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ARTICLE

Mapping Meteorological Drought Periods in South Sulawesi Using the Standardized Precipitation Index with the Power Law Process Model

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ABSTRACT

A drought is when reduced rainfall leads to a water crisis, impacting daily life. Over recent decades, droughts have affected various regions, including South Sulawesi, Indonesia. This study aims to map the probability of meteorological drought months using the 1-month Standardized Precipitation Index (SPI) in South Sulawesi. Based on SPI, meteorological drought characteristics are inversely proportional to drought event intensity, which can be modeled using a Non-Homogeneous Poisson Process, specifically the Power Law Process. The estimation method employs Maximum Likelihood Estimation (MLE), where drought event intensities are treated as random variables over a set time interval. Future drought months are estimated using the cumulative Power Law Process function, with the β and γ parameters more significant than 0. The probability of drought months is determined using the Non-Homogeneous Poisson Process, which models event occurrence over time, considering varying intensities. The results indicate that, of the 24 districts/cities in South Sulawesi, 14 experienced meteorological drought based on the SPI and Power Law Process model. The estimated number of months of drought occurrence in the next 12 months is one month of drought with an occurrence probability value of 0.37 occurring in November in the Selayar, Bulukumba, Bantaeng, Jeneponto, Takalar and Gowa areas; in October in the Sinjai, Barru, Bone, Soppeng, Pinrang and Pare-pare areas; as well as in December in the Maros and Makassar areas.

Keywords: Meteorological Drought; Non-Homogeneous Poisson Process; Point Process; Power Law Process; Standardized Precipitation Index; South Sulawesi-Indonesia

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1. Introduction

South Sulawesi plays a strategic role in maintaining the stability of national food security, especially in Eastern Indonesia. The province is one of Indonesia's leading rice producers, with milled dry grain production reaching 5.3 million tons in 2019, which, if converted into rice, is around 3 million tons; this means that South Sulawesi recorded a surplus of nearly 2 million tons. This makes the province a significant food barn in Eastern Indonesia (KTI) and one of the national best contributors to food security[1]. However, considerable challenges remain, mainly due to climate change and droughts that impact agricultural production. In 2023, South Sulawesi experienced a prolonged drought until November[2]. This condition seriously threatens the farming sector, especially regarding water availability for irrigation and the increased risk of crop failure.

Drought is among the most destructive natural disasters in almost all geographical areas[3]. Based on their impact, droughts can be categorized into four types: (1) meteorological droughts, which occur when rainfall is below average for a period of time; (2) hydrological droughts, which are characterized by reduced water availability on the surface and in the soil; (3) agricultural droughts, which cause a decline in agricultural production due to reduced water supply; and (4) socio-economic droughts, which are associated with disruptions in the supply and demand of economically valuable goods[4]. Meteorological drought is often the initial trigger for other types of droughts. Its impact on human activities is evident in two main aspects: reduced groundwater availability and quality and reduced agricultural yields[5, 6].

Drought is characterized by a decrease in rainfall that lasts for an extended period, such as a season or even a year, and can occur in almost all climate zones in areas with high and low rainfall[7]. Rainfall is the main parameter in monitoring drought conditions, so the accuracy of rainfall data is crucial in determining the availability of water in a region[8]. Various rainfall-based drought indices have been developed for assessment and monitoring. These indices include the Standardized Precipitation Index (SPI)[9], the Palmer Drought Severity Index (PDSI)[10], the Percent of Normal Index (PNI)[11], the Effective Drought Index (EPI)[12], etc. Among these indices, SPI is widely used to assess meteorological drought, including in Indonesia (BMKG, 2024). Drought assessment using SPI has proven effective, as Faisol et al. used SPI to describe agricultural drought in West Papua, Indonesia[13]. Pramudya and Onishi showed that the current use of SPI can help refine drought assessment by describing erratic rainfall conditions and weather anomalies in Tegal City[14].

The SPI was first developed by McKee in 1993 and has been standardized internationally so that it can be used in different geographic locations with varying data on rainfall. SPI is calculated by fitting rainfall data to a gamma probability distribution function (Γ) and converting the Γ distribution to a normal distribution. The SPI is derived from cumulative rainfall for a specific time period according to the needs of the analysis. SPI classifies drought levels into three categories: drought, severe drought, and extreme drought[9]. The calculation of SPI is more straightforward than other indices because it only requires precipitation data. The SPI is particularly useful in drought risk analysis and estimation in areas with limited data and where other parameters, such as river flow, evapotranspiration, and soil moisture, may not be available. SPI can determine droughts' duration, size, and intensity and define different types of droughts, such as hydrological, agricultural, and environmental droughts[15].

The advantage of SPI is the ease of monitoring drought conditions. However, SPI has the limitation of only being able to provide information on drought conditions based on current or past rainfall data. Therefore, appropriate efforts are needed for more effective planning in anticipating future droughts, such as analyzing to predict drought periods. Predicting drought periods is one of the most challenging climate problems for scientists and hydrologists because droughts are complex, and their occurrence is random and varies over time[3].

One of the relevant stochastic processes for modeling drought events is the Non-Homogeneous Poisson Process. The Non-Homogeneous Poisson Process allows for capturing fluctuations and changes in event occurrence over time, which may be more appropriate for analyzing dynamic and unstable phenomena[16]. The non-homogeneous Poisson process is a counting process that describes random events that occur at specific time intervals, with the intensity of events changing over time[17]. The Non-Homogeneous Poisson Process is a generalization of the Poisson Process, also called the Non-Stationary Poisson Process. This is because the incidence rate in the Non-Homogeneous Poisson Process is not

constant. In a Non-Homogeneous Poisson Process, the intensity or incidence rate is represented by the intensity function λ(t). The intensity function λ(t) describes how the incidence rate changes over time[18]. Non-homogeneous Poisson processes have been used in various fields, for example, to model repairable system failures[19], analyze extreme rainfall[20], and estimate the number of ozone exceedances[21].

Specific models of the Non-Homogeneous Poisson Process include Goel-Okumoto (GOP)[22], Musa-Okumoto (MO)[23], and Power Law Process[17]. The Power Law Process is the Duane[24], Crow-AMSAA, or Weibull process model. This is because the ROCOF (Rate of Occurrence of Failures) is a function of t that has the same shape as the hazard rate of the Weibull distribution. The Power Law Process can model a functional relationship between two variables, where one variable changes with the rank of the other[25]. Two categories of data cases can be applied in estimating the Power Law Process model: the time interval between events and the number of events observed in the specified interval[17].

This study uses the Power Law Process as a particular case model of the Non-Homogeneous Poisson Process to describe the varying drought intensity in the South Sulawesi region. Drought intensity is obtained using the SPI index with a time scale of one month. The selection of the Power Law Process is based on the characteristics of the model that can interpret the event's magnitude, which is inversely proportional to its intensity. This is in line with the results of the characterization of drought intensity, which shows that extreme drought events occur less frequently than severe drought and drought events in the South Sulawesi region. The Power Law Process model estimation uses a data case where the number of drought events obtained is considered a random variable within a predetermined observation time (time truncated)[17]. The results of the model fit test showed that out of 24 districts/cities in South Sulawesi, 14 districts/cities showed a fit of drought intensity with the Power Law Process model with parameter estimation values β and γ greater than 0. These estimated values were used to calculate the number of drought events that will occur in the future using the expectation function of the Power Law Process. The estimated values are mapped to provide information on the period of drought events that will occur in the future.

2. Materials and Methods

2.1. Materials

2.1.1. Study Areas

This research covers 24 districts/cities in South Sulawesi, which are located between latitude 0°12′−8′ South Latitude and longitude 116°48′−122°36′ East Longitude bordering West Sulawesi to the north, Bone Bay and Southeast Sulawesi to the northeast, Makassar Strait to the west, and the Flores Sea to the south (**Figure 1**). The climate of South Sulawesi is wet tropical, with two main seasons, namely the rainy and dry seasons.

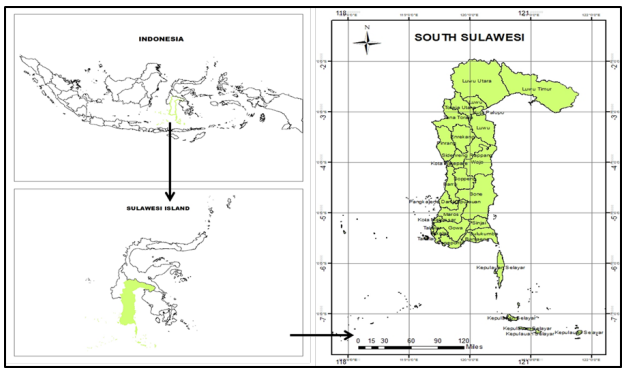


Figure 1. Research location.

2.1.2. Data Collection

The data used in this research is secondary data in the form of monthly rainfall amounts for 42 years or 516 months (January 1981−December 2023) in each district/city in South Sulawesi (**Table 1**) obtained based on coordinates (single point latitude and longitude) on the NASA website POWER Project's Data Access Viewer (https://power.larc.nasa.gov/data-access-viewer/).

Table 1. List of regency/city coordinates in South Sulawesi for collecting rainfall data on the NASA POWER website.

City/Regency	Latitude	Longitude	City/Regency	Latitude	Longitude
Selayar	−6.0143	120.4977	Wajo	−4.1279	120.0296
Bulukumba	−5.5483	120.1967	Sidrap	−3.8633	119.9643

Table 1. *Cont.*

Bantaeng	−5.5472	119.9508	Pinrang	−3.7891	119.6483
Jeneponto	−5.6765	119.7483	Enrekang	−3.5696	119.7768
Takalar	−5.4228	119.4647	Luwu	−3.1954	120.1837
Gowa	−5.3161	119.7157	Tana Toraja	−3.0957	119.8508
Sinjai	−5.2356	120.1607	Luwu Utara	−2.3952	120.1597
Maros	−5.0052	119.5726	Luwu Timur	−2.5396	121.1366
Pangkep	−4.5328	119.5934	Toraja Utara	−2.8839	119.8702
Barru	−4.4262	119.6957	Makassar	−5.1469	119.4308
Bone	−4.6853	120.1286	Pare-Pare	−4.0061	119.6201
Soppeng	−4.3333	119.8906	Palopo	−2.9987	120.1815

2.2. Methods

2.2.1. The Standardized Precipitation Index (SPI) as a Drought Indicator

SPI is a drought measuring tool used to evaluate and monitor precipitation patterns over various time periods. SPI measures how wet or dry an area is compared to normal conditions based on historical precipitation data. The SPI calculation in this research uses the method proposed by McKee. The calculation begins by converting the observed rainfall data to a gamma distribution as Equation (1) using the following equation[9]:

$$g(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} x^{\alpha-1} e^{-\frac{x}{\beta}} \text{ for } x, \beta, \alpha > 0 \quad (1)$$

where the gamma function as Equation (2) is obtained from the integral:

$$\Gamma(\alpha) = \int_0^{\infty} y^{\alpha-1} e^{-y} dy \quad (2)$$

To determine the parameters α and β in Equation (3), the following formula is used:

$$\alpha = \frac{\left(\bar{x}\right)^2}{Sd^2} \text{ and } \beta = \frac{\bar{x}}{\alpha} \quad (3)$$

With mean and standard deviation is given by Equation (4) as follows:

$$\bar{x} = \frac{\sum x}{n} \text{ and } Sd = \sqrt{\frac{(x - \bar{x})^2}{n-1}} \quad (4)$$

The gamma distribution is undefined for $x = 0$, therefore, for zero-valued precipitation, the following cumulative probability is used by Equation (5):

$$H(x) = q + (1-q)\, g(x) \quad (5)$$

where q is the probability of zero rainfall, and q is the number of zero rainfall events divided by the amount of data. Calculating the SPI value as Equations (6), (7), and (8) then changes the gamma distribution of rainfall to a normal distribution with the following equation.

For $0 < H(x) \leq 0.5$

$$SPI = -\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right), \quad (6)$$

where:

$$t = \sqrt{ln\left(\frac{1}{(H(x))^2}\right)}$$

for $0.5 < H(x) \leq 1$, we have Equation (7) as follows:

$$SPI = \left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right), \quad (7)$$

where:

$$t = \sqrt{ln\left(\frac{1}{(1 - H(x))^2}\right)} \quad (8)$$

with:

$c_0 = 2.515517$ $\quad$ $d_1 = 1.432788$
$c_1 = 0.802853$ $\quad$ $d_2 = 0.189269$
$c_2 = 0.010328$ $\quad$ $d_3 = 0.001308$

Drought occurs when the SPI reaches drought intensity with SPI ≤ -1, while the drought will end if the SPI ≥ 1. The classification of drought intensity for a specific time scale can be seen in **Table 2** below:[9]

Table 2. Classification of SPI Values.

SPI Values	Classifications
(−0.99)–0.99	Normal
(−0.1)–(−1.49)	Drought
(−1.5)–(−1.99)	Severe drought
≤−2.00	Extreme drought

2.2.2. Power Law Process

A process of calculating $\{N(t), t \geq 0\}$ is said to be a Non-Homogeneous Poisson process with an intensity function $\lambda(t)$, $t \geq 0$, if[18]:

- $N(0) = 0$
- $\{N(t), t \geq 0\}$ has free increase
- $P\{N(t+h) - N(t) = 1\} = \lambda(t) + o(h)$, and
- $P\{N(t+h) - N(t) \geq 2\} = o(h)$, where h > 0 and $o(h)$ is a small number that meets the conditions $\lim_{h \to 0} \frac{o(h)}{h} = 0$.

In general, $\{N(t), t \geq 0\}$ is expressed as a Non-Homogeneous Poisson process based on the Equation (9) as follows:

$$P\left(N_{(t)} = n\right) = \frac{\left[\int_0^t \lambda(t)dt\right]}{n!} exp^{-\int_0^t \lambda(t)dt} \quad n = 0, 1, 2 \ldots n \tag{9}$$

The Power Law Process is described as a Non-Homogeneous Poisson Process $\{N(t), t \geq 0\}$ with the intensity function as Equation (10) given by Rigdon and Basu[17]:

$$\lambda(t) = \left(\frac{\beta}{\gamma}\right)\left(\frac{t}{\gamma}\right)^{\beta-1}, \gamma > 0, \beta > 1, t > 0 \tag{10}$$

The expected value function as Equation (11) is given by Rigdon and Basu[17]:

$$m(t) = \left(\frac{t}{\gamma}\right)^{\beta} \tag{11}$$

2.2.3. Power Law Process Model Suitability Testing

To test the suitability of the Power Law model, the Cramér-von Mises test is used with the hypothesis:

H_0: The intensity of the incident is in accordance with the Power Law Process model

H_1: The intensity of the incident does not match the Power Law Process model

The Cramér-von Mises test statistics are expressed as Equation (12) on the following equation[17]:

$$C_R^2 = \frac{1}{12(n)} + \sum_{i=1}^{n}\left(\bar{R} - \frac{2i-1}{2n}\right)^2 \tag{12}$$

$\bar{R}$ is the power transformation ratio given by Equation (13):

$$\bar{R} = \left(\frac{t_i}{t_n}\right)^{\bar{\beta}} \tag{13}$$

$\bar{\beta}$ is an unbiased estimator given by the Equation (14):

$$\bar{\beta} = \frac{(n-2)}{\sum_{i=1}^{n} \ln\left(\frac{t_n}{t_i}\right)} \tag{14}$$

The H_0 decision is accepted if the C_R^2 test statistical value based on calculations is smaller than the critical value for the Cramér-von Mises Test, which means the Power Law Process Model is appropriate. If the test statistic value C_R^2 is greater than the critical value for the Cramér-von Mises test then H_0 is rejected, which means the model is not suitable.

2.2.4. Power Law Process Parameter Estimation

Let $t_1, t_2, t_3, \ldots, t_n$ be independent random samples from a distribution, with a joint probability density function $f(t_1, t_2, \ldots, t_n; \beta, \gamma)$ where n denotes the number of events that occurred up to time t_i for $0 < t_1 < t_2 < \cdots < t_n$. If the joint probability density function is expressed as a function of β and γ then the likelihood function in Equation (15) is denoted as $L(t_1, t_2, \ldots, t_n; \beta, \gamma)$. The possibility function for parameters β, γ is given as follows[17]:

$$L(t_1, t_2, \ldots, t_n; \beta, \gamma) = \left(\prod_{i=1}^{n} \lambda(t_i; \beta, \gamma)\right) exp\left(-\int_0^{t_n} \lambda(t_i; \beta, \gamma)\, dt\right), \quad 0 < t_1 < t_2 < \cdots < t_n < \infty \tag{15}$$

Based on the maximum likelihood estimator (MLE's), it can be obtained estimator as Equations (16) and (17):

$$\widehat{\beta} = \frac{n}{\sum_{i=1}^{n} \ln\left(\frac{t}{t_i}\right)} \tag{16}$$

and

$$\widehat{\gamma} = \frac{t}{n^{\frac{1}{\widehat{\beta}}}} \tag{17}$$

3. Results

3.1. Calculation of the Standardized Precipitation Index (SPI) for 1 Month Period in South Sulawesi

This research uses SPI calculations on a 1-month time scale to evaluate drought in the short term. The period used is 42 years, from January 1981 to December 2023. The SPI calculation process is based on Equations (1)–(9) using data on the monthly rainfall amount in each district/city in South Sulawesi. The 1-month SPI calculation results in each district/city in South Sulawesi are presented in **Figure 2**.

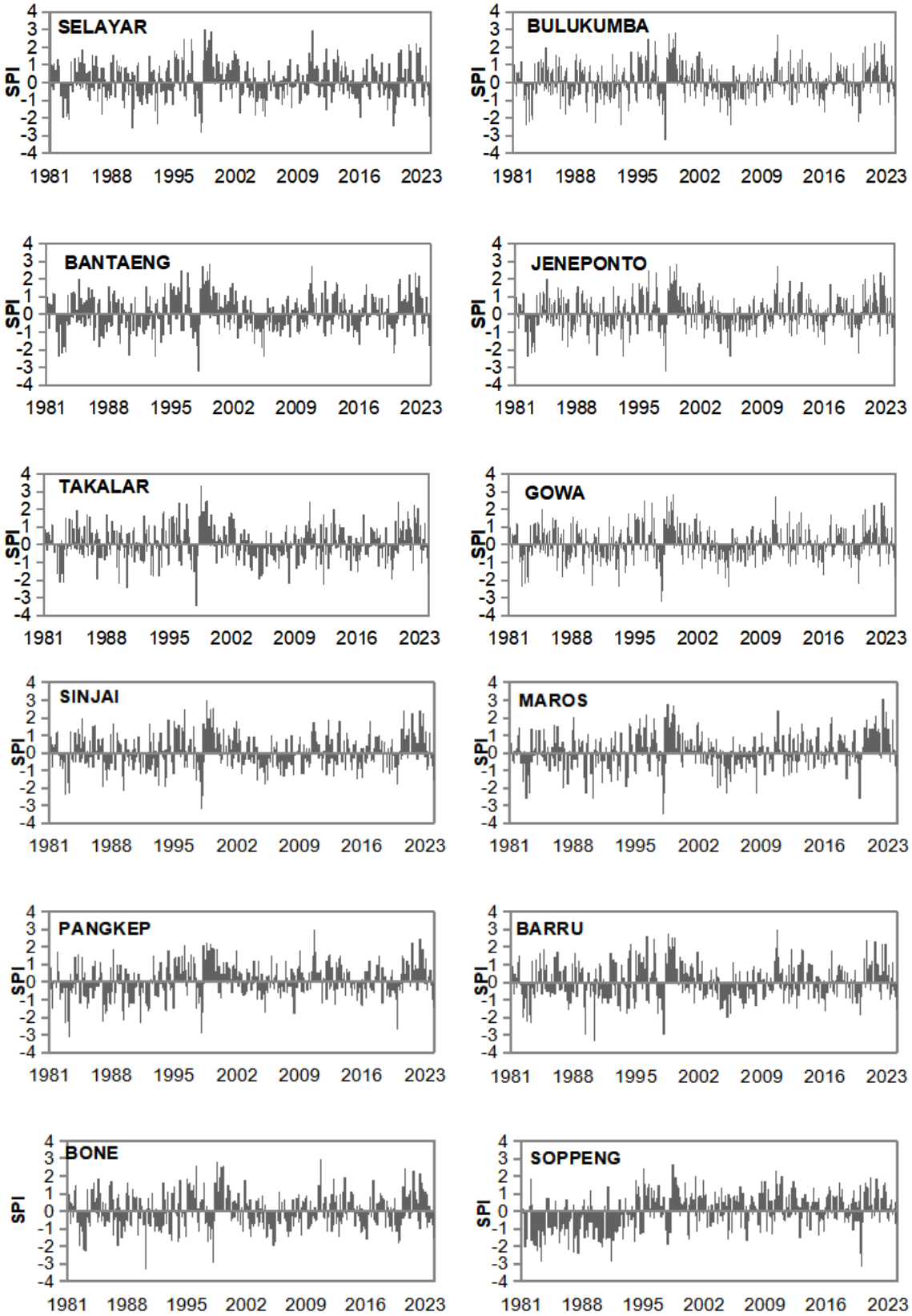


Figure 2. *Cont.*

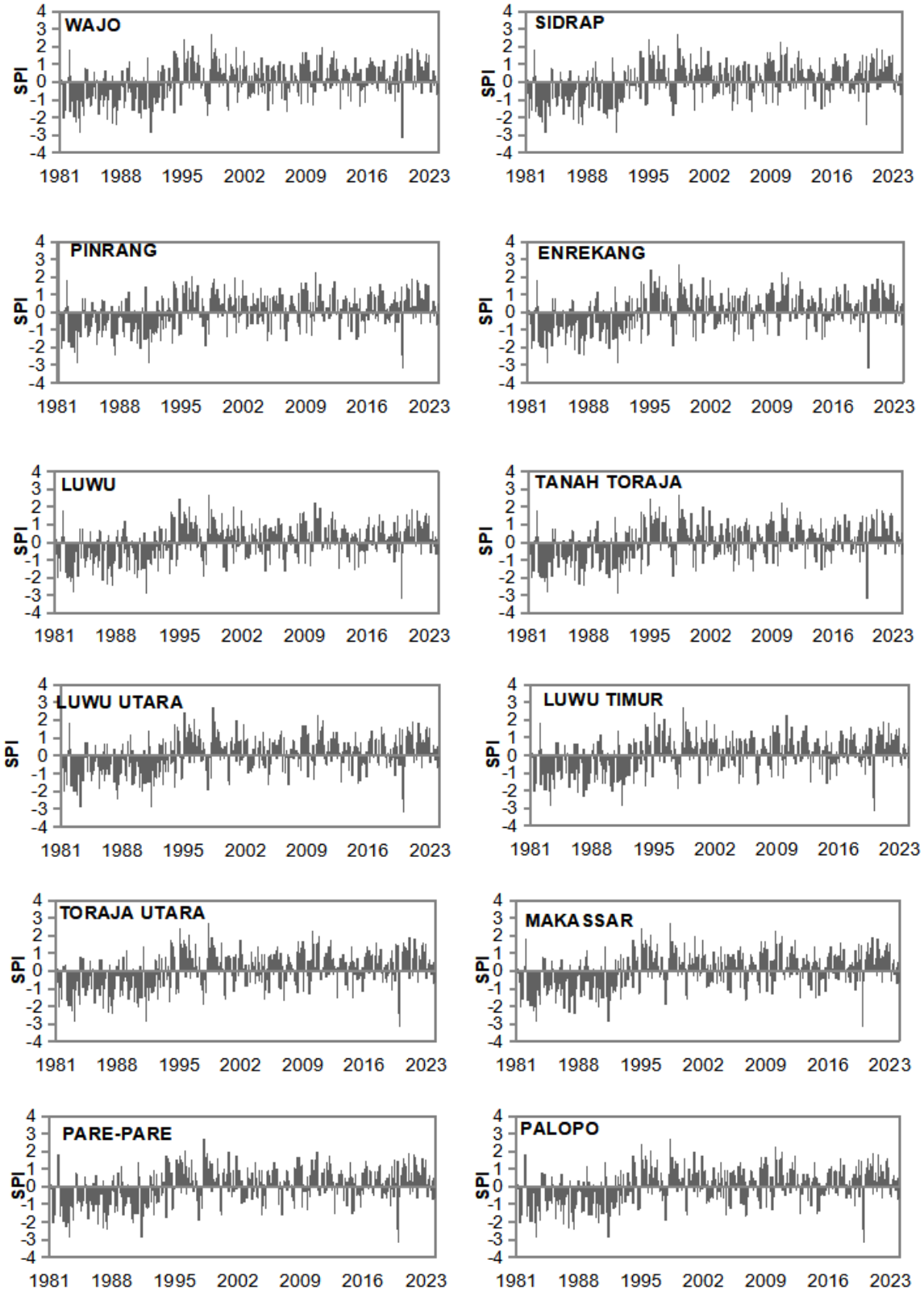


Figure 2. SPI-1 month value in South Sulawesi.

3.2. Identification of Drought Based on SPI in South Sulawesi

McKee, Doesken and Kleist used the classification system shown in **Table 1** to determine drought intensity by categorizing it into moderate, severe, and extreme drought[9]. The results of identifying the number of droughts based on the level of drought that has been classified from the value of $SPI \leq -1$ in each district/city in South Sulawesi are presented in **Figure 3**.

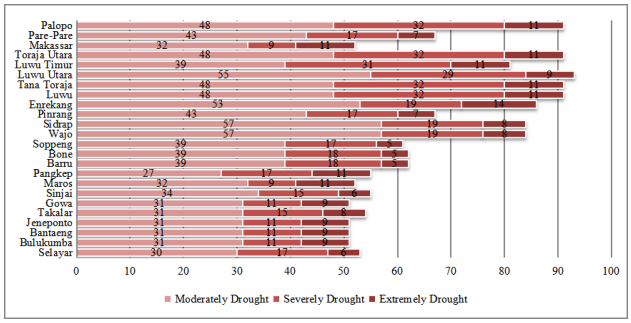


Figure 3. Distribution of SPI drought levels that have occurred in South Sulawesi during observations 1981–2023.

3.3. Testing the Suitability of the Power Law Process Model

To test the level of suitability of the intensity of SPI drought events in each district/city of South Sulawesi with the Power Law Process modal, a test was conducted using the Cramér-von Mises test $\left(C_R^2\right)$. C stated that the drought intensity followed the model, and temporary H_1 said otherwise. The statistical test results are then compared with the critical value. If the value C_R^2 is smaller than the critical value, then H_0 is accepted, indicating suitability to the model. However, if the C_R^2 value is greater than the critical value, H_1 is accepted, indicating a mismatch with the model. **Table 3** displays the results of the Cramér-von Mises test obtained using calculations in Equations (13)–(15).

3.4. Power Law Process Parameter Estimation

The estimated value of the Power Law Process model is calculated using the Maximum Likelihood Estimation (MLE) method based on Equations (17) and (18) for 14 districts/cities in South Sulawesi that fit the model. The data used are the time of drought events based on chronological order in 516 months of observation (t_i), the number of identified drought events (n) and the observation time interval (t). The parameter estimation results for 14 districts/cities in South Sulawesi are presented in **Table 4**.

The estimated parameter values in **Table 4** are used to calculate the number of drought events that will occur in the future using the Power Law Process expectation function in Equation (12). Previously, estimates were made of the number of drought events that had occurred during 516 months of observation. This estimation aims to validate the model's accuracy and ensure that the expected number of drought months corresponds to the number of drought events during that period. The results of the comparison between the actual number of events and the predicted number of events in 516 months of observations in 14 districts/cities of South Sulawesi are shown in **Figure 4**.

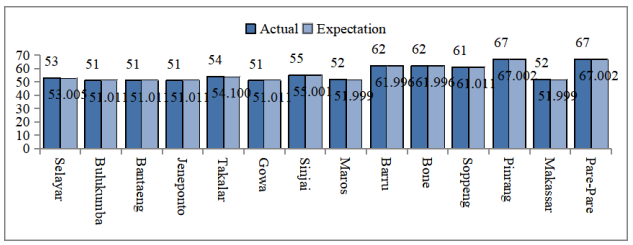


Figure 4. Comparison of actual drought events and suspected droughts in 14 districts/cities in South Sulawesi within a monitoring period of 516 months.

3.5. Calculation of the Number and Time of Meteorological Drought Events in South Sulawesi for the Next 12 Months

For example, the time of the drought event in each observation area is $t_i < t_2 < \cdots < t_n < t$, where t is the end time of the observation period and $N(t) = \{N, t_i < t_2 < \cdots < t_n; (0, t]\}$, N states the number of months of drought events in a time interval $(0, t]$. It is known that the total number of months observed from 1981−2023 is t = 516 months. The month period estimated in this research is s = 12 months into the future. So, the time interval is extended to 516 + 12 = 528.

In the 516th month, the expected number of drought events was calculated, which agreed with the actual number of observations. Next, calculations were carried out to predict the number of drought events in the following months, namely the 517th to the 528th month. The time interval from the 517th month to the 528th month is the prediction pe-

riod, where the 517th month is January 2024, and the 528th month is December 2024. The estimated number of months of drought occurrence in each estimation time is presented in **Figure 5**.

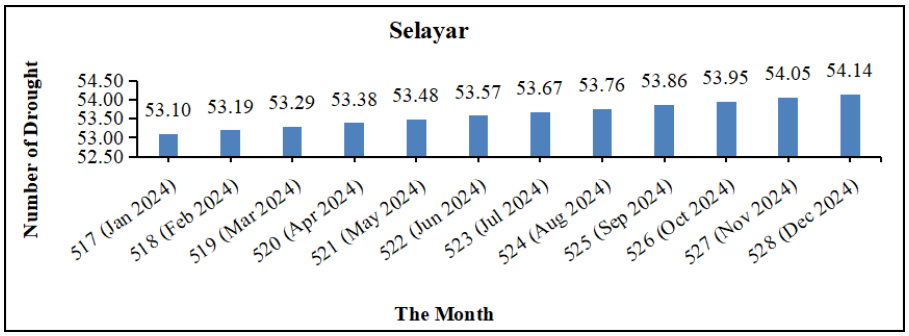
Table 3. Cramér-von Mises test results.

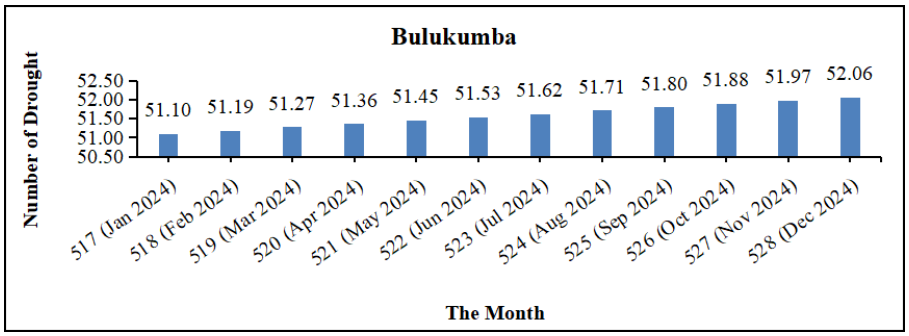
Districts/Cities	C_R^2	Critical Value	Decision
Selayar	0.12	0.22	H_0 accepted
Bulukumba	0.05	0.22	H_0 accepted
Bantaeng	0.05	0.22	H_0 accepted
Jeneponto	0.05	0.22	H_0 accepted
Takalar	0.07	0.22	H_0 accepted
Gowa	0.05	0.22	H_0 accepted
Sinjai	0.06	0.22	H_0 accepted
Maros	0.21	0.22	H_0 accepted
Pangkep	0.38	0.22	H_0 rejected
Barru	0.12	0.22	H_0 accepted
Bone	0.12	0.22	H_0 accepted
Soppeng	0.15	0.22	H_0 accepted
Wajo	0.55	0.22	H_0 rejected
Sidrap	0.55	0.22	H_0 rejected
Pinrang	0.11	0.22	H_0 accepted
Enrekang	0.80	0.22	H_0 rejected
Luwu	0.92	0.22	H_0 rejected
Tana Toraja	0.92	0.22	H_0 rejected
Luwu Utara	1.13	0.22	H_0 rejected
Luwu Timur	0.63	0.22	H_0 rejected
Toraja Utara	0.92	0.22	H_0 rejected
Makassar	0.21	0.22	H_0 accepted
Pare-Pare	0.11	0.22	H_0 accepted
Palopo	0.92	0.22	H_0 rejected

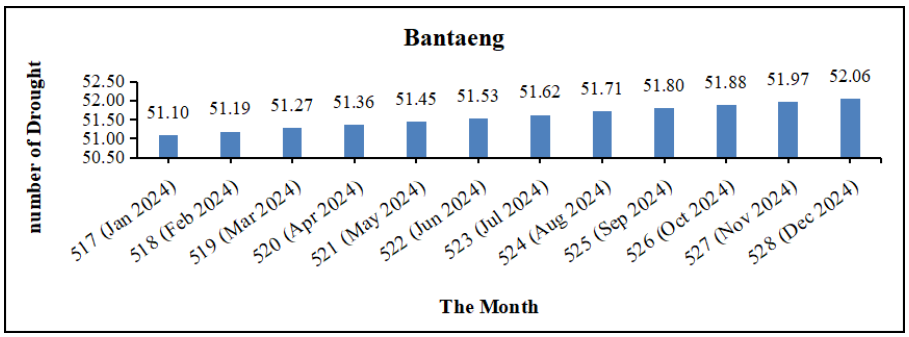
Table 4. Estimated values of Power Law Process parameters.

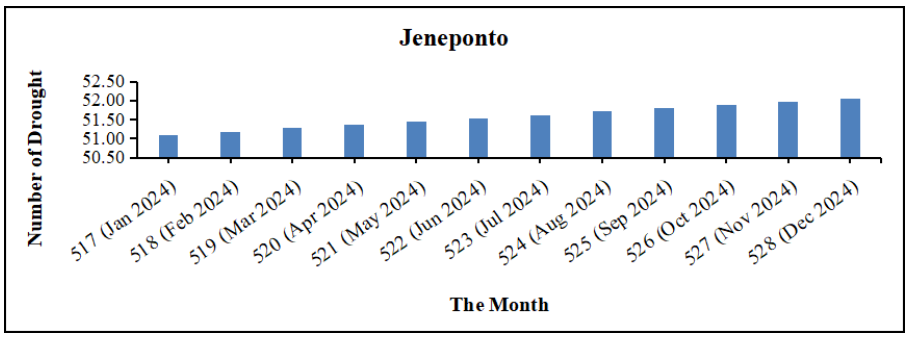
Districts/cities	$\widehat{\beta}$	$\widehat{\gamma}$
Selayar	0.9222	6.9641
Bulukumba	0.8838	6.0321
Bantaeng	0.8838	6.0321
Jeneponto	0.8838	6.0321
Takalar	1.089	13.216
Gowa	0.8838	6.0321
Sinjai	0.96658	8.1677
Maros	0.8497	4.9331
Barru	0.8749	4.6132
Bone	0.8749	4.6132
Soppeng	0.8608	4.3503
Pinrang	0.76167	2.0662
Makassar	0.8497	4.9331
Pare-Pare	0.76167	2.0662

The monthly probability of a drought event is obtained using the Non-Homogeneous Poisson Process. Calculations are based on Equation (10) by utilizing the expected value from the Power Law Process for each month in the prediction period, namely the 517th month to the 528th month. The n value in the Non-Homogeneous Poisson Process calculation represents the estimated number of months of drought events that may occur where n is adjusted to the number of estimated time intervals ($n = s$). The results of this calculation show the monthly probability value of a drought event. The distribution of probability values for months of drought occurrence in 12 estimated time blocks is presented in **Figure 6**.









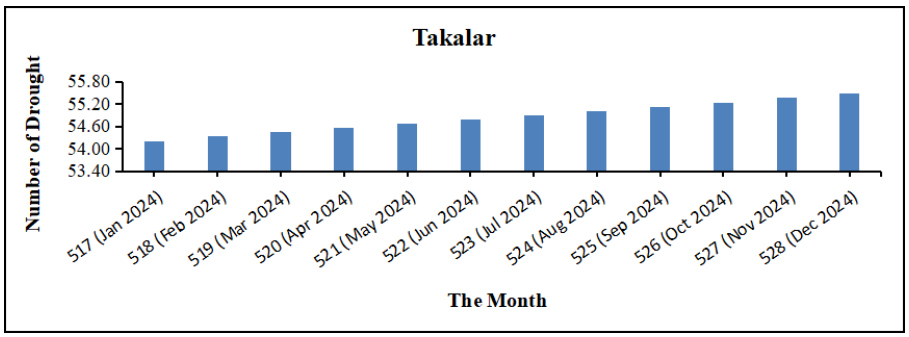
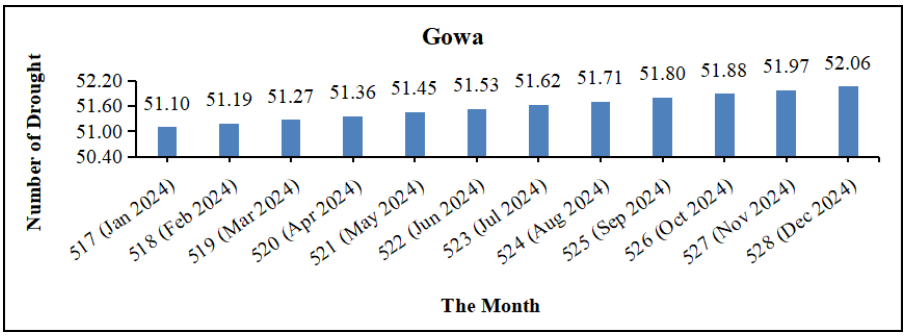
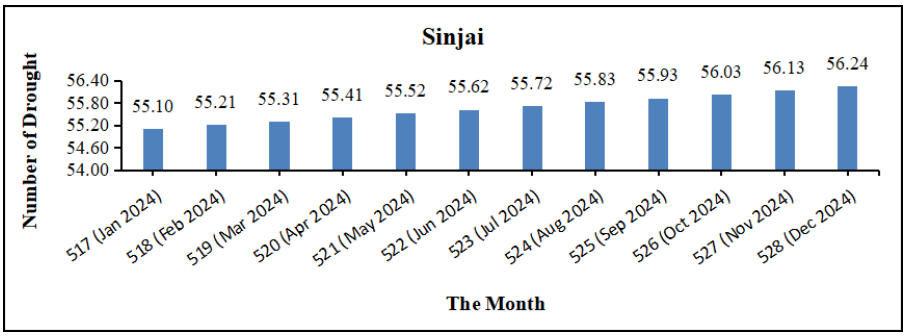
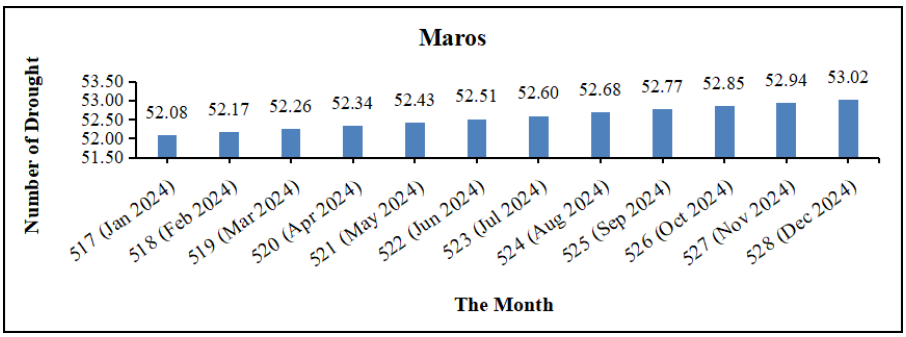
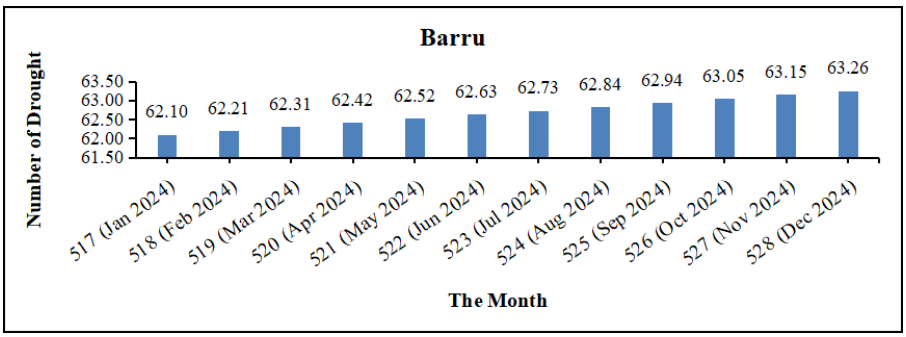


Figure 5. *Cont.*









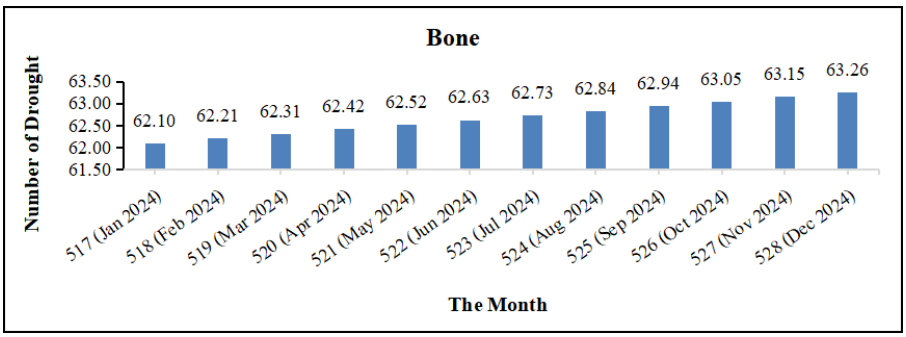


Figure 5. *Cont.*

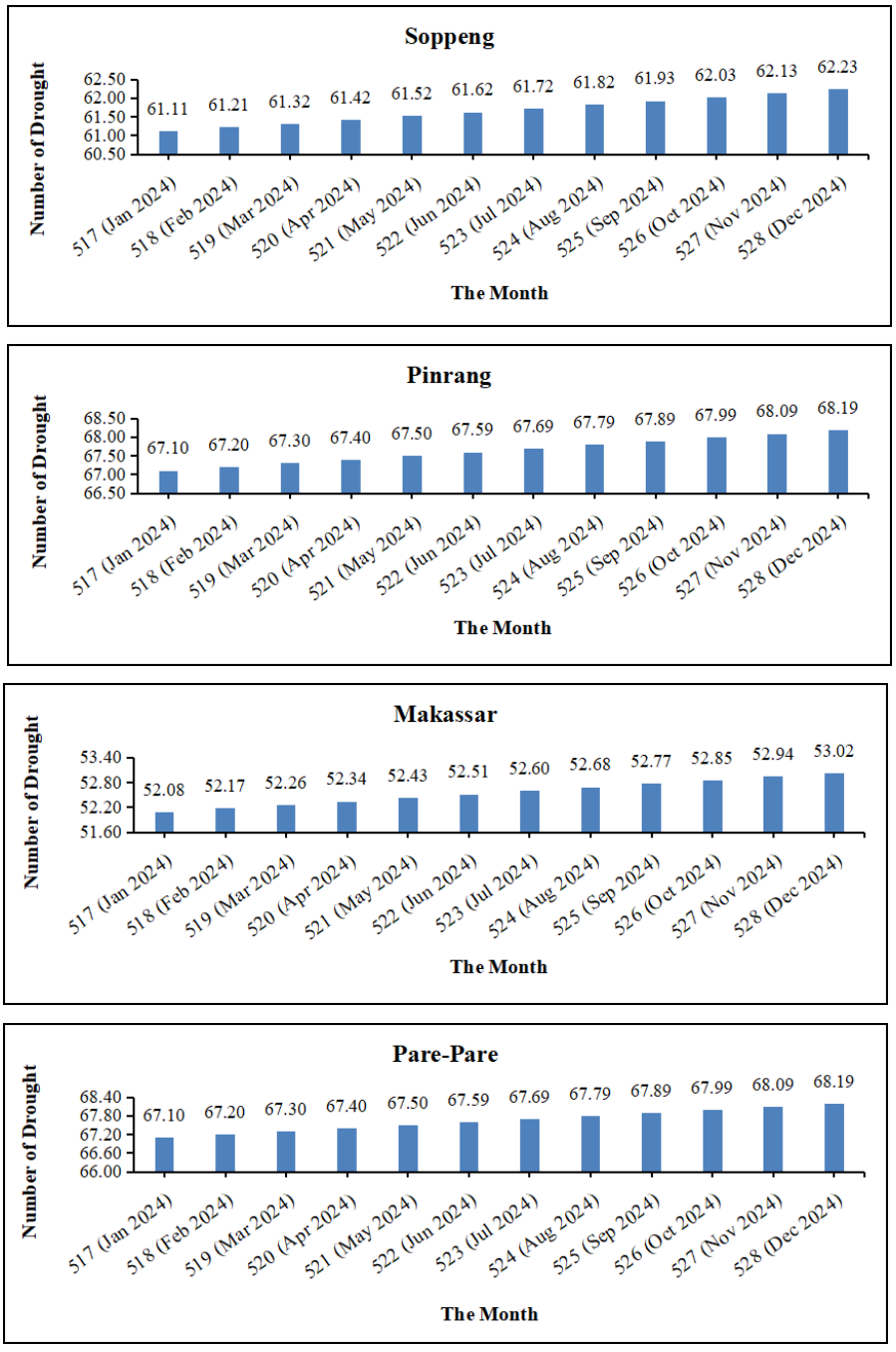


Figure 5. Estimated number of drought events in the future 12 months in 14 districts in South Sulawesi.

4. Discussion

4.1. Standardized Precipitation Index (SPI) for One Month Period in South Sulawesi

McKee first developed SPI in 1993, and it has been standardized internationally for use in various geographic locations with different rainfall data. SPI is calculated by fitting rainfall data to a gamma probability distribution function (Γ) and changing the Γ distribution to a normal distribution [9]. In this study, the SPI calculation uses a 1-month time scale to assess short-term drought in each district/city in South Sulawesi with a calculation period of 42 years, starting from January 1981 to December 2023. Generally, the longer the period used to calculate SPI, the greater the possibility of obtaining better results [26]. A positive SPI calculation result indicates that rainfall is higher than the median, while a neg-

ative SPI value indicates lower rainfall. Because SPI can similarly reflect normal, wet, and dry climate conditions, wet periods can be monitored using SPI[9].

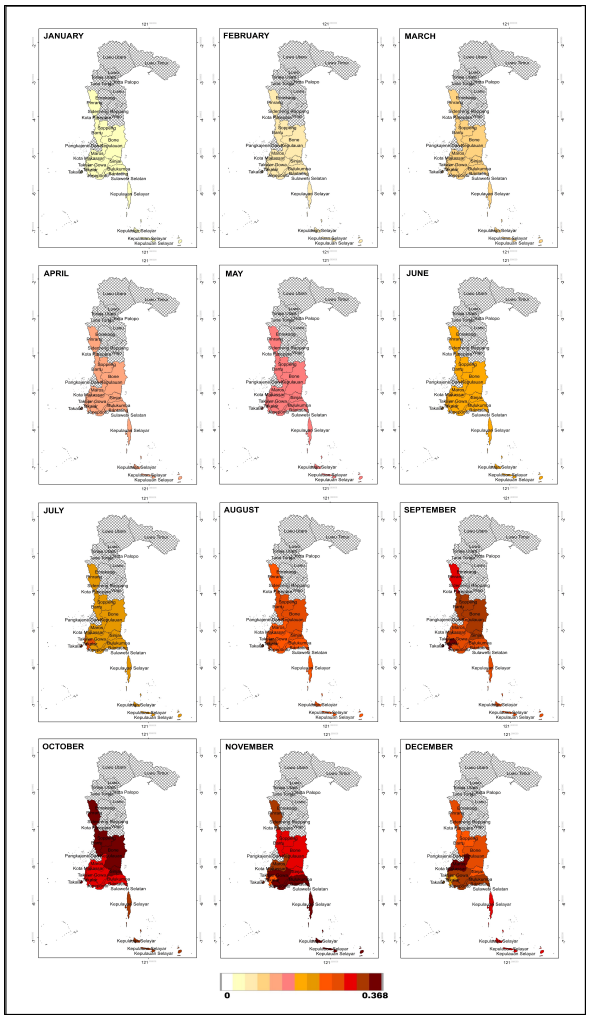


Figure 6. Distribution of probability months for drought in 14 districts/cities in South Sulawesi.

The SPI calculation results in each district/city in South Sulawesi presented in **Figure 2** show apparent fluctuations between wet and dry periods. SPI values ≥ 1 indicate periods with higher rainfall, categorized as wet, moist, and extreme conditions. On the other hand, an SPI value ≤ −1 suggests a period of less than average rainfall, which results in drought varying from dry, very light to extremely dry.

4.2. Distribution of Drought Levels in South Sulawesi

McKee, Doesken and Kleist, used the classification system shown in **Table 1** to determine drought intensity. Drought is identified when SPI values are consistently negative and reach −1.0 or less. A drought is considered to end when the SPI value becomes positive. Thus, each drought event has a duration determined by its start and end periods and its intensity for each month during the event. The number of months with a negative SPI value can be used to measure the drought's duration, while the drought's magnitude is calculated based on the lower SPI value[9].

Drought events identified based on negative SPI values, as shown in **Figure 2**, vary in each district/city in South Sulawesi. Over the last 516 months, North Luwu Regency recorded the highest number of drought events, namely 93 months, with the lowest SPI value reaching −3.37. This value shows an extreme drought event that occurred in December 2019. On the other hand, the Gowa, Jeneponto, Bantaeng, and Bulukumba regions experienced the most extreme drought in January 1998, with an SPI value of −3.23.

The distribution of drought incidence levels for each region in South Sulawesi can be seen in **Figure 3**. From this data, it can be seen that areas in South Sulawesi tend to experience lighter levels of drought more frequently. However, extreme drought events can still occur sporadically. This means that although very severe droughts do not happen often, the risk of extreme drought still exists and needs to be watched out for.

4.3. Modeling the Intensity of Drought Events in the Power Law Process

Based on the distribution of levels of drought events in South Sulawesi, a distribution pattern of event intensity was obtained, indicating that extreme dry events occur less frequently than events categorized as very dry or dry. In a stochastic process framework, the observed drought pattern can reflect the characteristics of the Power Law Process model, where the intensity of an event is inversely proportional to its frequency.

Therefore, to test the suitability of the data with the Power Law Process model, the Cramér-von Mises test was used[17]. This test aims to verify whether the distribution of drought event intensity matches the expected model. Drought event data are sorted chronologically for this purpose, where, for example, January 1981 is considered the 1st month, February 1981 the 2nd month, January 1982 the 13th month, February 1982 the 14th month, and so on. This

sorting process continues from year to year until it reaches December 2023, which is the 516th month.

The test results based on **Table 3** show that there are 14 districts/cities in South Sulawesi with SPI drought incidence intensity according to the Power Law Process model. This is obtained from the C_R^2 value being smaller than the critical value. On the other hand, one district/city with C_R^2 values that exceed the critical value indicates a mismatch with the model. So, in modeling drought using the Power Law Process in South Sulawesi, researchers selected 14 districts/cities that fit the model for further analysis.

4.4. Power Law Process Parameter Estimation

The Power Law Process model estimation can be applied to two categories of data generally observed: the time interval between events and the number of events in a specific time interval [17, 27]. In analyzing time intervals between events, the main focus is observing the time between each event. In contrast, in examining the number of events in a time interval, the data collected is the number of events that occur.

This research uses the Power Law Process estimation method applied to the second category by observing the number of drought events in a predetermined time interval. The estimation method uses Maximum Likelihood Estimation (MLE) [28, 29]. The number of drought events was calculated based on identifying events with the value of SPI ≤ -1 during the 516-month observation period (January 1981 to December 2023) in each region studied. The results of estimating Power Law Process parameters using the Maximum Likelihood method for 14 districts/cities in South Sulawesi are presented in **Table 4**. These values can be used to estimate the number of drought events that may occur in the future using the Power Law Process expectation function.

Before that, an estimate was made of the number of drought events that had occurred during the 516 months of observation. This estimation aims to validate the model's accuracy and ensure that the predicted number of drought months corresponds to the number of drought events during that period. The results of the comparison between the actual number of events and the expected number of events in 516 months of observations in 14 districts/cities of South Sulawesi are shown in **Figure 4**. This figure shows that the predicted number of drought months is in line with the number of drought events that occurred during that period. **Figure 4** shows a good match between the actual droughts and the expected droughts based on the Power Law Process expectation function in 14 districts/cities in South Sulawesi, with a relatively small difference in values below 0.1. Thus, the Power Law Process expectation function is proven to be reliable for predicting the number of drought events that will occur in the future.

4.5. Estimation of Future Drought Periods

This research estimates the drought period for the next 12 months. The estimation process begins by adding 12 months to the main observation period, which lasts 516 months, bringing the total time interval to 528. Using the expectation function from the Power Law Process, predictions of the number of months of drought events are made within the 528-month time interval. Interpretation of the estimation time based on the 1981−2023 year range is as follows: the 1st month is January 2023, and the 516th month is December 2023. For the estimated months, the 517th month is January 2024 to the 528th month, precisely December 2024.

Suppose there is an increase in drought events compared to the previous observation period. In that case, this increase indicates the number of drought events that may occur in the future. In other words, the number of drought months predicted is the difference between the number of predicted drought events and the number of previously observed drought events.

Figure 5 shows that in the next 12 months, the 14 districts/cities in South Sulawesi are expected to experience an increase in the number of drought events by one month. For a more precise illustration, for example, in Selayar Regency, during the 516-month observation period, 53 months of drought were recorded (see **Figure 4** for the actual number of drought events in Selayar Regency). After considering the additional 12 months, for a total of 528 months, the expected number of drought events in Selayar Regency is estimated to increase to 54.14 months (see **Figure 5**). This means an increase of 1.14 months in drought events compared to the initial observation period (516 months). **Figure 5** shows that the 14 districts/cities in South Sulawesi are estimated to experience an increase in drought events by one month from the previous observation period.

Therefore, as a mitigation and planning step to deal with a drought event of 1 month in the future, the probability of a drought event month is calculated using the Non-Homogeneous Poisson Process. The Non-Homogeneous Poisson Process is a method used to model random events that occur within a specific time interval, with the event's intensity changing over time[17]. In this context, the intensity of drought events obtained from the Power Law Process model can be considered a particular case of the Non-Homogeneous Poisson Process. In other words, the Non-Homogeneous Poisson Process allows for calculating the probability of a drought event corresponding to changes in the event's intensity over time.

The results of calculating the probability of months of drought occurrence for the 14 districts/cities in South Sulawesi are presented as a spatial distribution in **Figure 6**. This figure shows the probability distribution for the months of drought occurrence in all areas studied. For more detailed information, the mapping of the monthly probability of drought events for each district/city can be seen in **Figures 7–20**. In this mapping, the month with the highest likelihood of short-term drought events is marked with a darker color, with a maximum probability value reaching 0.37. Conversely, months with lower odds are shown in lighter shades. A probability value of 0.37 was recorded in November in the Selayar, Bulukumba, Bantaeng, Jeneponto, Takalar, and Gowa areas; in October in the Sinjai, Barru, Bone, Soppeng, Pinrang, and Pare-pare areas; as well as in December in the Maros and Makassar areas. Thus, these months show a higher probability of drought than others, meaning they are the most likely to experience drought in the next 12 months.

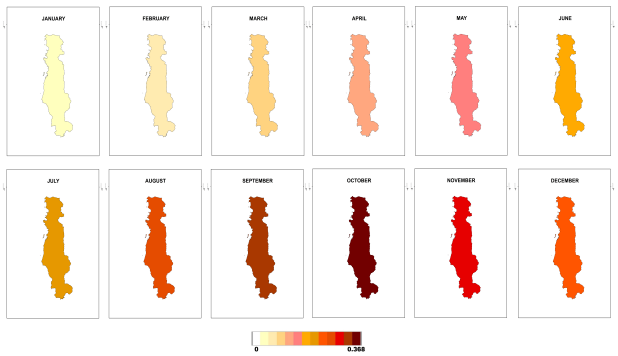


Figure 7. Distribution of probability months for drought in Barru Regency.

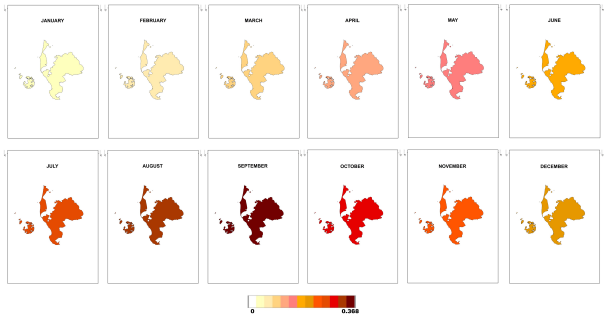


Figure 8. Distribution of probability months for drought in Takalar Regency.

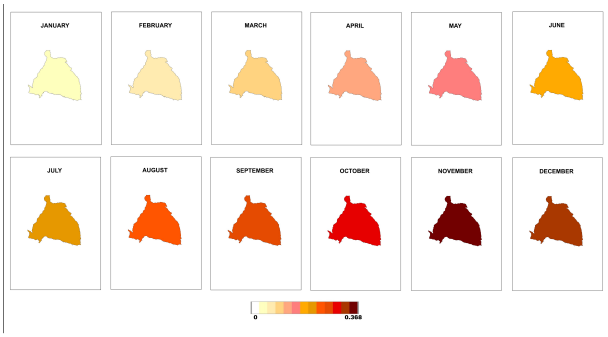


Figure 9. Distribution of probability months for drought in Bantaeng Regency.

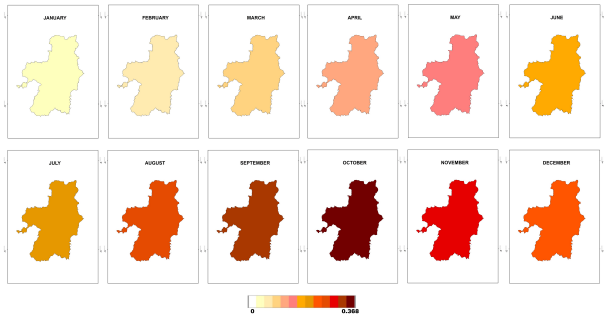


Figure 10. Distribution of probability months for drought in Bone Regency.

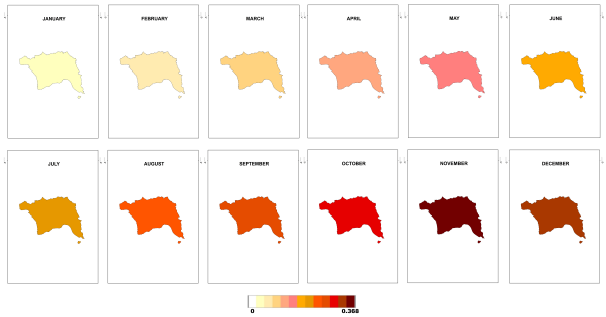


Figure 11. Distribution of probability months for drought in Bulukumba Regency.

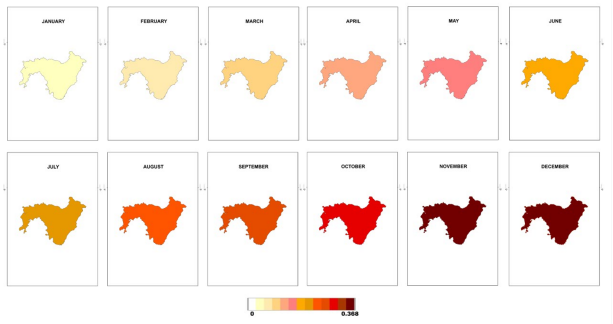


Figure 12. Distribution of probability months for drought in Gowa Regency.

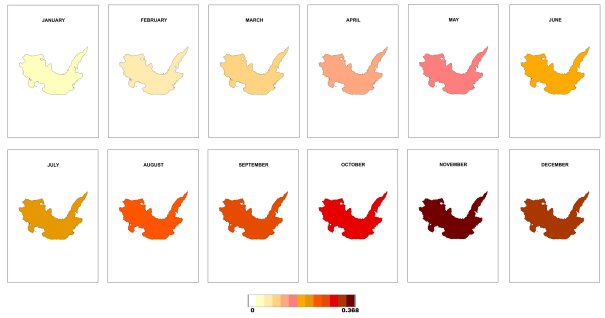


Figure 13. Distribution of probability months for drought in Jeneponto Regency.

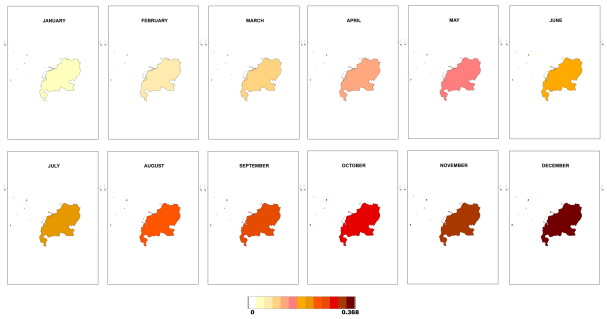


Figure 14. Distribution of probability months for drought in Makassar City.

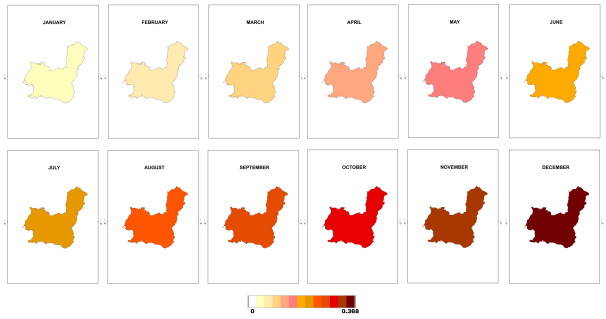


Figure 15. Distribution of probability months for drought in Maros Regency.

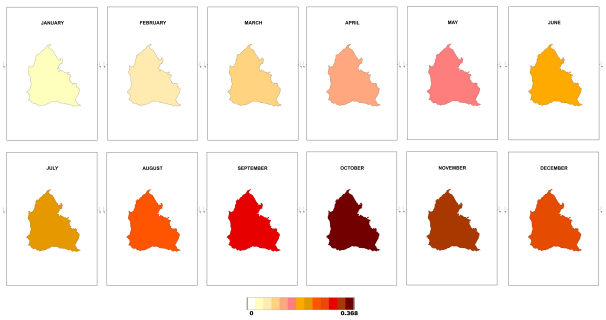


Figure 16. Distribution of probability months for drought in Parepare City.

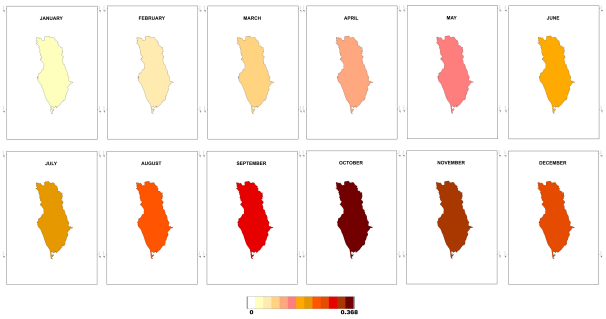


Figure 17. Distribution of probability months for drought in Pinrang Regency.

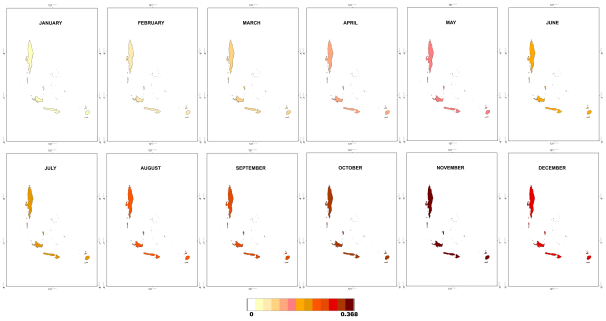


Figure 18. Distribution of probability months for drought in Selayar Regency.

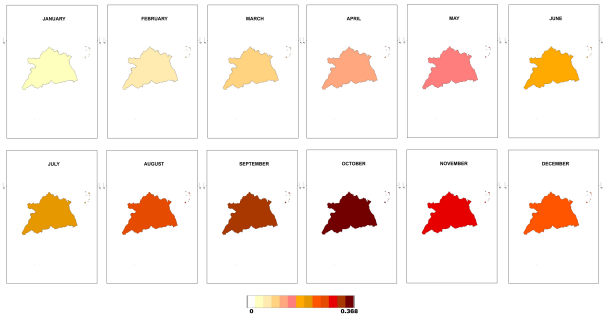


Figure 19. Distribution of probability months for drought in Sinjai Regency.

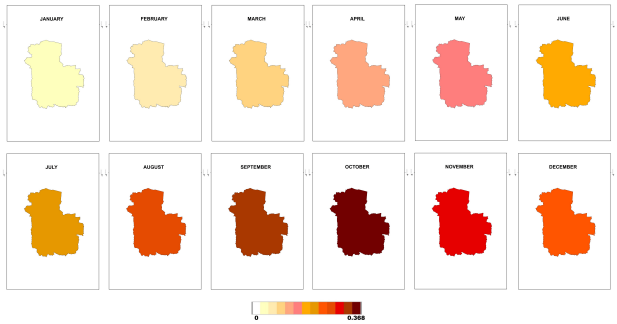


Figure 20. Distribution of probability months for drought in Soppeng Regency.

5. Conclusions

Characteristics of the intensity of short-term meteorological drought events using the Standardized Precipitation Index (SPI) for one month in South Sulawesi show that the intensity distribution of extreme drought events occurs less frequently compared to moderate drought and severe drought events. The results of Power Law Process parameter estimation based on SPI-based cases of short-term meteorological drought event data show parameter values β and γ that are greater than 0, where of the 24 districts/cities in South Sulawesi, there are 14 districts/cities with drought event intensity, that is by the model Power Law Process. The estimated number of short-term meteorological drought events in the next 12 months using the Non-Homogeneous Poisson Process in the 14 districts/cities is one month with a month probability value of a drought event of 0.37 occurring in November in the Selayar, Bulukumba, Bantaeng, Jeneponto, Takalar, and Gowa; in October in the Sinjai, Barru, Bone, Soppeng, Pinrang and Pare-pare areas; as well as in December in the Maros and Makassar areas.

Author Contributions

N.S. conducted a literature study on meteorological drought problems, characterized the short-term drought index, and estimated Power Law Process parameters. N.H.A. conducted data recording. S. and A.K.J. conducted data analysis. E.T.H. conducted a mapping location of the meteorological drought.

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Institutional Review Board Statement

The study does not require ethical approval.

Informed Consent Statement

Not applicable.

Data Availability Statement

The author agrees to share their research data upon request.

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Conflicts of Interest

There is no conflict of interest related to this article.

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