato W 2013 Copula Methods in Finance (America: Institute of Physics)
[4] Clayton D G 1978 A Model for Association in Bivariate Life Tables and Its Application in Epidemiological Studies of Familial Tendency in Chronic Disease Incidence Biometrika 65(1) 141–51
[5] Embrechts, Paul, Lindskog F and Mcneil A 2003 Modelling Dependence with Copulas and Applications to Risk Management (Elsevier: Handbook of Heavy Tailed Distributions in Finance)
[6] Frank M J 1978 On the Simultaneous Associativity of F(x, Y) and X + Y - F(x, Y) Aequationes Mathematicae 18(1–2) 266–67
[7] Heo J H and Salas J D 1996 Estimation of Quantiles and Confidence Intervals for the Log-Gumbel Distribution Stochastic Hydrology and Hydraulics 10(3) 187–207
[8] Haijun L 2008 Tail Dependence Comparison of Survival Marshall-Olkin Copulas Methodology and Computing in Applied Probability 10(1) 39–54
[9] David O 1982 A Model for Association in Bivariate Survival Data Journal of the Royal Statistical Society. Series B (Methodological) 44(3) 414–22
[10] Bill R and Nelsen R B 2000 An Introduction to Copulas Technometrics 42(3) 317
[11] Sklar A 1959 Fonctions de Répartition À N Dimensions et Leurs Marges Publ. Inst. Statist. Univ. Paris 8 229–231