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Article

Response of PM2.5 Concentrations at the GAW Bukit Kototabang Station to ENSO Phases Based on Superimposed Epoch Analysis

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Abstract. This study aims to analyze the response of PM2.5 concentrations and rainfall to the El Niño and La Niña phases at the Global Atmosphere Watch (GAW) Bukit Kototabang station, West Sumatra, using the Superposed Epoch Analysis (SEA) method. Observational data of PM2.5 from the Beta Attenuation Monitor (BAM) 1020, rainfall from the Automatic Agroclimate Weather Station (AAWS), and sea surface temperature (SST) in the Niño 3.4 region were analyzed for the period October 2021 to May 2025. A total of 31 extreme rainfall events were identified as reference points (epochs) and classified into El Niño and La Niña periods. The results show that during the La Niña phase, an average rainfall increase of 41.1 mm effectively reduces PM2.5 concentration anomalies by approximately ±3.1 μg/m³. In contrast, during the El Niño phase, although rainfall increases by 33.5 mm, PM2.5 concentrations remain highly variable, with anomaly increases of approximately ±1.3 μg/m³, due to drier air masses and lower rainfall intensity. The combined results of SEA analysis and the Monte Carlo test indicate a 13-day SST lead during the El Niño period and a 9-day lag during the La Niña period. This study reveals that ENSO influences both rainfall and air quality at the GAW Bukit Kototabang station.

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1. Introduction

The El Niño–Southern Oscillation (ENSO) is a natural mode of climate variability resulting from dynamic interactions between the ocean and atmosphere in the tropical Pacific Ocean. This phenomenon is characterized by fluctuations in sea surface temperature (SST) anomalies in the Niño 3.4 region, as well as changes in the Walker circulation. The Niño 3.4 region represents the core area of ocean–atmosphere coupling that is highly sensitive to ENSO development, and is therefore widely used as a primary indicator for determining El Niño and La Niña phases. ENSO consists of three main phases: El Niño, characterized by anomalous warming of SST; La Niña, characterized by anomalous cooling of SST; and neutral conditions. Each phase exerts distinct influences on rainfall patterns, air temperature, and global atmospheric dynamics, including over the Indonesian region [1]. This variability occurs on an interannual timescale (approximately 2–7 years) and plays an important role in modulating extreme climate events such as droughts, floods, and variations in air quality [2].

Particulate Matter 2.5 (PM2.5) refers to fine particulate matter with a diameter of ≤2.5 µm, originating from both natural and anthropogenic sources, and capable of remaining suspended in the atmosphere for extended periods [2]. Its concentration is strongly influenced by meteorological conditions such as rainfall, which plays a role in reducing particulate levels through wet deposition (wet scavenging), as well as by climate variability that governs regional atmospheric dynamics [3]. In addition, due to its small size, Particulate Matter 2.5 (PM2.5) can penetrate deep into the respiratory system and pose significant impacts on human health [4].

The Global Atmosphere Watch (GAW) Bukit Kototabang Station is one of the global atmospheric monitoring stations operating under the World Meteorological Organization (WMO) network, and serves as a strategically located observation site for examining the relationship between climate variability and air quality in the equatorial region. The station is equipped with high-resolution atmospheric monitoring instruments, including Particulate Matter 2.5 (PM2.5) measurements using the Beta Attenuation Monitor (BAM) 1020, along with other meteorological parameters. Its location, which is relatively distant from major urban emission sources, makes Bukit Kototabang a representative site for observing the influence of regional to global processes, including the El Niño–Southern Oscillation (ENSO), on air quality dynamics [5].

The station is designed to observe background atmospheric conditions in relatively clean environments with minimal anthropogenic influence, allowing the data obtained to more accurately represent regional to global conditions. Furthermore, the location of Bukit Kototabang in a non-urban area, far from direct emission sources, makes it an ideal site for studying aerosol variability and pollutants such as Particulate Matter 2.5 (PM2.5) without significant interference from local activities. This enables a more representative analysis of the influence of meteorological factors and large-scale atmospheric dynamics compared to local effects [6].

Previous studies have demonstrated a close relationship between rainfall variability, aerosols, and the influence of global climate drivers such as the El Niño–Southern Oscillation (ENSO), commonly analyzed using the Empirical Orthogonal Function (EOF) method. ENSO plays a significant role in controlling rainfall variability in Indonesia, contributing approximately 13.07% [7], as Indonesian waters are highly sensitive to sea surface temperature (SST) anomalies in the Niño 3.4 and Niño 3 regions. Meanwhile, other studies have reported an increase in PM10 concentrations associated with wet scavenging processes during dust seasons, and a decrease in particulate concentrations during the rainy season in the Guadeloupe Archipelago [8].

In contrast to previous studies, which predominantly rely on EOF and climatological approaches, this study integrates rainfall, aerosol (PM2.5/PM10), and SST variables within an event-based framework to investigate lag-time patterns and the dynamics of wet scavenging processes before, during, and after ENSO events. This approach enables a more detailed and specific identification of atmospheric responses to global climate variability in tropical regions. Other studies in Indonesia have primarily focused on rainfall trend analysis [9] and projections using CMIP6 models [10], without incorporating the Superposed Epoch Analysis (SEA) technique, which is capable of isolating temporal response signals from background noise. In contrast, another study applied SEA to investigate the occurrence of ionospheric scintillation during geomagnetic storms in Pontianak [11], and found that strong scintillation events emerged approximately 6 hours after weak-to-moderate storms and around 12 hours after strong storms.

Based on these studies, this research aims to fill the existing literature gap by providing a new perspective on the influence of the El Niño–Southern Oscillation (ENSO) on rainfall variability at the GAW Bukit Kototabang station. This study employs the Superposed Epoch Analysis (SEA) method to evaluate the responses of Particulate Matter 2.5 (PM2.5) and rainfall to extreme ENSO phases, particularly in terms of temporal response before and after the defined epoch time. Conducted in the Kototabang region of West Sumatra, this study focuses on a strategically important location that has not been comprehensively explored in the past decade, thereby offering a more detailed understanding of climate–air quality interactions in the tropical region [12].

2. Experimental Section

2.1. Study Site

The Global Atmosphere Watch (GAW) Bukit Kototabang Station is located in West Sumatra Province, Indonesia, as shown in Figure 1. It is geographically situated at 0°12′07″ S and 100°19′05″ E, at an elevation of approximately 845 meters above sea level. The station is equipped with a Particulate Matter 2.5 (PM2.5) monitoring instrument, namely the Beta Attenuation Monitor (BAM) 1020, which acquires real-time data with a temporal resolution of 5 minutes, as well as an Automatic Agroclimate Weather Station (AAWS).

Figure 1. The study area at the Global Atmosphere Watch (GAW) Bukit Kototabang Station, West Sumatra, Indonesia

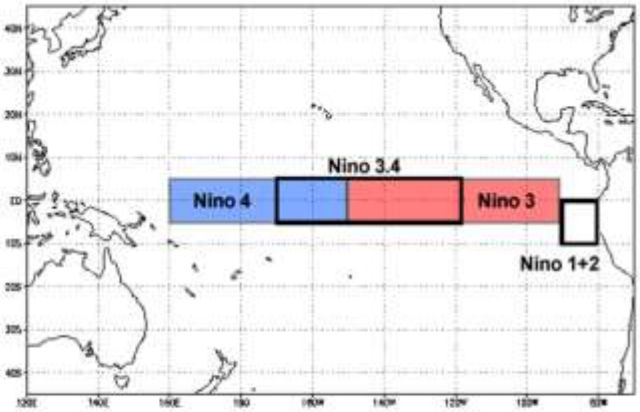


Figure 2. NINO3.4 Region at Pacific Ocean

The Niño 3.4 index is calculated based on sea surface temperature (SST) anomalies within the region bounded by 5°N–5°S and 170°W–120°W in the equatorial Pacific Ocean shown as Figure 2. This region represents a key area of ocean–atmosphere interaction and is widely used to monitor the variability of the El Niño–Southern Oscillation (ENSO

). The index is typically derived from SST anomaly data relative to a long-term climatological mean, allowing for the identification of anomalous warming or cooling conditions.

2.2. Data Collection

This study analyzes particulate matter with an aerodynamic diameter of less than 2.5 µm (PM2.5) measured using a Beta Attenuation Monitor (BAM) model 1020, which operates automatically and provides real-time observations. The BAM 1020 outputs data at a 5-minute temporal resolution, which were subsequently processed into daily mean values to ensure consistency with daily precipitation and sea surface temperature (SST) data. The dataset covers the period from October 1st 2021 to May 31th 2025 with complete data availability (100%) as shown in Figure 3 , which was generated using the *openair* package in RStudio [13].

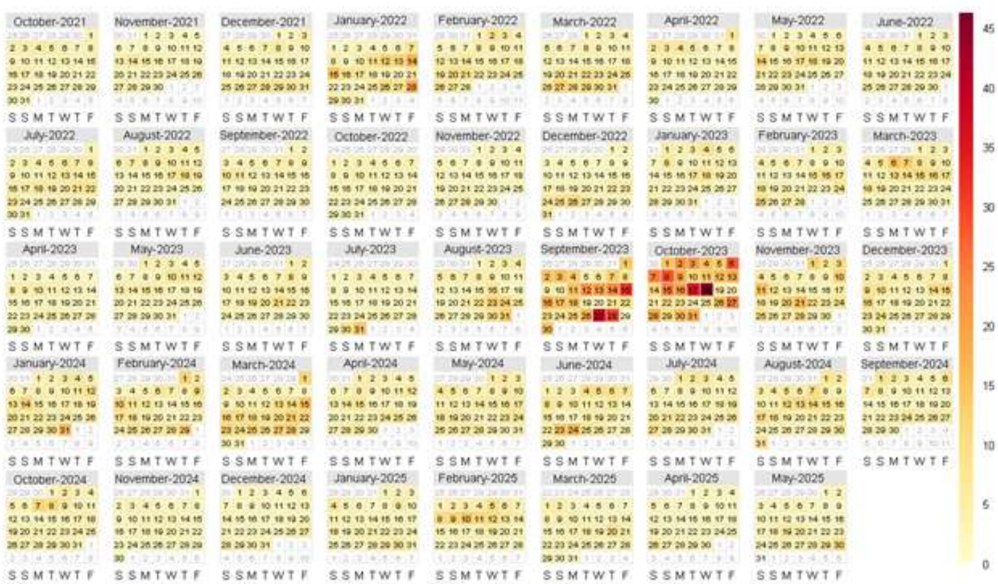


Figure 3. Callendar Plot PM2.5 GAW Bukit Kototabang

Precipitation data were obtained from an Automatic Agroclimate Weather Station (AAWS) installed at the GAW Bukit Kototabang Station. The instrument records rainfall with a 1-minute temporal resolution, which was subsequently aggregated into daily mean values. The dataset spans the period from October 2021 to May 2025 with complete data availability (100%).

The Oceanic NinoIndex (ONI), shown in Figure 4, was used to identify the occurrence of El Nino and La Nina phases [14]. For comparison, daily sea surface temperature (SST) data over the Nino3.4 region, as illustrated in Figure 4, were employed. This region, located in the equatorial Pacific Ocean Figure 2, represents the primary monitoring area for ENSO activity.

The daily SST data were obtained from Climate Reanalyzer (2026) [15] for the period from October 2021 to May 2025. The classification criteria for ENSO phases are defined using threshold values of ≥ +0.5°C for El Niño and ≤ −0.5°C for La Niña [16]. As shown in Figure 4, the La Niña periods considered in this study span from October 2021 to February 2023, covering two distinct events, while the El Niño period extends from April 2023 to May 2024, representing a single event.

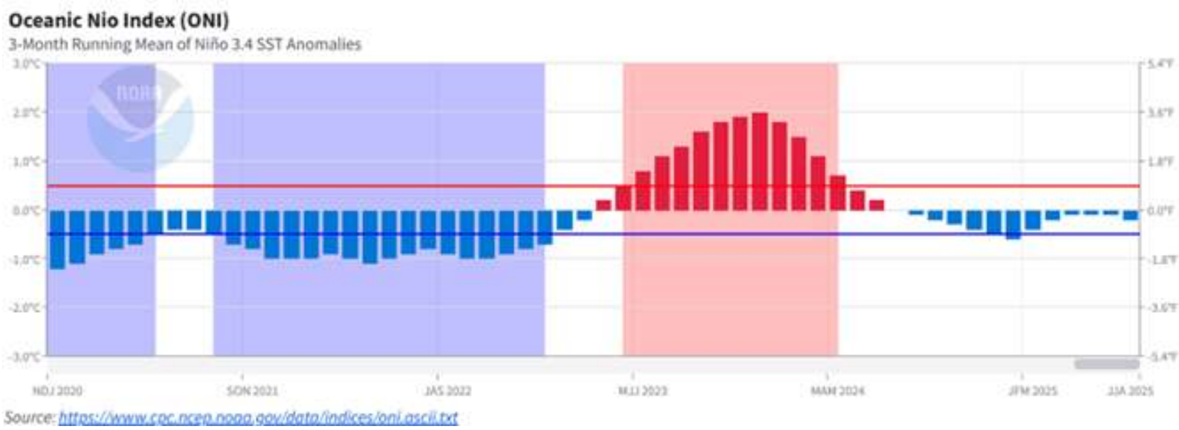


Figure 4. 3-Month MA ONI Index SST Anomalies 2021 - 2025

2.3. Data Analysis

The dataset used in this study exhibits 100% data availability for precipitation, sea surface temperature (SST), and Particulate Matter 2.5 (PM2.5), thus no gap-filling or data imputation procedures were required. Outliers in the PM2.5 and precipitation data were filtered using the z-score method [17,18] to remove anomalous values, including negative measurements and extreme spikes, based on a threshold of $|z| > 3$.This approach ensures that the dataset remains robust and representative by minimizing the influence of non-physical or instrument-related errors [19]. The application of z-score filtering is widely adopted in environmental data analysis to improve data quality and enhance the reliability of statistical interpretations.

Figure 5. Analysis workflow

Extreme rainfall events were identified using a percentile-based approach defined as $R(t) \geq P_{95}$, where daily rainfall exceeding the 95th to 99th percentiles of the precipitation distribution was classified as extreme [10],[20]. Superimposed Epoch Analysis (SEA) is a statistical method used to identify the mean response of a variable to specific events by aligning (superimposing) time series data relative to a common reference point, referred to as an epoch [21] . SEA can be expressed as: $\bar{X}(t) = \frac{1}{N}\sum_{i=1}^{N} X_{i,t}$ where $\bar{X}(t)$represents the mean values of PM2.5 concentration, Nino 3.4 sea surface temperature, and precipitation at the GAW Bukit Kototabang Station at time $t$relative to the event. SEA calculations were performed using the SEAarray statistical analysis package in Python Module [22]. To examine temporal trends, a time window of 20 days prior to the event (epoch-1) and 60 days after the event (epoch+1) was applied.

The analysis window was set from -20 to +60 days relative to the epoch to accommodate differences in temporal scales among variables. Atmospheric variables such as rainfall and $PM_{2.5}$ generally respond on shorter timescales of about 1–2 weeks, whereas oceanic variables such as Niño 3.4 SST exhibit greater thermal inertia, ranging from 4 to 8 weeks [23-24], resulting in a slower and more persistent response. This approach enables a more comprehensive identification of relationships among variables before and after the main event (epoch).

Rainfall, SST, and $PM_{2.5}$ data were then divided into two main periods based on ENSO phases, namely the La Niña period from October 2021 to February 2023 and the El Niño period from April 2023 to May 2024. This classification aims to compare the characteristics of each variable's response under different climate conditions, particularly in identifying changes in extreme patterns and anomalies associated with ENSO variability.

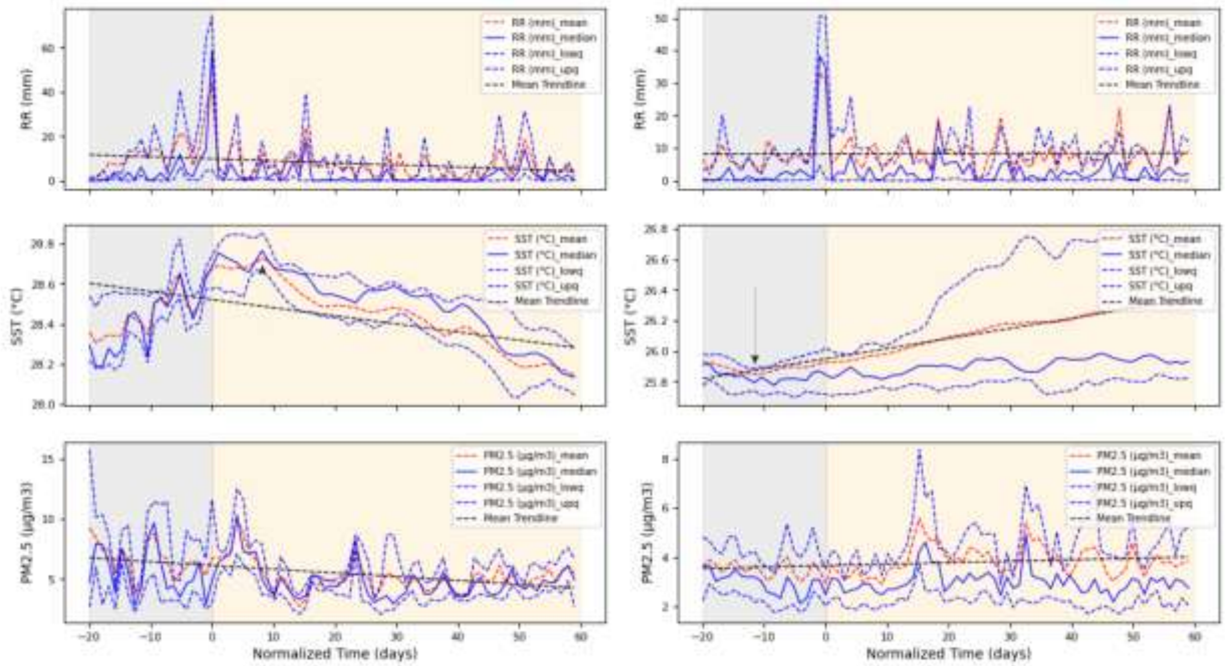
3. Results and Discussion

As a time reference for the script input, the dates listed in Table 1 were used as the epoch time (Rstart). The epoch -1 (Istart) was defined as -20 days prior to the epoch time, and +60 days were assigned for epoch +1 (Rend). The reference time (epoch time) was determined based on extreme conditions (p95) of rainfall measured at the GAW Bukit Kototabang station, since rainfall is more sensitive to intraseasonal dynamics, particularly convective processes, compared to variables such as SST and PM2.5 [25,26]. A total of 31 events were identified during the study period, consisting of 15 days at El Niño events and 16 days at La Niña events.

Table 1. Reference Date

El Nino		La Nina	
02/05/2023	16/11/2023	31/10/2021	12/09/2022
06/05/2023	20/11/2023	09/12/2021	21/09/2022
09/06/2023	07/03/2024	26/12/2021	26/10/2022
14/06/2023	22/03/2024	28/02/2022	11/11/2022
04/11/2023	07/04/2024	16/03/2022	02/01/2023
05/11/2023	22/04/2024	09/06/2022	23/01/2023
10/11/2023	12/05/2024	24/08/2022	31/01/2023
15/11/2023		29/08/2022	19/02/2023

The SEA analysis results in Figure 6 show that during the La Niña period, rainfall at the GAW Bukit Kototabang station increases at the epoch time by 41.1 mm. The SST approaching the epoch time rises to 28.7°C, and then decreases after approximately 5 days. Around day-3, an increase in temperature is observed, followed by an increase in rainfall. The PM2.5 concentration during this period shows a general decreasing trend, with temperature variability also declining after the rainfall event, indicated by a slope value of -0.0313.



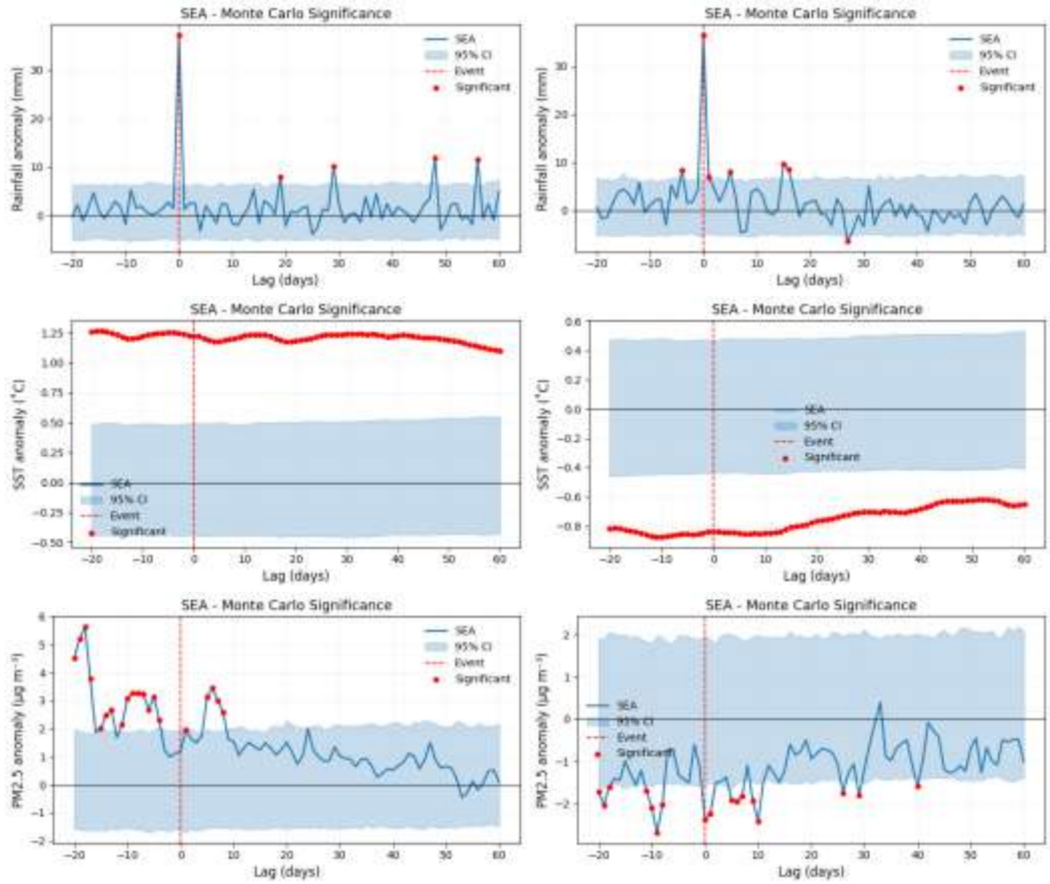
(a) (b)

Figure 6. Superimposed Epoch Analysis (SEA) Output of Rainfall, SST, and PM2.5 during (a) La Nina (b) el Nino

During the El Niño period, the average rainfall at the epoch time increased by 33.5 mm. In this period, the Niño 3.4 region SST initially shows a decrease to 25.9°C at day-13 before the epoch time, followed by a continuous increase after the event. The PM2.5 concentration during this period exhibits relatively large fluctuations compared to the La Niña period, even after rainfall events.This indicates that during El Niño conditions, drier air masses tend to carry more pollutants than during La Niña, so that even after rainfall occurs, the process of wet scavenging is not sufficiently effective due to the relatively lower rainfall amounts [8].

To validate the statistical significance of anomalies in rainfall, PM2.5 concentration, and Niño 3.4 SST during the Superposed Epoch Analysis (SEA) composite period, this study applies a Monte Carlo significance test [27]. This procedure involves random resampling of the original time series data with 1.000 to 10.000 iterations to construct a null hypothesis probability distribution. Through this method, confidence thresholds (e.g., 95% or 99% confidence intervals) are derived from the random distribution, represented by the blue shaded region in Figure 7. If the mean values of variables on days surrounding the key date fall outside the percentile range of the Monte Carlo distribution, the anomalies are considered statistically significant and not merely a result of background atmospheric variability[28]. The significant values in Figure 7 are indicated by red dots.

The study conducted in Kayu Tanam, West Sumatra [9], did not apply any statistical tests to evaluate the significance of the relationship between rainfall and the Madden–Julian Oscillation (MJO) phases. In contrast, this study employs two statistical tests, namely the p-value and the Monte Carlo test, to ensure that the measured parameters are statistically significant and have a meaningful influence.



(a) (b)

Figure 7. SEA – Monte Carlo Anomaly Significance Test (a) La Nina (b) El Nino

The results of the Monte Carlo significance test indicate exceptions in the RR (-1) and Particulate Matter 2.5 (PM2.5) (+0) values during the La Niña period. Specifically, no significant values were identified for rainfall (RR) during La Niña, while the PM2.5 lag was observed at day +1, with a value of 1.9667 and an associated significance level of 0.0032. The Monte Carlo test results are ranked in the table below based on the maximum test values for each El Niño and La Niña period.

Table 2. Monte Carlo significance Test El Nino Period

	Lag (days)	SEA Value	CL Lower (2.5%)	CL Upper (97.5%)	p-value
RR	0	37.2281	-4.9984	6.436400	0.00001
RR	48	11.8271	-4.8112	6.7788	0.0037
SST	-10	-0.876	-0.4434	0.4809	0.0005
SST	0	-0.8383	-0.4371	0.469	0.0005
SST	6	-0.854	-0.4384	0.4779	0.0005
PM2.5	-9	-2.6955	-1.5083	1.9574	0.0030
PM2.5	0	-2.3769	-1.5647	1.9623	0.0125
PM2.5	10	-2.4188	-1.5292	1.9717	0.0008

Table 3. Monte Carlo significance Test La Nina Period

	Lag (days)	SEA Value	CL Lower (2.5%)	CL Upper (97.5%)	p-value
PM2.5	-18	5.6371	-1.6146	1.8451	0.00008
PM2.5*	1	1.9667	-1.6653	1.8329	0.00032
PM2.5	6	3.4498	-1.5361	1.9057	0.0005
RR	-4	8.3544	-5.1504	6.2398	0.001
RR	0	36.4556	-5.2423	6.2016	0.00002
RR	15	9.6356	-5.1694	6.5082	0.002
SST	-19	1.2670	-0.4429	0.4886	0.0003
SST	0	1.224	-0.4414	0.4936	0.00026
SST	30	1.2399	-0.4551	0.5080	0.0002

The value of the SEA value above is the value with the highest level of confidence that is outside the Monte Carlo threshold of the CL Lower – CL Upper distribution (2.5% - 97.5%). This means that data outside this range is statistically significant data followed by a significant p-value < 0.05. In this case, the Monte Carlo test is used for anomalous data to eliminate seasonal averages and leave deviation values due to events [29].

The results obtained using the Superposed Epoch Analysis (SEA) method demonstrate distinct advantages compared to studies employing Empirical Orthogonal Function (EOF) analysis [8] and trend analysis conducted in Kayu Tanam, West Sumatra [9]. The SEA method is capable of isolating specific events from multiple occurrences by stacking them [22], thereby indirectly reducing noise or random fluctuations [30-31]. In contrast, EOF and trend analysis are not able to clearly distinguish between small- and large-scale fluctuations, as they rely on aggregated patterns or single-event interpretations. Furthermore, the SEA method is superior in explaining the relationships and interactions among the variables studied.

4. Conclusion

This study concludes that the ENSO phenomenon plays a crucial role in modulating PM2.5 concentrations and rainfall at the GAW Bukit Kototabang station. Using the Superposed Epoch Analysis (SEA) method, it was found that the La Niña phase produces a stronger rainfall response (41.1 mm), resulting in a more consistent reduction in PM2.5 concentrations through the wet scavenging mechanism.

In contrast, during the El Niño phase, although rainfall events occur (33.5 mm), PM2.5 concentrations exhibit greater fluctuations, indicating that the wet deposition process is less effective in cleansing the atmosphere due to drier air conditions and a higher regional pollutant load. This analysis also identifies a 13-day lead time in the decrease of sea surface temperature (SST) in the Niño 3.4 region prior to peak rainfall during the El Niño phase, as well as a 9-day lag during the La Niña phase. These findings highlight the importance of considering global climate phases in predicting background air quality in tropical regions.

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