doi: 10.37905/jgeosrev.v8i1.32484 ejurnal.ung.ac.id/index.php/jgeosrev

Vol. 8, No. 1, January 2026: 30-40

Jambura Geoscience Review

p-ISSN 2623-0682 | e-ISSN 2656-0380

Department of Earth Science and Technology, Universitas Negeri Gorontalo

Analysis of Drought Characteristics in West Java Based on Return Period of Consecutive Dry Days

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ARTICLE INFO

Article history:
Received: 7 June 2025
Accepted: 8 December 2025
Published: 15 January 2026

Keywords:
Consecutive dry days;
Drought; Return period

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ABSTRACT

Drought is one of the climate change phenomena that must be faced every year in some regions in Indonesia. West Java is a region that often experiences drought in Indonesia. Prolonged droughts are routinely experienced in some areas of West Java, while shorter periods of drought occur between rainfall events in several other regions of West Java. The characteristics of drought in West Java can be analyzed using one of the climate indicators, Consecutive Dry Days (CDD), based on the calculation of the return period of the climate indicator. Therefore, this study aims to analyze the characteristics of drought in West Java based on the calculation of the return period of the parametric distribution function by the CDD. Graph comparison and the Anderson-Darling test were used to estimate the parametric distribution function. Hourly ERA5-Land precipitation (1981–2022) was aggregated to daily totals; annual CDD was defined as the longest run of days with rainfall <1 mm, and return periods were computed using cut-off levels at the 75%, 85%, and 95% quantiles of the regional CDD distribution to map recurrence potential across cities and regencies. Based on the study's results, most of the CDD data in the West Java region have the fittest parametric distribution, namely the inverse Gaussian distribution, followed by the generalized extreme values, Weibull, and lognormal distributions. Further return period analysis shows that the area with the shortest return period to drought so that extreme drought often occurs, is the Indramayu Regency area. In that case, the areas with the longest drought return period are Bogor Regency, Bogor City, and Tasikmalaya City. These findings provide a distribution-based quantification of spatial drought recurrence in West Java to support early-warning and water-resources planning.

How to cite: Nabila, A. (2026). Analysis of Drought Characteristics in West Java Based on Return Period of Consecutive Dry Days. *Jambura Geoscience Review, 8*(1), 30-40. https://doi.org/10.37905/jgeosrev.v8i1.32484

1. INTRODUCTION

Drought is one of the phenomena of climate change in Indonesia. Drought is a severe problem in most regions of Indonesia that must be faced every year, especially on the island of Java. This condition significantly affects the agricultural and economic sectors, considering that Java Island is one of Indonesia's leading producers of agricultural commodities. One of the areas that often experiences extreme drought is found in West Java Province. The National Oceanic and Atmospheric Administration, NOAA (2020) revealed that the decrease in rainfall intensity compared to normal conditions is an anomaly of typical weather conditions in an area that results in drought in several regions of West Java. Drought is a condition in which the area, land, and people cannot meet their needs because they experience a water shortage.

Drought often causes impacts in various sectors of life, including economic, social, and environmental (Haile et al., 2020). The decrease in soil moisture content due to drought causes reduced irrigation of agricultural land (Bachmair et al., 2016; Hao et al., 2014), which reduces the area of planting land and the quality of crops. On the other hand, the degradation of environmental quality due to reduced groundwater content directly impacts the agricultural sector (Malki et al., 2017; Satoh et al., 2021). Regular monitoring of drought conditions is essential to take mitigation measures; one way to understand the severity of a drought is to use drought indices for prediction, evaluation, detection, and monitoring (Pratiwi et al., 2018; Bachmair et al., 2016; Haile et al., 2020; Pulwarty & Sivakumar, 2014; Sharafi et al., 2020; Nurdiati et al., 2021).

Although various indices exist, quantifying the spatial heterogeneity of drought recurrence at the city/regency scale in West Java remains limited. Prior studies seldom use Consecutive Dry Days (CDD) explicitly as the basis for return-period analysis to diagnose where extreme dry spells recur most and least frequently. This constrains early-warning design and water-resources planning that require recurrence-aware metrics.

To address this, we adopt a distribution-based return-period framework for CDD using ERA5-Land precipitation. Historical rainfall from ERA5-Land is available as global gridded data suitable for deriving CDD and related climate indicators over Indonesia. In this work, hourly precipitation (1981–2022) is aggregated to daily totals; days with rainfall <1 mm are flagged as dry, the annual CDD is taken as the longest dry run per year, and return periods are computed at 75%, 85%, and 95% quantile cut-offs to capture gradients of recurrence potential across West Java's cities and regencies.

CDD is commonly defined as the maximum number of consecutive days with daily rainfall (RR) <1 mm (Supari et al., 2017; Vinnarasi & Dhanya, 1955), and has been used to characterize evolving drought and rainfall patterns (Pattipeilohy et al., 2022; Guo et al., 2017; Song et al., 2015). Indonesian applications routinely apply the 1 mm day^{-1} threshold to convert daily rainfall to dry-spell sequences, from which CDD is computed (Najib et al., 2021; Nurdiati et al., 2021).

Parametric distribution fitting provides a principled way to summarize CDD behavior and to support probabilistic inference. Prior hydrometeorological studies show that selecting an appropriate distribution enables estimation of event-length characteristics and design values (e.g., Alam et al., 2018; Zhang et al., 2017). In our context, candidate families (e.g., inverse Gaussian, generalized extreme value, Weibull, lognormal, gamma) are evaluated and selected using goodness-of-fit statistics (Anderson–Darling, 5% level) and p-values, consistent with established distribution-fitting practice.

For recurrence quantification, we employ the cumulative distribution function (CDF) of CDD to compute return periods following Shiau and Shen (2001) as summarized in our methodological section, using quantile-based cut-offs (75%, 85%, 95%) to represent progressively rarer dry-spell severities. This approach links fitted CDD distributions with the expected interarrival time of exceedances, yielding interpretable metrics for regional planning.

Despite increasing attention to drought diagnostics in Indonesia including applications of CDD and studies of return periods in other provinces there remains a lack of CDD-based, distribution-driven return-period mapping at city/regency resolution focused on West Java. Moreover, previous work seldom integrates ERA5-Land derived CDD with an explicit recurrence framework to rank administrative areas by drought recurrence. These gaps motivate the present study.

This study aims to analyze drought characteristics in West Java Province by calculating the return period of Consecutive Dry Days (CDD) using ERA5-Land precipitation. We hypothesize that the distributional form and return-period characteristics of CDD can effectively represent the spatial variability and recurrence potential of drought events across West Java. The novelty lies in explicitly integrating CDD analysis with a distribution-based return-period framework to produce recurrence-aware drought maps at the city/regency scale. The scope covers ERA5-Land hourly precipitation aggregated to daily values for 1981–2022, derivation of annual CDD, parametric distribution fitting with Anderson–Darling selection, and return-period estimation at the 75%, 85%, and 95% CDD cut-offs for all cities and regencies in West Java.

2. METHOD

2.1. Materials

Hourly precipitation from ERA5-Land over Java (January 1981–December 2022; NetCDF; variables: longitude, latitude, time, total precipitation "tp", unit m) was used and then converted to millimeters. The study domain was clipped to West Java prior to processing. The analysis unit is the annual CDD (longest dry spell per year) for each grid/city–regency.

2.2. Sample Preparation

(1) Spatial subsetting to West Java. (2) Hourly–to–daily aggregation by 24-hour summation and unit conversion (m→mm). (3) Daily dry-day indicator construction using the 1 mm threshold to flag dry spells. (4) Annual CDD derivation as the longest run of dry days per calendar year.

2.3. Computation Procedure

Seven candidate probability distributions were tested to model the annual Consecutive Dry Days (CDD) data at each grid point and administrative area in West Java, namely: Generalized Extreme Value (GEV), Exponential (EXP), Gamma (GAM), Inverse Gaussian (ING), Log-logistic (LL), Lognormal (LN), and Weibull (WB). Each distribution was fitted using annual maximum CDD data, and the best-fitting distribution was determined using the Anderson–Darling (AD) test at a 5% significance level. The distribution model with a p-value greater than 0.05 was considered the best fit for the respective location.

In the second stage, the Cumulative Distribution Function (CDF) was calculated to obtain the CDF value of each grid point. The definition of a continuous Cumulative Distribution Function is as follows:

$$F(x) = P(X \leq x) = \int_{-\infty}^{x} f(t)\,dt, \qquad for\ -\infty < x < \infty, \tag{1}$$

where $F(x)$ is defined as the continuous CDF, and $f(t)$ is the probability distribution function (pdf) of X at point t.

The return period ($E(RP)$) was then computed based on the fitted CDF values using the following equation:

$$E(RP) = \frac{E(L)}{1 - F_{N_s}(n_s)} \tag{2}$$

where L is the interarrival time, $E(L)$ is the expected value of the interarrival time, and $F_{N_s}(n_s)$ is the CDF of CDD, while N_s is the number of days without rain in a year or the CDD value.

For each quantile threshold (75%, 85%, and 95%), the return period was obtained using the following relationships:

For the 75% limit:

$$\mathrm{E}_{75\%}(\mathrm{RP}) = \frac{1}{1 - \mathrm{F}_{\mathrm{N_s}}(30)} \tag{3}$$

For the 85% limit:

$$\mathrm{E}_{85\%}(\mathrm{RP}) = \frac{1}{1 - \mathrm{F}_{\mathrm{N_s}}(41)} \tag{4}$$

For the 95% limit:

$$\mathrm{E}_{95\%}(\mathrm{RP}) = \frac{1}{1 - \mathrm{F}_{\mathrm{N_s}}(74)} \tag{5}$$

Equations (1)–(5) were applied consistently to estimate the return periods for all cities and regencies in West Java. The results were then visualized and tabulated to show the spatial distribution of drought recurrence intensity across the study area.

2.4. Parameters

The parameters of each fitted distribution were estimated according to the native parameterization of each family, including: shape and scale parameters for Weibull (WB) and Gamma (GAM); location, scale, and shape for Generalized Extreme Value (GEV); mean and shape for Inverse Gaussian (ING); and location and scale parameters for Lognormal (LN), Log-

logistic (LL), and Exponential (EXP) distributions. These parameters were derived from the annual maximum CDD dataset at each grid point and administrative region across West Java to obtain the cumulative distribution function $F_X(\cdot)$.

Thresholds for the drought recurrence mapping were determined from the pooled quantiles of the regional CDD distribution, namely $u_{0.75} = 30$, $u_{0.85} = 41$, and $u_{0.95} = 74$days. These thresholds were then used in the computation of the return period values $E_{75\%}(RP)$, $E_{85\%}(RP)$, and $E_{95\%}(RP)$through Equations (1)–(5) in the *Computation Procedure* section.

2.5. Statistical Analysis

Model selection and evaluation were conducted using the Anderson–Darling (AD) goodness-of-fit test at a significance level of $\alpha = 0.05$. The null hypothesis (H_0) stated that the sample data follow the tested distribution. The best-fitting model for each location was identified as the distribution with the highest p-value ($p > 0.05$), which indicates the greatest conformity between the observed annual CDD data and the theoretical probability distribution. This procedure ensured that the chosen parametric model accurately represents the statistical behavior of drought events at the local scale, consistent with the computation framework applied in the *Computation Procedure*.

3. RESULTS AND DISCUSSION

3.1. Extraction of CDD Data and Spatial Pattern in 2022

The rainfall data used in this study are ERA5-Land hourly precipitation over Java Island from January 1981 to December 2022 in Network Common Data Format (NetCDF), with four variables: longitude, latitude, time, and total precipitation (tp). The tp variable is provided in metres and was converted to millimetres. The extraction stages consisted of: (a) cutting the data domain to West Java so that the rainfall matrix corresponds to the latitude–longitude range of the province; (b) converting hourly rainfall into daily rainfall by summing 24-hour totals; (c) filtering daily rainfall so that days with rainfall less than 1 mm are coded as 1 (dry) and the others as 0 (wet); and (d) converting the series of dry days into annual CDD by counting, for each year, the maximum number of consecutive dry days. After this sequence, annual CDD data were obtained for all grid points in West Java for the 1981–2022 period.

Figure 1 presents the spatial distribution of CDD in West Java for 2022. Most regions exhibit relatively low CDD values in that year, indicating short dry spells. Tasikmalaya City and Sukabumi Regency show the lowest CDD values, whereas the highest CDD values are concentrated around Indramayu Regency. This spatial contrast is consistent with previous findings that northern coastal areas of Java experience more persistent dry conditions than the mountainous western and southern regions (Parkhurst, 2023; Nainggolan et al., 2020; Ren et al., 2020). These patterns further support the use of CDD as a key indicator for diagnosing regional drought risk (Guo et al., 2017; Song et al., 2015; Song et al., 2020).

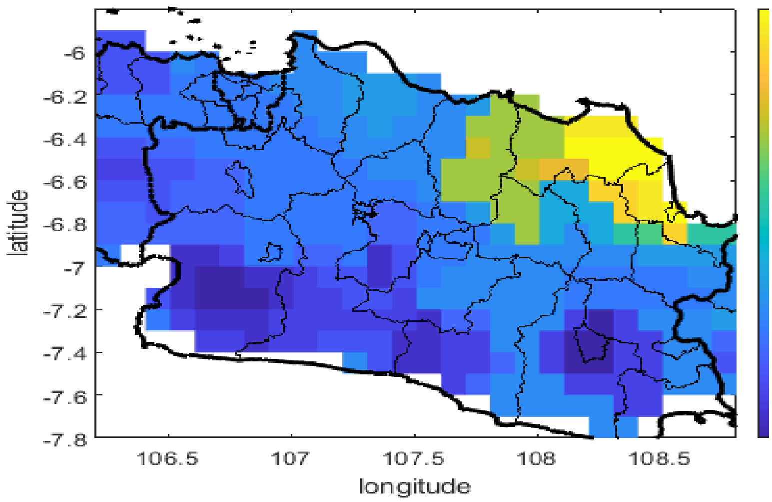


Figure 1. Spatial distribution of Consecutive Dry Days (CDD) in West Java for 2022.

3.2. Fitting Distribution

Fitting distribution is carried out to identify the most suitable probability distribution for the annual CDD data obtained previously. As an illustration, the fitting process for Indramayu Regency is shown in Figure 2. The figure displays the histogram of the annual CDD and the probability density functions (PDFs) for the seven candidate distributions: Generalized Extreme Value (GEV), Exponential (EXP), Gamma (GAM), Inverse Gaussian (ING), Log-logistic (LL), Lognormal (LN), and Weibull (WB). Based on Figure 2, the PDFs of the GEV, GAM, and WB distributions visually follow the shape of the histogram fairly well.

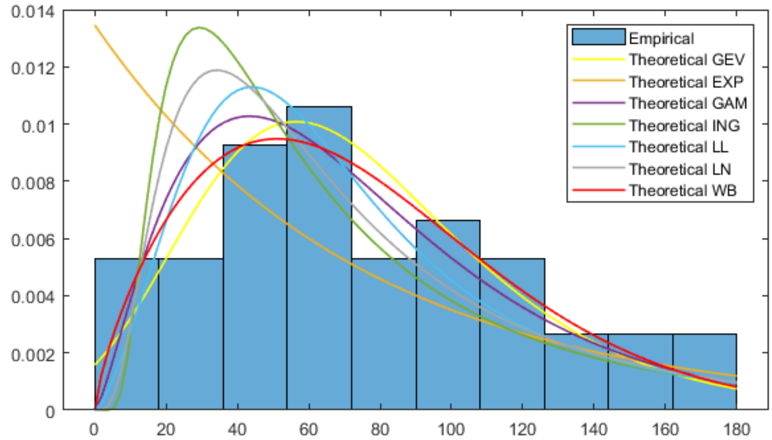


Figure 2. Histogram of annual CDD in Indramayu Regency and the fitted probability density functions (pdfs) of seven candidate distributions.

To quantify the goodness of fit, a statistical hypothesis test was carried out using the Anderson–Darling test with a significance level of 5%. The null hypothesis (H_0) states that the data follow the tested distribution, whereas the alternative hypothesis (H_1) states that they do not. The most suitable distribution for a data group is selected based on the largest p-value among those distributions that meet the criterion p-value > 0.05.

Table 1. Anderson–Darling (AD) test results for the seven fitted distributions in Indramayu Regency.

Distribution	p-value	Results
Exponential	0.0404	Reject H_0
Invers gaussian	0.2743	Receive H_0
Log logistics	0.7192	Receive H_0
Lognormal	0.5754	Receive H_0
Generalized extreme value	0.9576	Receive H_0
Gamma	0.9599	Receive H_0
Weibull	0.9946	Receive H_0

The same procedure was applied to the annual CDD data for all cities and regencies in West Java. The resulting best-fit distributions and p-values are summarised in Table 2.

Overall, most of the annual CDD data in West Java follow the inverse Gaussian distribution, followed by the generalized extreme value, lognormal, and Weibull distributions with various p-values. This pattern is in line with previous works that showed the importance of testing several candidate distributions when modelling hydrometeorological extremes, as different climates and regions may favour different distribution families (Alam et al., 2018; Zhang et al., 2017). The dominance of the inverse Gaussian and GEV distributions suggests that the tail behaviour of CDD in West Java is heavy enough to justify using flexible, asymmetric distributions, which is crucial for reliable estimation of rare but impactful long dry spells.

From a practical perspective, the identification of appropriate distributions for CDD at each location is a critical intermediate step for the return period analysis. Accurate distribution fitting provides a sound probabilistic basis for estimating the cumulative distribution function (CDF) and, consequently, for computing the recurrence characteristics of drought events through the return period formulation used in this study (Nova et al., 2019; Chen & Guo, 2019; Nurdiati et al., 2022).

Table 2. Summary of best-fit distributions and p-values for annual CDD data across cities and regencies in West Java.

City/Regency Name	Distribution (p-value)
Bogor Regency	inverse gaussian (0.6460)
Sukabumi Regency	generalized extreme value (0.9174)
Cianjur Regency	inverse gaussian (0.8680)
Bandung Regency	inverse gaussian (0.5719)
Garut Regency	inverse gaussian (0.9013)
Tasikmalaya Regency	generalized extreme value (0.7951)
Ciamis Regency	inverse gaussian (0.9781)
Kuningan Regency	lognormal (0.6141)
Cirebon Regency	lognormal (0.6634)
Majalengka Regency	Weibull (0.4221)
Sumedang Regency	inverse gaussian (0.7379)
Indramayu Regency	Weibull (0.9946)
Subang Regency	lognormal (0.9215)
Purwakarta Regency	inverse gaussian (0.9882)
Karawang Regency	inverse gaussian (0.9239)
Bekasi Regency	inverse gaussian (0.8700)
West Bandung Regency	generalized extreme value (0.8969)
Pangandaran Regency	generalized extreme value (0.9403)
Bogor City	inverse gaussian (0.6919)
Sukabumi City	inverse gaussian (0.9332)
Bandung	inverse gaussian (0.5581)
Cirebon City	lognormal (0.7017)
Bekasi City	inverse gaussian (0.8979)
Depok City	Weibull (0.5845)
Cimahi City	inverse gaussian (0.4340)
Tasikmalaya City	inverse gaussian (0.6562)
Banjar City	lognormal (0.7744)

3.3. Return Period Characteristics of CDD

The return period calculation uses the equation of Shiau and Shen (2001) as presented in Equations (2)–(5) in the Methods section (Chen & Guo, 2019). The expected value of the return period is expressed as a function of the interarrival time and the CDF of CDD. This calculation is carried out with three different limit values: 75%, 85%, and 95% of the overall CDD distribution in West Java.

Figure 3 shows the histogram of the pooled annual CDD data together with the 75%, 85%, and 95% cut-off values. From Figure 3, it can be concluded that the limits correspond to CDD values of 30, 41, and 74 days, respectively. These thresholds represent progressively more severe and rarer dry spells.

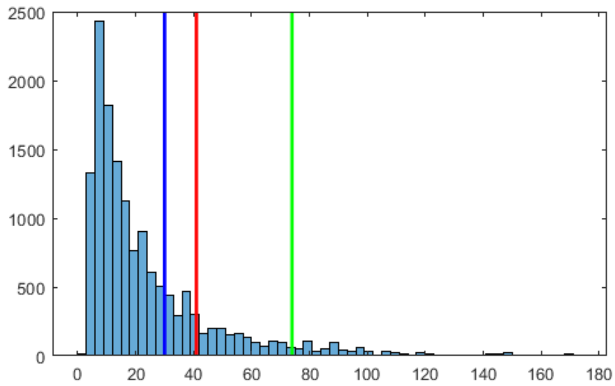


Figure 3. Histogram of the overall annual CDD data with 75%, 85%, and 95% cut-off values.

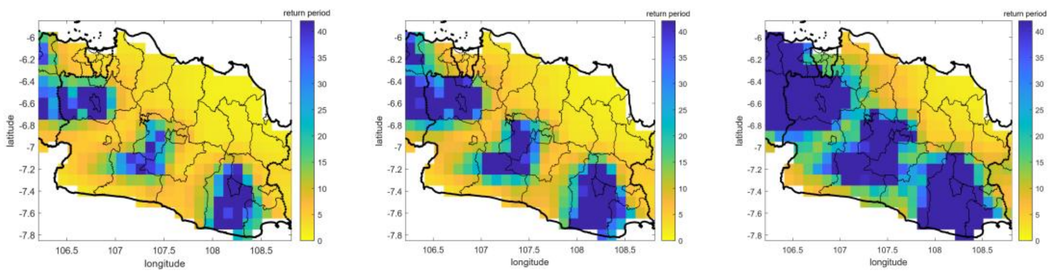
Using Equations (2)–(5), the return period is calculated for all cities and regencies in West Java.

Table 3. Calculated return periods for 75%, 85%, and 95% CDD thresholds for all cities and regencies in West Java.

City/Regency Name	Return period (years)		
	75%	85%	95%
Bogor Regency	>42	>42	>42
Sukabumi Regency	10.353	17.4413	36.8691
Cianjur Regency	4.431	8.09	>42
Bandung Regency	26.618	>42	>42
Garut Regency	6.195	13.8234	>42
Tasikmalaya Regency	24.902	>42	>42
Ciamis Regency	23.031	>42	>42
Kuningan Regency	2.591	3.96	11.86
Cirebon Regency	1.5488	2.07	4.86
Majalengka Regency	1.705	2.29	6.66
Sumedang Regency	3.260	5.79	28.32
Indramayu Regency	**1.183**	**1.34**	**2.25**
Subang Regency	2.305	3.44	9.92
Purwakarta Regency	3.860	7.19	39.75
Karawang Regency	3.654	6.37	28.48
Bekasi Regency	5.203	10.34	>42
West Bandung Regency	11.353	20.65	>42
Pangandaran Regency	16.995	31.92	>42
Bogor City	>42	>42	>42
Sukabumi City	3.980	7.2503	36.8691
Bandung	14.928	>42	>42
Cirebon City	1.346	1.72	3.51
Bekasi City	3.834	6.80	31.9208
Depok City	16.494	>42	>42
Cimahi City	38.266	>42	>42
Tasikmalaya City	>42	>42	>42
Banjar City	4.616	8.16	33.1227

At the 95% limit, 14 cities/regencies in West Java have return periods over 42 years, indicating areas with the slowest recurrence of very long dry spells and rare extreme drought. At the 85% limit, nine cities/regencies experience extreme drought least frequently: Bogor Regency, Bandung Regency, Tasikmalaya Regency, Ciamis Regency, Bogor City, Bandung City, Depok City, Cimahi City, and Tasikmalaya City. When the limit is 75%, three areas—Bogor Regency, Bogor City, and Tasikmalaya City—have the longest return periods, showing infrequent moderate-to-severe dry spells.

In contrast, Indramayu Regency is consistently identified as the area that most often experiences extreme drought at all three thresholds. It has the shortest return period to drought, which means that long dry spells recur quickly.



(a) limit at 75% (b) limit at 85% (c) limit at 95%

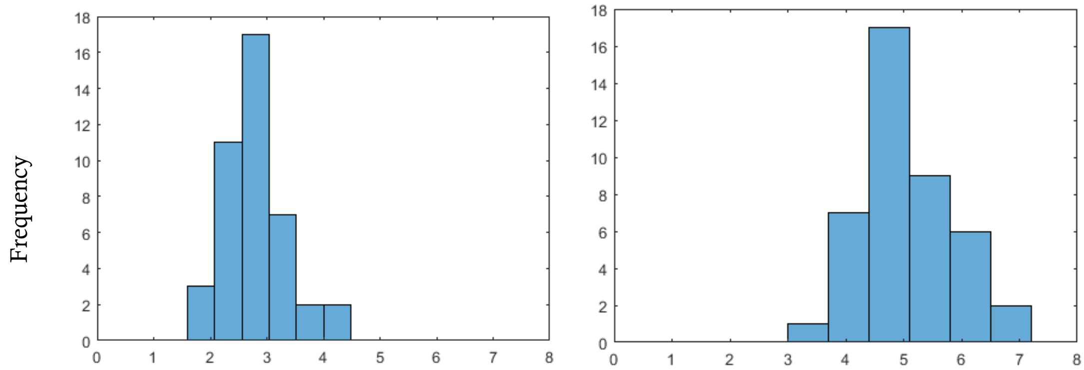
Figure 4. Map of the return period calculation results with several boundary values in West Java for several boundary values.

Figure 4 visualises the spatial distribution of return period for the 75%, 85%, and 95% limits. In West Java, most areas show low return periods at 75% and 85% limits, indicating frequent moderate and severe droughts. These findings align with other drought analyses in Indonesia, which report short recurrence intervals for dry extremes in Java (Nova et al., 2019; Parkhurst, 2023; Nainggolan et al., 2020).

Distribution fitting and return period estimation show drought recurrence patterns in West Java. Areas with heavier tails and higher CDD values have shorter return periods, as seen in northern coastal regencies like Indramayu. Locations like Bogor and Tasikmalaya City show lower CDD values with longer recurrence intervals, indicating low drought risk. This coherence between CDD patterns and return periods validates the methodology for drought risk assessment in similar climates (Guo et al., 2017; Song et al., 2015; Song et al., 2020).

3.4. Contrasting Rainfall and CDD Patterns in Bogor and Indramayu

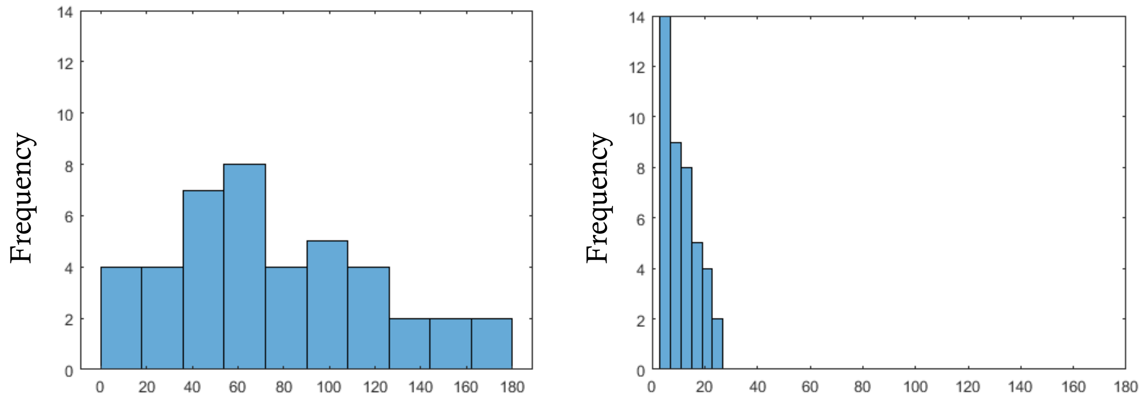
Further analysis was carried out by examining the distribution patterns of average annual rainfall and annual CDD in the regions that experience extreme drought most frequently and least frequently. This comparison aims to link the return period results with the underlying rainfall and CDD characteristics. One of the areas that most rarely experiences extreme drought is Bogor Regency, whereas the area that most often experiences extreme drought is Indramayu Regency.



(a) (b)

Figure 5. Histogram of average rainfall data per year in (a) Bogor and (b) Indramayu Regencies.

Figure 5 shows that the average frequency of annual rainfall in Indramayu Regency is in the range of about 1–5 mm, while in Bogor Regency it is around 3–8 mm. This indicates that the average amount and frequency of rainfall per year in Indramayu Regency are lower than in Bogor Regency.



(a) (b)

Figure 6. Histogram of annual CDD data in (a) Indramayu Regency and (b) Bogor Regency.

Figure 6 presents histograms of the annual CDD for Bogor and Indramayu Regencies. The figure shows that annual CDD in Indramayu Regency ranges from approximately 0–180 days, whereas in Bogor Regency it is only about 0–30 days. Thus, Indramayu Regency experiences much longer consecutive dry periods than Bogor Regency.

These contrasting rainfall and CDD characteristics help explain the markedly different return periods obtained in the previous subsection. Indramayu Regency combines relatively low average rainfall with long CDD, leading to short return periods and frequent extreme drought events within a 42-year span. Conversely, Bogor Regency has relatively high average rainfall and short CDD, resulting in long return periods and rare occurrence of extreme drought over the same time horizon.

This behaviour is consistent with previous studies that link prolonged dry spells and reduced rainfall to enhanced drought risk in monsoon-influenced regions (Bachmair et al., 2016; Haile et al., 2020; Guo et al., 2017). Overall, the comparison between Bogor and Indramayu underscores the importance of jointly considering rainfall intensity, CDD, and return period in developing effective drought monitoring and mitigation strategies for West Java.

4. CONCLUSIONS

The study's analysis of rainfall data, transformed into annual Consecutive Dry Days (CDD) data, reveals that the inverse Gaussian distribution most accurately fits the majority of areas in West Java. This is followed by the generalized extreme value, lognormal, and Weibull distributions, which also demonstrate strong suitability for modeling drought patterns in the region. Through return period analysis, Indramayu Regency was identified as the area with the shortest return period to extreme drought events, indicating a high frequency of such events. In contrast, Bogor Regency, Bogor City, and Tasikmalaya City exhibited the longest return periods, signifying that extreme droughts are less common in these regions.

The findings underscore the variation in drought risk across West Java, providing valuable insights for regional drought preparedness and water resource management. For future research, a more comprehensive joint return period analysis could be conducted using a multivariate approach. This would involve integrating additional variables, such as temperature or other climate indicators like the number of heavy precipitation days (R10 and R20) or Consecutive Wet Days (CWD). Incorporating these factors could offer a more nuanced understanding of the interplay between different climate conditions and the occurrence of droughts, leading to more robust models and improved forecasting capabilities.

5. REFERENCES

Alam, M. A., Emura, K., Farnham, C., & Yuan, J. (2018). Best-fit probability distributions and return periods for maximum monthly rainfall in Bangladesh. *Climate, 6*(1). https://doi.org/10.3390/cli6010009

Bachmair, S., Stahl, K., Collins, K., Hannaford, J., Acreman, M., Svoboda, M., Knutson, C., Smith, K. H., Wall, N., Fuchs, B., Crossman, N. D., & Overton, I. C. (2016). Drought indicators revisited: the need for a wider consideration of environment and society. *Wiley Interdisciplinary Reviews: Water, 3*(4), 516–536. https://doi.org/10.1002/wat2.1154

Chen, L., & Guo, S. (2019). Drought Analysis Using Copulas. *Springer Water, 1965*, 97–116. https://doi.org/10.1007/978-981-13-0574-0_5

Guo, E., Liu, X., Zhang, J., Wang, Y., Wang, C., Wang, R., & Li, D. (2017). Assessing spatiotemporal variation of drought and its impact on maize yield in Northeast China. *In Journal of Hydrology (Vol. 553)*. https://doi.org/10.1016/j.jhydrol.2017.07.060

Haile, G. G., Tang, Q., Li, W., Liu, X., & Zhang, X. (2020). Drought: Progress in broadening its understanding. *Wiley Interdisciplinary Reviews: Water, 7*(2), 1–25. https://doi.org/10.1002/WAT2.1407

Hao, Z., AghaKouchak, A., Nakhjiri, N., & Farahmand, A. (2014). Global integrated drought monitoring and prediction system. *In Scientific data (Vol. 1)*. https://doi.org/10.1038/sdata.2014.1

Malki, M., Bouchaou, L., Hirich, A., Ait Brahim, Y., & Choukr-Allah, R. (2017). Impact of agricultural practices on groundwater quality in intensive irrigated area of Chtouka-Massa, Morocco. *Science of the Total Environment, 574*, 760–770. https://doi.org/10.1016/j.scitotenv.2016.09.145

Nainggolan, H. A., Burhanudin, Muslihah, D. W., & Virgianto, R. H. (2020). Inovasi Model Prediksi Titik Api Menggunakan Consecutive Dry Days (CDD) pada Wilayah Lahan Gambut Provinsi Riau. *Buletin GAW Bariri, 1*(1), 12–19. https://doi.org/10.31172/bgb.v1i1.6

Najib, M. K., & Nurdiati, S. (2021). Koreksi Bias Statistik Pada Data Prediksi Suhu Permukaan Air Laut Di Wilayah Indian Ocean Dipole Barat Dan Timur. *Jambura Geoscience Review, 3*(1), 9–17. https://doi.org/10.34312/jgeosrev.v3i1.8259

Najib, M. K., Nurdiati, S., & SopaheluwakanArdhasena. (2021). Copula - based joint distribution analysis of the ENSO effect on the drought indicators over Borneo fire - prone areas. Modeling Earth Systems and Environment, 0123456789. https://doi.org/10.1007/s40808-021-01267-5

NOAA. (2020). NOAA Science Report 2019. 84. https://nrc.noaa.gov/Council-Products/NOAA-Science-Report

Nova, M., Gara, I., Dwiridal, L., Nugroho, S. (2019). Analisis Karakteristik Periode Ulang Curah Hujan Dengan Metode Iwai Kadoya Untuk Wilayah Sumatera Barat. *Pillar of Physics, 12*, 47–52.

Nurdiati, S., Bukhari, F., Julianto, M. T., Sopaheluwakan, A., Aprilia, M., Fajar, I., Septiawan, P., & Najib, M. K. (2022). The impact of El Niño southern oscillation and Indian Ocean Dipole on the burned area in Indonesia. *Terrestrial, Atmospheric and Oceanic Sciences, 0*. https://doi.org/10.1007/s44195-022-00016-0

Nurdiati, S., Sopaheluwakan, A., & Septiawan, P. (2021). Spatial and Temporal Analysis of El Niño Impact on Land and Forest Fire in Kalimantan and Sumatra. *Agromet*, *35*(1), 1–10. https://doi.org/10.29244/j.agromet.35.1.1-10

Nurdiati, S., Sopaheluwakan, A., Septiawan, P., & Ardhana, M. R. (2022). Joint Spatio-Temporal Analysis of Various Wildfire and Drought Indicators in Indonesia. *Atmosphere*, *13*(10), 1591. https://doi.org/10.3390/atmos13101591

Parkhurst, H. (2023). Analisis Karakteristik Kekeringan di Nusa Tenggara Menggunakan Pengukuran Return Period. *Jurnal Economic Excellence Ibnu Sina, 1*(4). https://doi.org/10.59841/excellence.v1i4.888

Pattipeilohy, W. J., Beis, D. S., & Hadi, A. S. (2022). Kajian Identifikasi Penurunan Tren Curah Hujan, CDD dan CWD di Kota Kupang, Nusa Tenggara Timur. *Buletin GAW Bariri, 3*(1), 8–16. https://doi.org/10.31172/bgb.v3i1.62

Pratiwi, N. A. H., Karuniasa, M., & Suroso, D. S. A. (2018). Exploring Historical and Projection of Drought Periods in Cirebon Regency, Indonesia. *E3S Web of Conferences, 68*, 1–7. https://doi.org/10.1051/e3sconf/20186802007

Pulwarty, R. S., & Sivakumar, M. V. K. (2014). Information systems in a changing climate: Early warnings and drought risk management. *Weather and Climate Extremes, 3*, 14–21. https://doi.org/10.1016/j.wace.2014.03.005

Ren, M., Xu, Z., Pang, B., Liu, J., & Du, L. (2020). Spatiotemporal variability of precipitation in beijing, China during the wet seasons. *Water (Switzerland), 12*(3). https://doi.org/10.3390/w12030716

Satoh, Y., Shiogama, H., Hanasaki, N., Pokhrel, Y., Boulange, J. E. S., Burek, P., Gosling, S. N., Grillakis, M., Koutroulis, A., Müller Schmied, H., Thiery, W., & Yokohata, T. (2021). A quantitative evaluation of the issue of drought definition: A source of disagreement in future drought assessments. *Environmental Research Letters, 16*(10). https://doi.org/10.1088/1748-9326/ac2348

Sharafi, L., Zarafshani, K., Keshavarz, M., Azadi, H., & Van Passel, S. (2020). Drought risk assessment: Towards drought early warning system and sustainable environment in western Iran. *Ecological Indicators, 114* (February), 106276. https://doi.org/10.1016/j.ecolind.2020.106276

Song, X., Song, S., Sun, W., Mu, X., Wang, S., Li, J., & Li, Y. (2015). Recent changes in extreme precipitation and drought over the Songhua River Basin, China, during 1960-2013. *Atmospheric Research, 157*, 137–152. https://doi.org/10.1016/j.atmosres.2015.01.022

Song, X., Zhang, C., Zhang, J., Zou, X., Mo, Y., & Tian, Y. (2020). Potential linkages of precipitation extremes in Beijing-Tianjin-Hebei region, China, with large-scale climate patterns using wavelet-based approaches. *Theoretical and Applied Climatology, 141*(3–4), 1251–1269. https://doi.org/10.1007/s00704-020-03247-8

Supari, Tangang, F., Juneng, L., & Aldrian, E. (2017). Observed changes in extreme temperature and precipitation over Indonesia. *International Journal of Climatology, 37*(4), 1979–1997. https://doi.org/10.1002/joc.4829

Vinnarasi, R., & Dhanya, C. T. (1955). Changing characteristics of extreme wet and dry spells of Indian monsoon rainfall. *Journal of Geophysical Research, 175*(4449), 238. https://doi.org/10.1038/175238c0

Zhang, X., Zwiers, F. W., Li, G., Wan, H., & Cannon, A. J. (2017). Complexity in estimating past and future extreme short-duration rainfall. *Nature Geoscience, 10*(4), 255–259. https://doi.org/10.1038/ngeo2911