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Research Paper

A copula-based joint return period approach to characterising extreme rainfall in West Java

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ABSTRACT

Climate change presents recurring challenges in understanding extreme weather events, particularly the persistence of dry and wet periods. West Java is among the region's most vulnerable to such rainfall variability. This study analyses the relationship between consecutive dry days (CDD) and consecutive wet days (CWD). It estimates joint return periods (JRP) using a copula-based approach to assess the spatial characteristics of climate extremes in West Java. Marginal distributions were fitted for each indicator, followed by copula modelling using the Inference Function for Margins method and model selection based on the Akaike's information criterion (AIC). The inverse Gaussian (ING) distribution was most suitable for CDD, while the generalised extreme value (GEV) distribution best represented CWD. We found that the Gaussian and Frank copulas best captured the overall dependence structure between CDD and CWD. JRP analysis showed that simultaneous extremes (AND scheme) were significantly rarer than single-variable extremes (OR scheme). These findings provide valuable input for identifying high-risk areas and developing more locally adaptive climate risk mitigation strategies.

Keyword: Consecutive dry days, Consecutive wet days, Copula, Joint return period, Rainfall, West Java

Global climate change significantly impacts climate patterns in specific regions worldwide, including Indonesia (Arnell *et al.,* 2019). The uncertainty in rainfall patterns is one of the most widely felt impacts of climate change in Indonesia, particularly in West Java. The region's complex topography and dense population further exacerbate the seriousness of changes in rainfall patterns (Sambou *et al.,* 2020). Similar findings have also been reported in Shiraz, Iran, where climate change was shown to influence extreme rainfall characteristics (Roshan *et al.,* 2019). In light of this, an in-depth analysis of rainfall patterns is essential for planning effective disaster risk mitigation and climate change adaptation strategies. Brown *et al.,* (2010) stated that analysing several climate indices, including consecutive dry days (CDD), helps better understand rainfall patterns. Previous studies by Nainggolan *et al.,* (2020) have examined drought characteristics using CDD as one of the climate indicators. However, CDD focuses solely on dry day patterns and ignores wet day occurrences. This results in a limited understanding of rainfall patterns occurring between dry spells. To fill this gap, consecutive wet days (CWD) is a relevant indicator that can be used (Beis *et al.,* 2022).

The bivariate copula method is a practical approach to examining the dependence between climate indicators (Abraj and Hewaarachchi, 2021). This approach is the foundation for analysing this study's joint return period (JRP). This study uses JRP analysis to characterise extreme rainfall events based on CDD and CWD through a copula-based approach. The JRP analysis is used to characterise extreme rainfall events based on both CDD and CWD using a copula-based approach (Vandenberghe *et al.,* 2012). Beis *et al.,* (2022) previously investigated the univariate use of CDD and CWD indicators in Kupang City. However, univariate analysis of extreme rainfall is generally limited to individual climate indicators, thus overlooking their dependency (Najib *et al.,* 2022). Bivariate copula-based JRP analysis has been conducted by Miao *et al.,* (2016), though their study only employed five copula functions: Frank, Gaussian, t-Student, and Gumbel copulas. Two additional copulas (Joe and Galambos) are introduced to address the limitations of previous models in capturing upper tail dependence. Joe copula offers a stronger and more flexible detection of upper tail dependence compared to Gumbel, while Galambos copula addresses dependency structures not captured by either Gumbel or

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Clayton copulas (Nelsen, 2006; Rahmatabadi *et al.,* 2023).

Previous research shows that bivariate copula-based JRP analysis for characterising extreme rainfall remains limited regarding copula function application and the development of advanced analyses. Therefore, this study aims to determine the most appropriate copula function for analysing extreme rainfall characteristics by calculating the JRP between CDD and CWD.

MATERIALS AND METHODS

Study location

This study focuses on the West Java Province, covering an area of approximately 34,817 km². Maps show West Java extending from 5°50' to 7°50' South Latitude (S) and from 106°24' to 108°48' East Longitude (E). West Java experiences a varied climate due to its diverse topography, ranging from mountains to coastal areas. This study uses data obtained from ERA5-Land. ERA5-Land is a global weather reanalysis dataset developed by the European Centre for Medium-Range Weather Forecasts (ECMWF) through the Copernicus Climate Change Service (C3S) project. This dataset provides historical weather and climate information based on weather observations (such as satellite observations, weather station data, and ocean data) and complex atmospheric models.

Data extraction

We performed data extraction on the collected dataset. Specifically, annual CDD and CWD values were derived from hourly precipitation data of ERA5-Land. The extraction process involved reading the data from the Network Common Data Format (NetCDF) into matrix form, converting the total precipitation variable into millimeters (mm), aggregating the hourly data into daily data, identifying daily precipitation events, and transforming the dry day data into annual CDD values and the wet day data into annual CWD values.

Distribution fitting

We conducted distribution fitting to determine the most appropriate probability distribution for each annual CDD and CWD dataset at every grid point in the selected areas, namely West Java. We identified the best-fitting distributions by comparing the empirical histograms of the data with the theoretical curves of seven candidate distributions: Generalised Extreme Value (GEV), Exponential (EXP), Gamma (GAM), Inverse Gaussian (ING), Log-Logistic (LL), Lognormal (LN), and Weibull (WB). The Anderson-Darling hypothesis test begins by stating that the null hypothesis (is that the data follows the selected distribution with the test statistic)

$$A^2 = -\left(\sum_{t=1}^{N}\frac{(2t-1)}{N}\left[\ln F\left(x^{(t)}\right) + \ln\left(1 - F\left(x^{(n+1-t)}\right)\right)\right]\right) - N, \qquad (1)$$

for the values of the sorted sample (Anderson, 2010). Estimate the parameters of each distribution () using the distribution estimator in the equation

$$\alpha_i = \arg\max_{\alpha} \ln \prod_{t=1}^{N} f_i\left(x_i^{(t)}; \alpha_i\right) = \arg\max_{\alpha} \sum_{t=1}^{N} \ln f_i\left(x_i^{(t)}; \alpha_i\right), \qquad (2)$$

where α_i is an estimate of the parameter α and f_i is a probability distribution function (PDF) of the variable X_i (Millar, 2011)

After selecting the best distribution function, we calculated the cumulative distribution function (CDF) for each best-fit distribution based on the annual CDD and CWD data. The definition of CDF from a continuous random variable to is

$$F(x) = P(X \le x) = \int_{-\infty}^{x} f(t)\,dt, \qquad \text{for } -\infty < x < \infty, \qquad (3)$$

where *F(x)* F is defined as a continuous CDF, *f(t)* is the PDF of *X* at the point (Walpole *et al.,* 1995). CDF measures the chances of each data point being smaller or equal to a specific value. In this step, we computed the CDF values based on the best-fit CDD and CWD distributions for all grid points in West Java.

Copula fitting

Copula fitting was performed to identify the best bivariate copula function for the combined two climate indicators (CDD and CWD) and derive values from the copula or joint CDF. The bivariate copula functions used are Gaussian, t-student, Clayton, Gumbel, Frank, Joe, and Galambos. In a bivariate copula, the variable has a marginal distribution function, i.e. (F_1, F_2).. After obtaining the marginal distribution function from the previous step, the original data is transformed using an equation $U_1=F_1(X_1)$ and $U_2=F_2(X_2)$, which is called a probability transformation. Using the CDF of each climate indicator (CDD and CWD), we transformed the data into variables the data into variables with a uniform (0,1) distribution, denoted as (U_1, U_2). The value of the copula parameter is estimated using the equation

$$\hat{\theta} = \arg\max_{\theta} \sum_{t=1}^{N} \ln c_{\boldsymbol{X}}\left(F_1\left(x_1^{(t)}; \hat{\alpha}_1\right), F_2\left(x_2^{(t)}; \hat{\alpha}_2\right); \theta\right), \qquad (4)$$

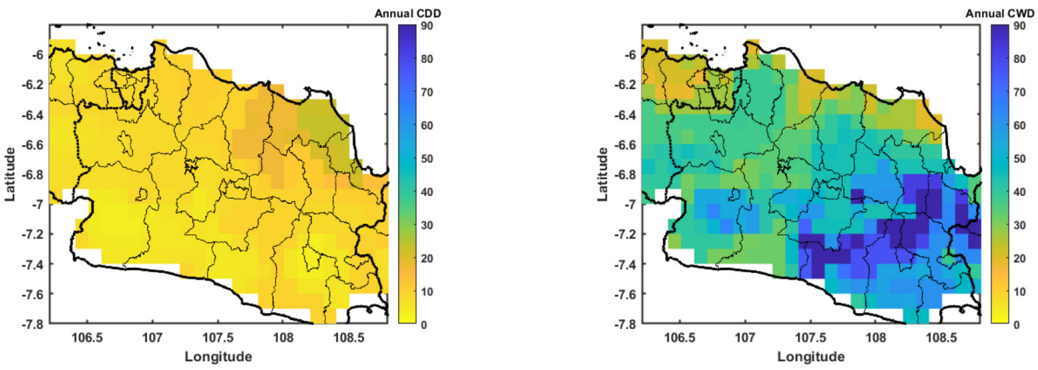
where $\hat{\theta}$ is an estimate of the copula parameter θ and c_x is a PDF of the copula (Wei *et al.,* 2020). After that, the copula C_x distribution function is identified based on one of the statistical values, such as Akaike's information criterion (AIC), using

$$AIC = 2k - 2\ lnL, \qquad (5)$$

where *k* is the number of parameters in the distribution function and *L* is the value of the likelihood of the distribution function (Grasa, 1989). The chosen copula model is the one with the lowest AIC value.

Joint return period calculation and analysis

Joint return period (JRP) is the average time between the combined events of two (or more) extreme variables that exceed a certain threshold (Vandenberghe *et al.,* 2012). At this stage, we calculated the JRP using percentile thresholds of 75%, 90%, and 95%, applying OR and AND schemes. The OR scheme, or mathematically, can be written "", represents at least one between CDD and CWD with multiple thresholds applied simultaneously. The AND scheme, or mathematically. can be written "$X_1 \cup X_2$". represents CDD as X_1 and CWD as X_2, with multiple thresholds applied simultaneously. Equations (6) and (7) present the two schemes.



(a) (b)

Fig. 1: Spatial distribution of annual (a) CDD and (b) CWD values in West Java Province (2022)

$$T^{OR}_{X_1,X_2}(x_1,x_2) = \frac{1}{1 - C_{X_1,X_2}\left[F_{X_1}(x_1), F_{X_2}(x_2)\right]} \tag{6}$$

$$T^{OR}_{X_1,X_2}(x_1,x_2) = \frac{1}{1 - C_{X_1,X_2}\left[F_{X_1}(x_1), F_{X_2}(x_2)\right]} \tag{7}$$

where Fx_1 is the CDF of X_1, Fx_2 is the CDF of X_2, the function Cx_1, x_2 is a copula function that connects the bivariate distribution Fx to its univariate distribution Fi for i=1,2 (Salvadori *et al.,* 2011).

RESULTS AND DISCUSSION

Data extraction

This study carried out data extraction through three main stages. First, convert the data per hour into daily data. Second, identifying the presence of dry days (dd) for CDD data and wet days (wd) for CWD data. Lastly, convert the dd data to annual CDD and the wd data to annual CWD. Fig. 1 and Fig. 2 below illustrates the results of the data extraction.

As shown in Fig. 1a, most areas of West Java experienced relatively low CDD values in 2022. In contrast, Fig. 1b reveals a more diverse range of CWD values across West Java. For instance, one grid point in Indramayu Regency recorded a CDD of 34 days and a CWD of 26 days. This condition suggests the simultaneous potential for both prolonged dry spells and extreme wet periods at the same location. Such conditions may disrupt cropping cycles, increase the risk of flooding and soil erosion, and underscore the urgent need to adapt infrastructure and health systems to cope with extreme weather events.

Distribution fitting

In this stage, we separately identified the most suitable distribution for CDD and CWD data. We applied the procedure described in the methodology section for distribution fitting. After completing the distribution fitting for each point, we summarised the results in a bar graph (Fig. 2), which displays the number of observation locations where each of the seven candidate distributions best fit the annual CDD data.

Based on Fig. 2 the distribution fitting results for the CDD and CWD indicators in West Java reveal a noticeable difference in their statistical characteristics. The ING distribution fits most of the CDD data, indicating that consecutive dry days in the majority of the areas tend to have a right-skewed and narrow distribution. In contrast, the GEV distribution fits most of the CWD data, suggesting that consecutive wet days exhibit more complex extreme behaviour with a broader spread.

Copula fitting

Following the selection of the best-fit distributions for annual CDD and CWD data, we identified the most appropriate bivariate copula model for each grid point across West Java. This identification aims to describe and analyze the shared distribution between CDD and CWD by looking at the dependencies between the two using the bivariate copula function approach. We estimated the copula parameters using the Inference Function for Margins (IFM) method. Based on the results of univariate distribution fitting for each climate indicator, we calculated the cumulative distribution function (CDF) for each variable. The CDF results then serve as inputs to combine the univariate distributions into a copula function. The second step of the IFM method is to estimate the parameters of the copula function using a bivariate copula estimator (equation 2). We applied the same copula fitting procedures to each grid point across the West Java region, as described in the methodology section on copula fitting. A summary of the copula fitting results is presented in Fig. 3. In most areas of West Java, the Gaussian and Frank copulas dominate as the best-fitting dependence models for describing the relationship between CDD and CWD. As shown in Fig. 3, the Gaussian copula is the most frequently selected, followed by the Frank copula. Both belong to symmetric copulas without tail dependence, indicating that the dependence between CDD and CWD across most of West Java is moderate (not too weak or too strong).

Joint return period analysis

The following analysis focuses on extreme rainfall characteristics in West Java through copula-based JRP calculations. There are two schemes applied to the JRP calculation, namely the OR and AND schemes. There are two schemes applied to the JRP calculation, namely the OR and AND schemes. JRP calculation is carried out by using the threshold values obtained by taking 75%, 90%, and 95% of the overall data of each indicator. Based on this, each limit of 75%, 90%, and 95% of the annual CDD has a limit

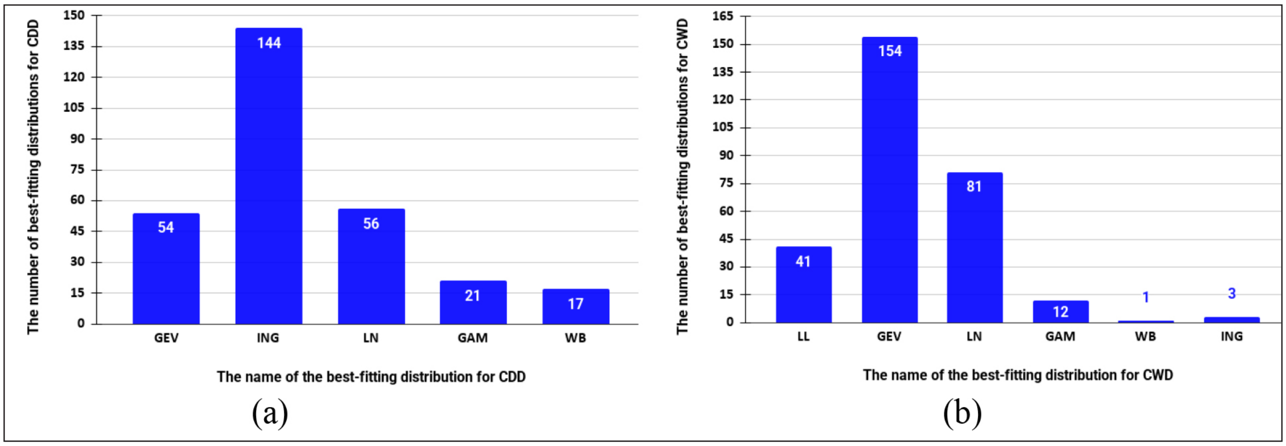


Fig. 2: Distribution fitting results for (a) CDD and (b) CWD in West Java

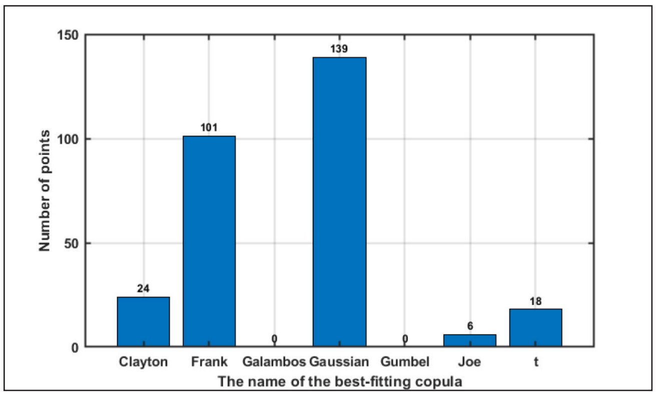


Fig. 3: Copula fitting results in the West Java region

value of 30, 53, and 74, respectively. The cut-off values for CWD were 81, 109, and 121, respectively. The JRP calculation uses equations (3) and (4). Based on this, Fig. 4 presents the results of the JRP calculation for the OR scheme.

The analysis of the JRP of the OR scheme (Fig. 4) shows that the higher the threshold used, the longer the JRP value and the more pronounced the spatial variation. At the threshold of 75% (Fig. 4a), most of West Java appears bright yellow, which indicates a low JRP value due to the high frequency of 30-day > CDD or 81-day > CWD that occurs almost every year. At the 90% threshold (Fig. 4b), the dominance of orange indicates that extreme events are less frequent, so the JRP value increases in general. At the 95% threshold (Fig. 4c), spatial variation is increasingly visible with various colours from yellow to green. The dark green reflects a very long JRP value, signalling that extreme events are rare.

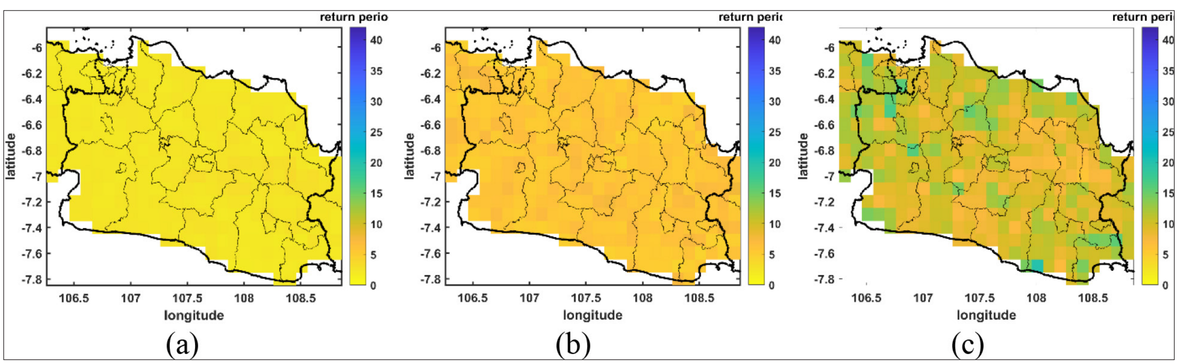


Fig. 4: Spatial JRP (OR) at (a) 75%, (b) 90%, (c) 95% threshold – West Java

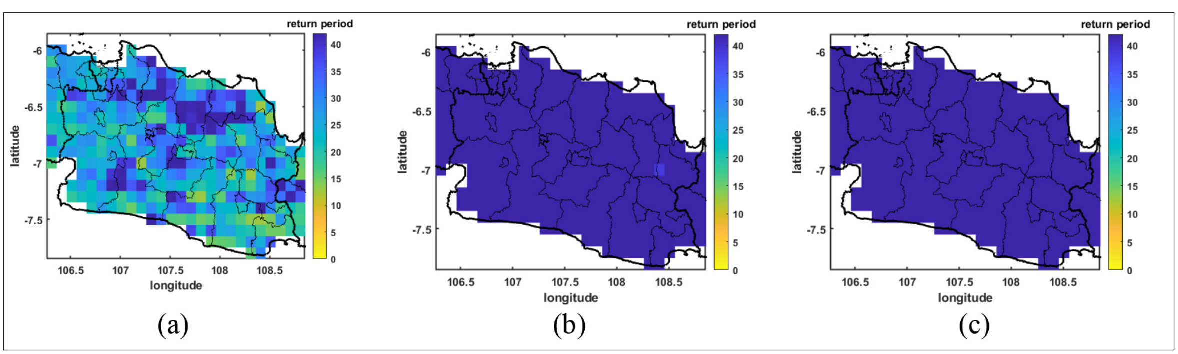


Fig. 5: Spatial JRP (AND) at (a) 75%, (b) 90%, and (c) 95% threshold – West Java

An overall increase in threshold values leads to an increase in the JRP values and highlights the influence of local climatic conditions on the spatial distribution of extreme events. Fig. 5 presents the JRP results under the AND scheme, which only records extreme events when both CDD and CWD simultaneously exceed the specified thresholds.

Unlike the OR scheme (Fig. 5), JRP in the AND scheme defines an extreme event as a condition in which both CDD and CWD simultaneously exceed specific threshold values (Fig. 5). The AND scheme produces extreme events much less frequently (Fig. 5). Fig. 5a displays a blue-green hue, indicating a relatively long and fairly variable JRP, which exceeds 13 years. The combination of extreme CDD and CWD events is complex to occur within a single year, leading to such long return periods. Fig. 5b and 5c reveal show that dark blue dominates the entire region, reflecting very long JRP values and indicating that extreme events involving both CDD and CWD rarely occur. The findings align with Miao *et al.,* (2016), who stated that the probability of simultaneous extreme CDD and CWD events is relatively low. Overall, the AND scheme generates significantly higher JRP values than the OR scheme, confirming that simultaneous extreme events involving consecutive dry days (CDD) and consecutive wet days (CWD) are rare in West Java. In contrast, separate extreme events occur more frequently.

CONCLUSION

Among the seven copula functions tested, the Gaussian and Frank copulas emerged as the best models for capturing the relationship between CDD and CWD across most areas of West Java, characterised by symmetrical and moderate dependence. In several specific locations, however, Joe, Clayton, and t-Student copulas provided a better fit for representing extreme upper-tail dependence. The JRP calculations using the OR scheme indicate that either CDD or CWD extreme events frequently occur, whereas the AND scheme reveals that simultaneous occurrences of both extremes are rare. Moreover, the spatial distribution of JRP values across West Java exhibits significant regional variation, highlighting differing levels of vulnerability to extreme events. These findings offer valuable insights for developing climate-based disaster risk adaptation and mitigation strategies, particularly in response to increasingly complex extreme weather patterns caused by climate change.

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Authors contribution: **A. Nabila:** Designing the study, preprocessing the dataset, analysing the result, and writing the manuscript; **S. Nurdiati:** Supervising mathematical aspects, proofreading, and final corrections to the manuscript; **IG. Purnaba**: Supervising mathematical aspects, proofreading, and final corrections to the manuscript; **MK. Najib:** Designing the study, analysing the results, and writing the manuscript.

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