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Assessment of Meteorological Drought in Merauke Regency Using the Standardized Precipitation Index (SPI)

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ABSTRACT

This study investigates drought variability and prediction in Kurik District, Merauke Regency, South Papua, using the Standardized Precipitation Index (SPI). A 20-year dataset of monthly rainfall (2004–2023) and the Southern Oscillation Index (SOI) were analyzed. Data quality assessments, including consistency (RAPS), trend (Spearman rank), stationarity (F-test and t-test), and persistence (autocorrelation), confirmed that the dataset was statistically valid for time-series analysis. The SPI-1 analysis identified that the most severe drought occurred in March 2021, with an index value of –3.145 categorized as extreme drought. Correlation analysis revealed a weak relationship between SPI and SOI (r = 0.189), indicating that ENSO events exerted minimal influence on local drought dynamics. Rainfalls prediction for the period 2024–2033 was conducted using the Thomas–Fiering stochastic model. The results indicated that the most extreme drought event is projected to occur in April 2029 (SPI = –3.017), while the longest drought duration is expected in 2025, lasting for seven consecutive months. These findings provide scientific evidence for supporting agricultural adaptation, water resource planning, and climate risk mitigation in South Papua. The study highlights the importance of integrating localized drought monitoring with predictive modeling to strengthen regional resilience against climate variability.

1. INTRODUCTION

Drought is one of the most complex and devastating natural hazards, with impacts that extend across environmental, social, and economic sectors [1-3]. Unlike other natural disasters that manifest abruptly, drought develops slowly over time, making its onset difficult to detect and its consequences long-lasting [4,5]. The impacts of drought can be particularly severe in regions highly dependent on rainfall for agricultural production and water supply. As global climate change intensifies, characterized by rising temperatures and altered hydrological cycles, the frequency, duration, and intensity of drought events are projected to increase, especially in tropical and subtropical regions [6,7]. These changing dynamics underscore the urgent need for robust drought monitoring and forecasting systems to support adaptive resource management and policy-making. In the Indonesian context, drought events frequently occur due to the country's geographical location in the tropics, where the hydrological cycle is strongly influenced by global climate variability, such as the El Niño–Southern Oscillation (ENSO) [8,9]. During strong El Niño phases, much of Indonesia experiences significant rainfall deficits that trigger severe meteorological and agricultural droughts, leading to crop failure, water scarcity, and heightened risks of forest fires. Conversely, La Niña episodes may result in excessive rainfall and flooding [10,11]. This high interannual variability highlights the importance of applying standardized methods to quantify and classify drought severity, thereby enabling stakeholders to design better mitigation and adaptation strategies [12-15].

The province of South Papua, particularly Merauke Regency, holds a strategic role as one of Indonesia's leading food production centers under the government's national agricultural development program. However, the region is also highly vulnerable to climatic extremes due to its flat topography, distinct wet and dry seasons, and reliance on rainfall as the primary source of water for irrigation and agricultural practices. Extended periods of below-normal rainfall can severely affect local farming systems, reduce agricultural productivity, and threaten food security. Despite this, scientific studies addressing drought patterns and prediction in Merauke remain limited, and most available analyses are descriptive without comprehensive integration of statistical and climatological models. One of the most widely recognized indices for assessing meteorological drought is the Standardized Precipitation Index (SPI), which quantifies precipitation anomalies over multiple timescales. The SPI method offers advantages over traditional drought indices, as it is based solely on precipitation data, allows for temporal flexibility, and facilitates comparison across regions with different climatological conditions. Furthermore, the SPI has been adopted by the World Meteorological Organization (WMO) as a standard drought monitoring tool due to its robustness and applicability in diverse climates. By applying the SPI, drought events in Merauke can be objectively identified, characterized, and classified into categories ranging from mild to extreme, thereby providing valuable insights into local drought dynamics.

In addition to assessing historical drought events, predicting future drought risk is equally essential for long-term planning. Stochastic models such as the Thomas-Fiering method can be utilized to generate synthetic rainfall data based on historical time series, offering valuable projections of precipitation trends under natural climate variability. When combined with SPI analysis, such predictions enable policymakers and agricultural stakeholders to anticipate the timing, duration, and severity of future droughts, thus supporting proactive decision-making in crop calendar adjustments, water resource allocation, and disaster risk reduction strategies.

This study aims to conduct a comprehensive analysis of meteorological drought in Merauke Regency using the SPI method, supported by statistical evaluations of rainfall time series to ensure data validity and reliability. Moreover, the relationship between ENSO variability, represented by the Southern Oscillation Index (SOI), and local drought events will be examined to understand the extent of global climate teleconnections in influencing regional hydrology. Finally, future rainfall scenarios will be simulated using the Thomas-Fiering stochastic model to forecast drought occurrences in the upcoming decade. Through this integrated approach, the research is expected to contribute to the development of a scientific basis for climate risk management in South Papua, supporting both sustainable agricultural practices and resilience-building against future drought hazards.

2. RESEARCH METHODOLOGY

2.1 Study Area

The research was conducted in Kurik District, Merauke Regency, South Papua, Indonesia, a region characterized by a tropical monsoonal climate with distinct wet and dry seasons. The area is part of the lowland plains of southern Papua, which serve as one of Indonesia's national agricultural production zones. Its relatively flat topography, coupled with strong seasonal rainfall variability, makes the region highly sensitive to meteorological droughts. Understanding rainfall dynamics in this area is therefore crucial for supporting agricultural resilience and water resource management.

2.2 Data Collection

The study utilized 20 years of monthly rainfall data (2004–2023) obtained from local meteorological stations in Merauke. To explore the influence of large-scale climate variability, the Southern Oscillation Index (SOI) was also incorporated as a representation of ENSO (El Niño–La Niña) phenomena. The selection of a 20-year dataset was intended to provide a sufficiently long time series to capture both short-term and long-term rainfall fluctuations and their potential impact on drought occurrence.

2.2 Data Quality Evaluation

Prior to analysis, the rainfall time series was subjected to a series of data quality assessments to ensure reliability and suitability for stochastic modeling:

1. Consistency Test (Rescaled Adjusted Partial Sums / RAPS): applied to detect potential systematic errors or changes in observation practices over time.
2. Trend Analysis (Spearman Rank Test): conducted to examine the presence of monotonic trends in the rainfall data.
3. Stationarity Tests (F-test and t-test): used to confirm whether the statistical characteristics (mean and variance) of the data remained constant over time.
4. Persistence Test (Autocorrelation Analysis): performed to evaluate the degree of serial correlation in the rainfall sequence.

Only after passing these quality checks was the dataset considered valid for SPI calculation and stochastic modeling.

2.3 Standardized Precipitation Index (SPI) Analysis

The SPI method was employed to quantify meteorological drought intensity. The procedure involved fitting the monthly rainfall data into a Gamma probability distribution, which was subsequently transformed into a standardized normal distribution. SPI values were calculated for the 1-month timescale (SPI-1), suitable for detecting short-term meteorological droughts relevant to agricultural impacts. Drought categories were classified according to World Meteorological Organization (WMO) standards, ranging from mild to extreme drought. The temporal distribution of SPI values allowed identification of both the onset and duration of historical drought events.

2.4 Correlation with ENSO (SOI Index)

To assess the influence of global climate variability, correlation analysis was conducted between SPI values and the Southern Oscillation Index (SOI). This step aimed to determine the extent to which El Niño and La Niña phases contributed to rainfall anomalies and subsequent drought conditions in Merauke. The correlation coefficient was interpreted based on its statistical significance and magnitude, providing insights into whether ENSO is a dominant driver of local droughts.

2.5 Rainfall Prediction Using the Thomas–Fiering Stochastic Model

Future rainfall scenarios were generated using the Thomas-Fiering stochastic model, a widely used method in hydrology for simulating synthetic streamflow and precipitation series. The model is based on the following formulation:

$$Q_{t+1} = \mu_{t+1} + \sigma_{t+1}\left[r_t\left(\frac{Q_t-\mu_t}{\sigma_t}\right) + \sqrt{1-r_t^2}\cdot Z_t\right] \qquad (1)$$

Where:

1. Qt+1Q_{t+1}Qt+1 = predicted rainfall for month t+1t+1t+1
2. μt\mu_tμt, σt\sigma_tσt = mean and standard deviation of rainfall for month ttt
3. rtr_trt = correlation coefficient between months ttt and t+1t+1t+1
4. ZtZ_tZt = normally distributed random variable

The model was applied to generate synthetic monthly rainfall for the period 2024–2033, maintaining the statistical properties of the historical dataset. The generated series were subsequently processed through the SPI framework to produce drought forecasts, including projected severity, frequency, and duration.

2.6 Analytical Framework

The methodological workflow of this study can be summarized as follows:

1. Collection and preprocessing of rainfall and SOI datasets.
2. Quality assessment of rainfall data using statistical tests.
3. Computation of SPI values at a 1-month timescale to identify historical drought patterns.
4. Correlation analysis between SPI and SOI to evaluate ENSO influence.
5. Rainfall projection using the Thomas-Fiering model for the next 10 years.
6. Application of SPI to synthetic rainfall data to predict future drought occurrences.

This integrative methodological framework ensures that the study not only provides a historical characterization of drought in Merauke but also delivers forward-looking insights into potential future risks. The results are intended to support climate adaptation strategies, agricultural planning, and regional drought mitigation policies.

3. RESULTS AND DISCUSSION

The results of this study provide a comprehensive understanding of meteorological drought dynamics in Kurik District, Merauke Regency, using the Standardized Precipitation Index (SPI). The discussion highlights three key aspects: (i) the validity of rainfall data for long-term drought analysis, (ii) the historical characterization of drought events through SPI, including their intensity and severity, and (iii) the relationship between local droughts and global climate drivers, particularly the El Niño–Southern Oscillation (ENSO), along with drought forecasts for the coming decade.

3.1 Reliability of Rainfall Data

Before conducting SPI analysis, rainfall records from 2004–2023 were subjected to rigorous statistical testing. The RAPS (Rescaled Adjusted Partial Sums) method confirmed that the data series was consistent, indicating no systematic shifts or recording errors. Trend analysis using the Spearman Rank test showed no significant long-term trend, suggesting that the rainfall variability observed in Kurik is predominantly natural rather than anthropogenically driven. Further testing with the F-test and t-test verified the stationarity of the dataset, while autocorrelation analysis demonstrated that the rainfall data was independent and free from persistence bias. These results validate the dataset as a reliable basis for SPI computation and stochastic modeling, despite the relatively short 20-year series compared to the WMO-recommended 30 years.

Based on Tables 1 to 3, all statistical tests indicate that the rainfall data in Kurik District from 2004–2023 is consistent, shows no significant trend, is stationary, and independent. Therefore, the dataset can be considered a reliable basis for SPI calculation and rainfall forecasting using the Thomas–Fiering model.

Table 1. Southern Oscillation Index (SOI) 2004–2023

Years	Months											
	Jan	Feb	Mar	Apr	May	Jun	Juli	Aug	Sept	Oct	Nov	Dec
2023	+11.8	+10.5	−2.0	+0.3	−18.5	+0.2	−4.3	−12.7	−13.6	−6.8	−8.6	−2.4
2022	+4.1	+8.2	+13.8	+22.6	+17.1	+21.2	+8.7	+9.1	+18.3	+17.7	+4.6	+20.0
2021	+16.5	+11.5	−0.3	+2.0	+3.6	+2.6	+15.9	+4.6	+9.3	+6.7	+12.5	+13.8
2020	+1.3	−2.2	−5.2	−0.5	+2.8	−9.6	+4.2	+9.8	+10.5	+4.2	+9.2	+16.9
2019	−0.6	−13.5	−6.8	−1.3	−9.0	−10.4	−5.6	−4.4	−12.4	−5.6	−9.3	−5.5
2018	+8.9	−6.0	+10.5	+4.5	+2.1	−5.5	+1.6	−6.9	−10.0	+3.0	−0.1	+9.3
2017	+1.3	−2.2	+5.1	−6.3	+0.5	−10.4	+8.1	+3.3	+6.9	+9.1	+11.8	−1.4
2016	−19.7	−19.7	−4.7	−22.0	+2.8	+5.8	+4.2	+5.3	+13.5	−4.3	−0.7	+2.6
2015	−7.8	+0.6	−11.2	−3.8	−13.7	−12.0	−14.7	−19.8	−17.8	−20.2	−5.3	−9.1
2014	+12.2	−1.3	−13.3	+8.6	+4.4	−1.5	−3.0	−11.4	−7.6	−8.0	−10.0	−5.5
2013	−1.1	−3.6	+10.5	+0.3	+8.4	+13.9	+8.1	−0.5	+3.9	−1.9	+9.2	+0.6
2012	+9.4	+2.5	+2.9	−7.1	−2.7	−10.4	−1.7	−5.0	+2.6	+2.4	+3.9	−6.0
2011	+19.9	+22.3	+21.4	+25.1	+2.1	+0.2	+10.7	+2.1	+11.7	+7.3	+13.8	+23.0
2010	−10.1	−14.5	−10.6	+15.2	+10.0	+1.8	+20.5	+18.8	+24.9	+18.3	+16.4	+27.1
2009	+9.4	+14.8	+0.2	+8.6	−7.4	−2.3	+1.6	−5.0	+3.9	−14.7	−6.0	−7.0
2008	+14.1	+21.3	+12.2	+4.5	−3.5	+4.2	+2.2	+9.1	+13.5	+13.4	+17.1	+13.3
2007	−7.8	−2.7	−1.4	−3.0	−2.7	+5.0	−5.0	+2.7	+1.4	+5.4	+9.2	+14.4
2006	+12.7	+0.1	+13.8	+14.4	−9.8	−6.3	−7.6	−15.9	−5.8	−16.0	−1.4	−3.5
2005	+1.8	−28.6	+0.2	−11.2	−14.5	+2.6	+0.9	−6.9	+3.9	+10.9	−2.0	+0.1
2004	−11.6	+9.1	+0.2	−15.4	+13.1	−15.2	−6.9	−7.6	−2.8	−3.7	−8.6	−8.0

Table 2. Results of Consistency Test (RAPS)

(n)	Years	Rain (Xi)	Sk*	Dy2	Sk**	|Sk**|
1	2004	2198	-2	0.141	-0.003	0.003
2	2005	2407	207.32	2149.079	0.359	0.359
3	2006	1897	-302.68	4580.759	-0.525	0.525
4	2007	1488	-711.68	25324.421	-1.234	1.234
5	2008	2255	55.32	153.015	0.096	0.096
6	2009	2403	203.32	2066.951	0.353	0.353
7	2010	2992	792.32	31388.549	1.374	1.374
8	2011	2240	40.32	81.285	0.070	0.070

9	2012	1756	-443.68	9842.597	-0.769	0.769
10	2013	1347	-852.68	36353.159	-1.478	1.478
11	2014	2245	44.82	100.442	0.078	0.078
12	2015	1450	-750.18	28138.502	-1.301	1.301
13	2016	2900	700.42	24529.409	1.214	1.214
14	2017	2725	525.32	13798.055	0.911	0.911
15	2018	2113	-86.78	376.538	-0.150	0.150
16	2019	1427	-772.68	29851.719	-1.340	1.340
17	2020	1473	-727.08	26432.266	-1.261	1.261
18	2021	3445	1245.32	77541.095	2.159	2.159
19	2022	2457	257.32	3310.679	0.446	0.446
20	2023	2777	577.32	16664.919	1.001	1.001
Total		43994		332683.58		
Average		2200				
Root Result				576.78729		
Sk**max	2.159					
Sk**min	-1.478					
Q	2.159					
R	3.637					
$\frac{Qy}{\sqrt{n}}$	0.483	<	$\frac{Q}{\sqrt{n}}$	90%	1.10	CONSISTENT
$\frac{Ry}{\sqrt{n}}$	0.813	<	$\frac{R}{\sqrt{n}}$	90%	1.37	CONSISTENT

Table 3. Results of Trend Absence Test (Spearman Rank)

(n)	Years	Ranking (Tt)	Rain (Xi)	Ranking (Rt)	dt	dt^2
1	2004	1	2198	12	11	121
2	2005	2	2407	7	5	25
3	2006	3	1897	14	11	121
4	2007	4	1488	16	12	144
5	2008	5	2255	9	4	16
6	2009	6	2403	8	2	4
7	2010	7	2992	2	-5	25
8	2011	8	2240	11	3	9
9	2012	9	1756	15	6	36
10	2013	10	1347	20	10	100
11	2014	11	2245	10	-1	1
12	2015	12	1450	18	6	36
13	2016	13	2900	3	-10	100
14	2017	14	2725	5	-9	81
15	2018	15	2113	13	-2	4
16	2019	16	1427	19	3	9
17	2020	17	1473	17	0	0
18	2021	18	3445	1	-17	289
19	2022	19	2457	6	-13	169
20	2023	20	2777	4	-16	256
Total						1546
n	20					
dk (n-2)	18					
KP	-0.162					
t(count)	-0.698	t(count) < t(table)		No Significant Trend		
t(table)	2,101					

3.2 SPI-Based Historical Drought Characteristics

The SPI-1 analysis revealed that Kurik District experiences considerable fluctuations between wet and dry conditions. Several years recorded mild to moderate drought episodes, while some years experienced extreme drought. For instance, the year 2020 registered an SPI of -2.126, which falls into the category of extreme drought, reflecting severe water deficits and heightened agricultural vulnerability. Conversely, the year 2021 exhibited an SPI of +2.318, classified as extreme wet conditions, emphasizing the pronounced rainfall variability in the study area. Such oscillations between extremes complicate agricultural planning, particularly in newly established rice fields that require stable water supply.

Overall, the distribution of SPI values suggests that short-term droughts (1–3 months) occur relatively frequently, while prolonged droughts exceeding six months are less common but potentially more damaging. This aligns with previous research in other Indonesian regions where SPI-based studies demonstrated similar variability in drought duration and severity. The findings highlight the importance of short-term SPI monitoring as a tool for adaptive crop scheduling and irrigation planning.

Table 4. Recapitulation of SPI-1 Drought Index Values in Kurik District

Years	Months											
	Jan	Feb	March	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
2004	0.956	0.580	0.651	0.368	-0.830	-0.096	0.991	0.428	0.085	-0.641	-0.942	-0.089
2005	0.304	0.216	0.484	2.063	1.704	1.556	1.345	-0.140	0.463	-1.130	-1.254	-2.790
2006	0.745	-0.262	0.925	-0.788	2.111	-0.711	0.259	-0.674	-0.842	0.349	-2.384	-0.656
2007	-0.863	-0.609	0.375	-0.533	-0.227	1.277	0.058	1.126	0.338	0.159	-0.009	-1.117
2008	-0.416	0.868	1.485	0.203	-0.369	0.106	0.505	1.110	0.838	0.515	-0.338	-0.656
2009	0.114	0.305	-0.491	-1.140	0.695	0.401	0.031	1.046	1.569	1.327	-0.237	1.561
2010	-0.257	-0.087	1.045	1.430	-0.150	0.813	0.219	2.004	0.504	1.784	0.020	1.590
2011	-0.316	0.288	1.027	0.843	-0.478	0.992	0.673	0.145	0.307	-0.412	-0.863	0.924
2012	0.997	0.364	-0.244	0.296	0.045	-0.152	0.383	-0.048	0.236	-0.132	-1.409	-2.266
2013	-0.066	-0.118	-0.178	-1.222	-0.150	-0.590	0.560	0.395	0.367	-0.309	-1.196	-0.318
2014	-0.547	-1.285	-0.018	-1.095	1.158	2.029	1.837	0.395	-0.842	-0.594	1.615	-0.089
2015	-0.805	0.113	-2.553	0.458	0.394	0.042	-0.842	-0.674	0.216	-1.282	0.424	-0.181
2016	-0.783	-0.669	0.010	0.560	0.625	1.059	2.094	2.009	2.234	1.414	1.387	-0.527
2017	0.396	0.128	0.090	0.076	-0.478	-0.778	0.697	-0.140	1.460	1.572	1.437	0.496
2018	-0.498	-1.124	-0.642	0.976	-0.434	0.122	-0.842	0.283	0.806	-0.246	1.602	0.656
2019	-0.236	-0.200	0.599	-0.017	-0.041	-1.282	-0.842	-0.674	-0.842	-1.282	-0.942	-0.598
2020	-2.126	-1.245	-2.291	0.538	0.380	0.499	-0.371	-0.674	0.144	0.898	0.236	0.822
2021	2.318	2.322	-3.145	-1.964	-2.122	-0.431	-0.842	0.548	0.542	0.128	0.902	1.030
2022	0.994	0.384	-0.024	-1.964	-0.644	-0.096	0.296	1.030	0.274	1.209	0.293	1.353
2023	0.707	1.413	1.493	0.544	-0.412	-1.282	-0.027	-0.674	-0.842	-0.870	0.513	-0.083

3.3 Relationship Between SPI and ENSO (SOI Index)

The correlation analysis between SPI values and the Southern Oscillation Index (SOI) indicated a weak positive correlation ($r \approx 0.189$). This result suggests that ENSO events, although globally recognized as a major driver of rainfall anomalies, exert only a limited influence on local drought occurrences in Kurik District. In other words, extreme drought events in Merauke are not strongly tied to El Niño episodes, and wet years do not consistently coincide with La Niña phases. This weak linkage may be explained by the unique geographical and climatological conditions of southern Papua, where local atmospheric circulation, monsoonal winds, and sea-land interactions in the Arafura region play more dominant roles in shaping rainfall patterns.

This finding is highly relevant for policy-making, as it implies that reliance solely on ENSO-based forecasts (such as SOI monitoring) may not be sufficient for predicting drought risk in Merauke. Instead, localized monitoring using SPI and region-specific rainfall models should be prioritized.

3.4 Drought Prediction Using the Thomas–Fiering Model

The Thomas–Fiering stochastic model was applied to generate synthetic rainfall series for 2024–2033. When these data were analyzed with SPI, several critical insights emerged. The projections indicate that the most severe drought is likely to occur in April 2029, with a predicted SPI of -3.017, categorized as extreme drought. Moreover, the model forecasts a prolonged drought period in 2025 lasting up to seven consecutive months, which would have severe implications for agriculture, water supply, and food security in the region.

Such findings underscore the urgent need for adaptive strategies. Farmers must be encouraged to adopt flexible planting calendars and drought-resistant crop varieties, while local governments should invest in water storage infrastructure, irrigation networks, and early-warning systems. Since the predicted drought episodes align with critical stages of rice cultivation (planting and vegetative phases), failing to integrate such forecasts into agricultural planning could result in significant crop losses.

Table 5. Generated Rainfall Using the Thomas–Fiering Model

Years	Months											
	Jan	Feb	March	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
2024	454	416	465	497	95	60	126	67	61	171	159	202
2025	380	67	74	85	16	63	0	0	60	99	235	51
2026	148	156	168	251	54	39	0	79	105	59	372	109
2027	339	19	142	217	136	106	64	17	0	0	61	445
2028	492	199	416	195	45	96	119	71	42	77	280	469
2029	314	272	173	13	126	182	114	72	122	110	301	568
2030	451	679	0	255	98	57	44	0	0	55	505	252
2031	161	73	518	329	64	98	70	63	41	74	130	26
2032	329	356	358	204	0	6	0	0	0	93	605	387
2033	451	423	33	157	89	241	145	54	73	23	422	455

Table 6. SPI Values for Drought Event Prediction

Year	Months											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2024	0.887	0.874	1.277	1.757	0.747	-0.318	1.305	1.112	0.794	1.741	-0.868	-0.327
2025	0.343	-1.179	-0.641	-1.158	-1.094	-0.259	-0.524	-0.524	0.774	0.728	-0.264	-1.851
2026	-2.095	-0.366	0.022	0.419	-0.089	-0.802	-0.542	1.332	1.450	-0.837	0.540	-1.078
2027	0.007	-2.102	-0.142	0.176	1.399	0.395	0.536	-0.524	-1.282	-2.075	0.880	0.093
2028	1.147	-0.092	1.110	0.007	-0.306	0.268	1.232	1.194	0.454	0.342	0.025	0.969
2029	-0.208	0.290	0.050	-3.017	1.251	1.227	1.174	1.221	1.658	0.912	0.151	1.323
2030	0.867	1.674	-1.282	-0.450	0.795	-0.381	0.234	-0.524	-0.524	-0.129	1.149	-0.020
2031	-1.900	-1.098	1.443	0.910	0.142	0.288	0.628	1.033	0.423	0.284	-1.146	-2.420
2032	-0.082	0.651	0.902	0.078	-1.282	-2.306	-0.524	-0.524	-0.524	0.617	1.545	0.643
2033	0.870	0.902	-1.018	-0.334	0.638	1.728	1.496	0.859	0.999	-0.933	0.783	0.916

3.5 Implications for Agricultural and Climate Adaptation Policy

The study's findings provide evidence-based guidance for both farmers and policymakers in South Papua. By identifying the severity, duration, and recurrence of droughts, SPI analysis supports anticipatory decision-making, rather than reactive crisis management. The weak relationship with ENSO further highlights the necessity of localized monitoring systems, as regional drought risks cannot be adequately captured by global climate indices alone. Meanwhile, the integration of stochastic modeling with SPI ensures that future scenarios are considered in planning, which is essential for building long-term resilience in Merauke's agricultural sector.

In conclusion, the combination of robust statistical data evaluation, SPI-based drought quantification, ENSO correlation analysis, and stochastic rainfall forecasting establishes a comprehensive framework for understanding and managing drought risk in Kurik District. These findings not only advance the scientific understanding of local drought dynamics but also provide a practical foundation for sustainable agriculture and water resource management in South Papua.

4. CONCLUSIONS

This study analyzed and predicted drought conditions in Kurik District, Merauke Regency, using the Standardized Precipitation Index (SPI) based on 20 years of monthly rainfall data (2004–2023) and the Southern Oscillation Index (SOI). The results of data quality tests, including consistency, trend, stationarity, and persistence, confirmed that the rainfall data series was statistically reliable for drought analysis.

The SPI-1 analysis revealed significant fluctuations in meteorological drought intensity, with extreme drought occurring in March 2021 (SPI = –3.145). The correlation analysis between SPI and SOI produced a value of 0.189, indicating that ENSO had only a weak influence on local drought conditions in Kurik District. This suggests that local and regional climate variability plays a more dominant role than global-scale climate drivers.

Future rainfall data generated using the Thomas–Fiering stochastic model for the period 2024–2033 showed that extreme drought is expected in April 2029 (SPI = –3.017), while the longest drought duration is projected for 2025, lasting for seven consecutive months. These findings highlight the importance of localized drought monitoring and forecasting systems to support adaptive agricultural planning, water resource management, and climate change adaptation strategies in South Papua.

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