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Extreme Rainfall Indices Trends in Indonesia During 1971-2020

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Abstract: This study investigates changes in the intensity, frequency, and duration of extreme rainfall events across Indonesia over the past 3 to 5 decades (1971–2020). Daily rainfall data of 172 Indonesian meteorological stations were examined, and only stations with more than 30 years of data were selected. This filtering process resulted in 101 validated time series used to calculate a subset of extreme rainfall indices based on ETCCDI (Expert Team on Climate Change Detection and Indices) standards. The analysis focuses on six main indices: PRCPTOT (total annual rainfall), SDII (average daily rainfall intensity), CWD (number of consecutive rainy days), R95p (percentile-based extreme rainfall), RX5day (cumulative maximum rainfall in 5 consecutive days) and CDD (number of consecutive dry days). The indices were computed using R programming, following the algorithm implemented in the RClimDex v1.0 software. Rainfall trends based on these indices were assessed using a non-parametric statistical framework, specifically the Mann–Kendall (MK) test in conjunction with Sen's Slope Estimator. In cases where significant autocorrelation was present in the data, the Modified Mann–Kendall (MMK) test was applied to ensure the robustness of the trend analysis. Comparative analysis with previous studies shows that, while overall rainfall trends are broadly consistent, the slope values in this research have substantially narrower range. PRCPTOT ranged from −29.64 to 101.02 mm/decade compared to the earlier study (−140.31 to 449.26 mm/decade), and SDII exhibited weaker trends (−0.11 to 0.16 mm/day), indicating less pronounced intensification. Similarly, CDD, CWD, RX5day, and R95p displayed more moderate changes, this moderation may be attributed to the more recent reference period, which reflects climate dynamics that differ from those observed in earlier decades. These findings highlight the influence of methodological and spatial differences and emphasize the need for sustained monitoring to inform climate adaptation and mitigation.

Keywords: Extreme rainfall indices; ETCCDI; Mann–Kendall test; Modified Mann–Kendall test

Introduction

Climate change has become an increasingly pressing global issue, characterized by the increasing frequency and intensity of extreme weather events such as heavy rains, heat waves, and droughts. Indonesia, as a Maritime Continent (as ocean-land interactions here are the primary drivers of global circulation) located in the maritime region of Southeast Asia, is particularly vulnerable to the impacts of climate change, especially in the form of variability in rainfall and temperature extremes (Aldrian & Budiman, 2011; Supari et al., 2018). In recent decades the analysis of extreme climates has evolved through a standardized statistical index-based approach. One of the most widely used approaches is the extreme climate index recommended by the Expert Team on Climate Change Detection and Indices (ETCCDI), which allows for consistent cross-region and time comparisons (Chervenkov & Slavov, 2020). These indices cover various aspects of temperature and precipitation extremes, such as the number of extreme hot days (TXx), the number of days of heavy rain (R95p),

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and the duration of consecutive dry days (CDD), all of which are calculated based on daily data that has been quality controlled. The study of these data using the ETCCDI method provides a more detailed picture of the trends and patterns of extreme climate change in various regions of Indonesia, as well as its implications for food security, water resource management, and climate adaptation policies (Ruminta et al., 2018; Supari et al., 2018).

While previous studies have examined extreme climate in Indonesia, research incorporating more recent datasets and wider spatial coverage remains relatively limited, particularly analyses employing ETCCDI indices to ensure consistent evaluation of temperature and precipitation extremes. The study by Supari et al. (2017) used data from 88 BMKG stations during the period 1983–2012 and found a significant warming trend, characterized by an increase in the frequency of hot days and hot nights, as well as a decrease in cold days. On the other hand, extreme precipitation trends show a spatially less consistent trend, despite an increase in daily rainfall intensity (SDII) and extreme rainfall (RX1day) in some areas. Another study by Supari et al. (2018) highlighted the influence of ENSO on seasonal variability and precipitation extremes in Indonesia, with the most significant impacts occurring during the dry season (JJA and SON), especially in the form of increasing consecutive dry days (CDD) during El Niño and increasing wet days (CWD) during La Niña. This study shows that ocean-atmosphere dynamics such as ENSO and IOD play an important role in shaping climate extremes in Indonesia's maritime region. Studies by Ruminta et al. (2018) and Mulsandi et al. (2024) also emphasize the importance of understanding seasonal variability and the influence of external factors such as sea surface temperature on extreme rainfall patterns and hydrometeorological disasters in Indonesia. Putra et al. (2021) conducted a review of disaster adaptation in the context of hydrometeorology and climate change during the period 2010–2020. The study reported that 92% of disasters in Indonesia were triggered by hydrometeorological factors, highlighting the urgent need for community-based climate adaptation and the strengthening of national policy frameworks.

The novelty of this study is that although previous studies have provided important insights into extreme rainfall trends in Indonesia, there are several research gaps that need to be filled, first the data time range: the study by Supari et al. (2017) used data up to 2012, while global and regional climate change shows an acceleration of extreme trends in the last decade. Research using more up-to-date data ranges than 1983–2012's study is needed to capture recent dynamics that have not been covered in previous studies. For example, the strong El Niño event of 2015/2016 or consecutive wet years due to a prolonged La Niña phenomenon (Avia & Sofiati, 2018). Second, the number and distribution of stations: further research is needed with a larger number of stations.

This study aims to analyze changes in extreme rainfall in Indonesia for the period 1971–2020 (longer and more recent than previous research) using a subset of the ETCCDI rainfall indices and based on data from 172 BMKG observational weather stations to obtain a high-quality dataset that more recently represents Indonesia. The results of this study are expected to provide a more comprehensive understanding of the dynamics of extreme climate in Indonesia and support evidence-based decision-making in climate change adaptation and mitigation planning.

Method

The methodology and data used in this study are presented in Flowchart 1. Daily rainfall observational data were obtained from the Indonesian Agency for Meteorology, Climatology, and Geophysics (BMKG). In total, data from 172 stations in the periods of 1971–2020 were analyzed and filtered to obtain a high-quality dataset that more recently represents. This study uses a non-uniform data range period across stations. Although a uniform period (e.g., 1991–2020) ensures comparability (Whitfield et al., 2021), its application would significantly reduce data availability and spatial coverage. Therefore, the longest available records (up to 50 years) were used to better capture long-term climate variability, complementing previous studies that primarily employed uniform periods. All datasets were organized in an agro-climatic format, including weather variables such as surface temperature, rainfall, sunshine duration, relative humidity, and wind speed and direction, with each variable recorded separately. The filtering process resulted in 101 validated time series used to calculate a subset of extreme rainfall indices (see Apendix).

Data preprocessing was carried out by converting raw data into a usable format (the R code is available through the link provided in the Code Availability Statement), which selected the relevant information, including station name, latitude, longitude, elevation, and rainfall data. All data used in this analysis has gone through *a quality control* process that includes checking the completeness and validity of the data in accordance with the standards set by the World Meteorological Organization (WMO). As part of the data cleansing procedure, rainfall values that have a negative value or categorized as invalid data (the official notation of missing data at BMKG using 4 digits: 9999) are converted to a missing value (*NA).* In BMKG data records, the code 8888 generally denotes trace or unmeasured rainfall (very small amounts, typically <0.5 mm), whereas 9999 indicates missing data. Therefore, these codes should be handled differently during data preprocessing. The value 8888 should be converted to 0 or a small positive value (e.g., 0.1 mm) following common WMO practice for trace rainfall, while 9999 should be treated as NA (missing data). Converting 8888 to NA would remove many days with very small rainfall amounts, which are important for accurately calculating the CDD index, as these trace events help distinguish between dry and wet-day sequences.

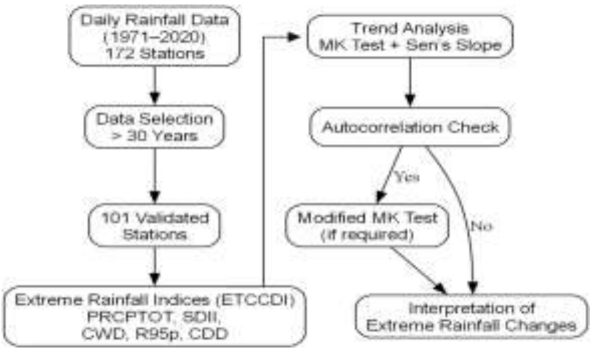

Figure 1. Methodology of the study

The analysis of the extreme indices was carried out based on the extreme climate index recommended by ETCCDI. To produce a valid and reliable analysis of extreme climate trends, the length of the data used is a crucial aspect of the research methodology. Based on the guidelines of the ETCCDI and the standards set by the WMO, it takes at least 30 years of daily data to calculate the extreme climate index in a statistically significant way. This time span allows the identification of long-term trends that go beyond variability between years and climate cycles such as ENSO, IOD, and MJO. In addition, adequate length of data increases the signal-to-noise ratio, so that the detected trends reflect more real climate change than natural fluctuations. Indices such as RX1day, and CDD require a sufficiently long distribution of data to produce stable percentiles and statistically testable trends (Zhang et al. 2005). The use of data during the period 1991–2020 in this study not only met international standards, but also provided an advantage in capturing the latest extreme climate dynamics that had not been covered in previous studies such as Supari et al. (2017) which used data up to 2012.

A total of 10 special ETCCDI indices related to rain (Tabel 1) were often used (PRCPTOT, R10mm, R20mm, RX1day, RX5day, SDII, CDD, CWD, R95p, and R99p). However, to simplify the analysis and interpretation of extreme rainfall trends, this study uses only the most representative indices from a group with similar characteristics. The R95p index was chosen to represent percentile-based extreme wet conditions, replacing R99p, which has a similar function but a narrower day coverage. Similarly, RX5day was chosen as an indicator of accumulative extreme rainfall intensity, replacing daily indices such as RX1day, R10mm, and R20mm. With this approach, the analysis focuses on six main indices: PRCPTOT (total annual rainfall), SDII (average daily rainfall intensity), CWD (number of consecutive rainy days), R95p (percentile-based extreme rainfall), RX5day (cumulative maximum rainfall in 5 consecutive days), and CDD (number of consecutive dry days). This index selection aligns with ETCCDI recommendations and previous studies that emphasize the importance of efficiency and relevance in selecting extreme rainfall indices for tropical regions such as Indonesia (Sillmann et al., 2013). Table 1 presents the indices' name, definition, and unit.

Table 1. List of rainfall extreme indices of ETCCDI

Index	Definition	Unit
PRCPTOT	Annual total PRCP in wetdays (RR ≥ 1 mm)	mm
R20mm	Number of days with daily rainfall ≥ 20 mm	day
RX1day	Maximum rainfall in 1 day over a period of time	mm
RX5day	Cumulative maximum rainfall in 5 consecutive days	mm
SDII	Simple Daily Intensity Index: total annual rainfall / number of rainy days ≥1 mm	mm/day
CDD	Consecutive Dry Days: the number of consecutive dry days (rainfall < 1 mm)	day
CWD	Consecutive Wet Days: the number of consecutive wet days (rainfall ≥ 1 mm)	day
R95p	Total rainfall from days with rainfall above the 95th percentile (very wet days)	mm
R99p	Total rainfall from days with rainfall above the 99th percentile (extremely wet days)	mm

In this study, to facilitate the computation of multiple indices across many stations, the calculations were developed and performed using R code available through the link in the section of code availability statement. This adaption is based on the RClimDex v1.0 software developed by the Climate Research Division, Environment Canada (Zhang & Yang, 2004).

To identify trends and statistical significance of extreme rainfall indices, a non-parametric statistical approach is a very effective method, especially when the data do not meet the assumptions of normal distribution or contain significant outliers (Venegas-Quiñones et al., 2019; Gupta & Verma, 2023). One of the most commonly used non-parametric methods is the *Mann-Kendall* (MK) test, which is able to detect the direction of the trend (increasing or decreasing) without requiring data distribution assumptions. To measure the magnitude of change, i.e., per year, *the Sen's Slope Estimator* is used, which provides a quantitative estimate of the rate of change in the trend. The level of statistical significance in this analysis is generally set at $\alpha = 0.05$, which indicates that the trend result is considered statistically significant if the the p-value is less than or equal to 0.05 (Aditya et al., 2021; Calma & Fajardo, 2022; Aswad et al., 2020).

The combination of the non-parametric Mann–Kendall (MK) test and the Sen's slope estimator is a very effective approach in the analysis of climate trends, as it is able to provide results that are not only statistically significant but also quantitatively meaningful. The MK test is used to detect the presence of monotonic trends in a time series without assuming a specific data distribution, making it particularly suitable for climate data that are often non-normal and contain outliers. However, because MK only identifies the direction of the trend (up or down), Sen's slope is used to calculate the median slope of all data pairs, provide a robust estimate of noise and extreme fluctuations, and show the rate of change per unit of time. This approach has been widely used in climatology and hydrology studies, as shown by Frimpong et al. (2022) in the analysis of temperature variability in Ghana, Agbo et al. (2023) in a comparison of climate trend detection methods in Nigeria. The two studies confirm that the combination of MK and Sen's slope provides a comprehensive and reliable approach in dealing with complex time series data and does not meet parametric assumptions.

For data that contains significant autocorrelation, the trend test uses *the Modified Mann-Kendall Test* (MMK). This is because the original MK test does not take into account serial correlations in the data being tested, which can lead to incorrect trend detection. The probability of detecting a trend increases when the time series shows a positive autocorrelation, a common characteristic of climate data (Hamed and Rao, 1998; Sa'adi et al. 2017). This detection error occurs because the presence of a significant positive autocorrelation will result in the variance used to calculate the statistics of the original MK test to be estimated lower (Supari et al., 2017). The selection of the ETCCDI method and non-parametric statistical tests with the Mann-Kendall test is based on its advantages in handling climate data that are not always normally distributed and have missing values (Zhang et al., 2005; Supari et al., 2017). The 1991–2020 time frame was chosen to update and expand the scope of previous studies (1983–2012), so as to capture the current extreme climate dynamics relevant to adaptation policies.

In this study, trend detection was performed using the Mann–Kendall trend test for time series without significant autocorrelation. For stations exhibiting significant serial correlation, the Modified Mann-Kendall test following Hamed and Rao (1988) was applied. This variance correction approach adjusts the variance of the test statistic to account for serial correlation and avoid inflated Type I errors.

In trend analysis of extreme precipitation indices (PRCPTOT, R10mm, R20mm, RX1day, RX5day, SDII, CDD, and CWD), the unit of the trend depends on the time scale used in the regression or Sen's slope calculation. When the time variable is expressed in years, the resulting trend is typically reported per year (e.g., mm year^{-1} or days year^{-1}). However, in climatological studies the trend is often converted to per decade by multiplying the annual value by 10, because decadal units provide a clearer interpretation of long-term climate variability and change. For example, PRCPTOT, RX1day, and RX5day trends are expressed in mm year^{-1} (or mm decade^{-1}), while R10mm, R20mm, CDD, and CWD are expressed in days year^{-1} (or days decade^{-1}), and SDII in mm day^{-1} year^{-1} (or mm day^{-1} decade^{-1}). Reporting trends per decade is therefore commonly preferred to facilitate comparison across climate change studies (Karl et al., 1999; Peterson et al., 2001; Zhang et al., 2011; Donat et al., 2013).

Result and Discussion

An overview of rainfall data is essential before analyzing extreme indices, as it provides baseline context for understanding spatial and temporal variability in precipitation patterns. This foundational insight helps ensure that subsequent interpretations of extreme events are grounded in the broader climatological behavior of the region. The characteristics of the rain data used are presented in several aspects, first the maximum rainfall in the analysis data period (1991-2020) is presented in Figure 1 which shows that the maximum rainfall of around 400-500 mm occurred at several stations in the Sumatra, Kalimantan and Sulawesi regions.

Figure 1. BMKG stations with maximum rainfall values, as indicated by the color gradation

Table 2. Stations with maximum rainfall > 400 mm

Station	Elevation (m)	Rainfall (mm)
Sultan Babullah	33	518.0
Majene	29	505.0
Sanggu	37	481.2
Minangkabau	6	470.0
Rahadi Oesman	9	441.7
FL Tobing	10	424.0
Bitung Maritime	4	419.0

Based on data from seven locations that show a significant maximum rainfall history, Table 2, namely Sultan Babullah (Ternate), Majene (West Sulawesi), Sanggu (Central Kalimantan), Minangkabau (West Sumatra), Rahadi Oesman (West Kalimantan), FL Tobing (North Sumatra), and Maritim Bitung (North Sulawesi). Geographically, most of these stations are located in regions with wet tropical climate characteristics, complex topography, and strong monsoon wind influence, thus contributing to extreme rainfall intensity.

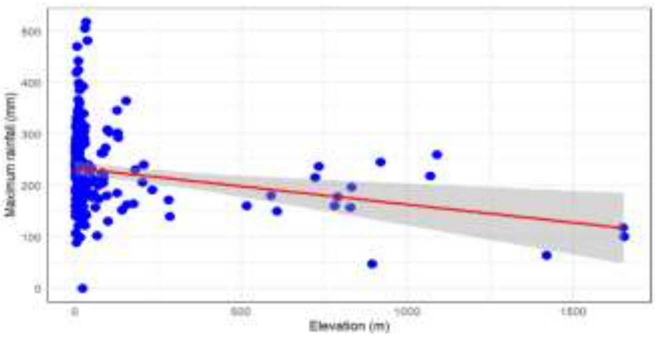

Figure 2. Relationship of maximum rainfall to elevation

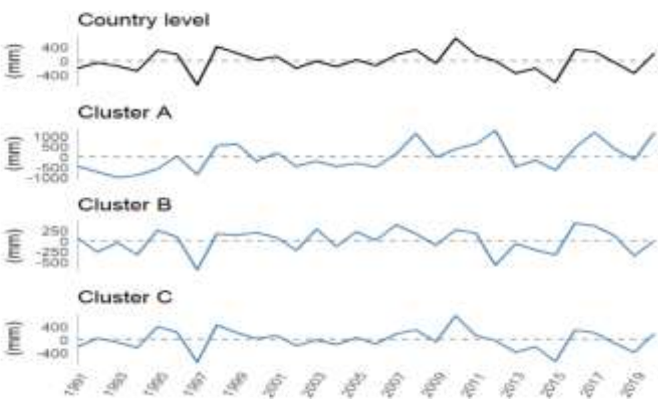

Figure 3. Indonesia's rainfall anomaly data from 1991-2020

Based on Indonesia's rainfall anomaly data (Figure 3), there was a sharp decline in 1997 related to strong El Niño events (Aldrian & Djamil, 2008; Fitria & Pratama, 2013; Yuda et al., 2020; Nabilah et al., 2017). This phenomenon significantly reduces rainfall in various regions of Indonesia, and can affect the results of the analysis of extreme rainfall index trends. If 1997 is at the beginning of the scope of the analysis data, then the trends that form tend to show a significant increase. Conversely, if the year is at the end of the data coverage, the trend forming can show a significant decline. This effect has been alluded to by Supari et al. (2017), who emphasize the importance of the position of extreme events in the data range to the interpretation of climate trends. Other studies have also shown that El Niño 1997/98 had a major impact on the decline in rainfall in Indonesia, with a very high intensity and a wide influence.

If in the data range there are years with extreme events such as El Niño 1997, then the analysis of the extreme rainfall index trend must be carried out carefully so that the results are not biased. It is important to conduct sensitivity analysis, compare trends with and without extreme years, and consider time segmentation or the use of robust statistical methods such as Modified Mann-Kendall. Supari et al. (2017) emphasize that the position of extreme events in the data range can affect the overall interpretation of climate trends, so trend analysis should take into account the climatological context and global climate variability such as ENSO.

For the autocorrelation aspect, the test results for all stations used are shown in Figure 4. The results showed that autocorrelation occurred in all index type variables (R10mm, R20mm, RX1day, RX5day, SDII, CDD, CWD, R95p, R99p, PRCPTOT) and significant categories occurred in about 15% of the total stations analyzed (172). These results are almost the same as those of Supari et al., 2017 who used a data range (1983-2012).

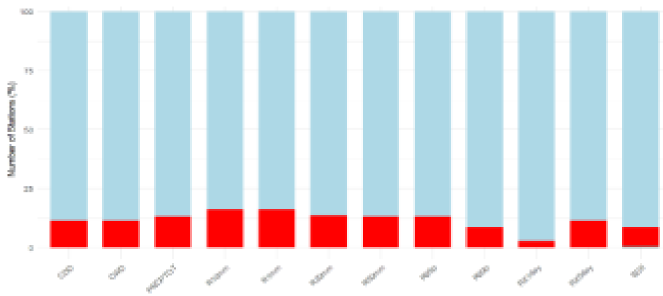

Figure 4. Autocorrelation test results for lag=1 (red indicates significant, sky blue is insignificant and black represents missing data)

Figure 5. Changes in PRCPTOT index. The triangle symbol represents an upward or downward trend, the round symbol indicates no trend. A colorless symbol indicates that the trend is insignificant at α=5%. Unit is in mm per decade.

Most stations show a statistically insignificant trend of PRCPTOT rainfall index (Figure 5), although some have fairly high slope values, such as Mozez Kilangin and Tanah Merah Stations (Central and South Papua). This indicates the potential for an increase in the intensity of extreme rainfall in the eastern region of Indonesia, but it is not strong enough to be categorized as a significant change. On the other hand, the Pasuruan Geophysical Station showed a significant negative trend, leading to a decrease in the incidence of extreme rainfall. These differences reflect the spatial variability in extreme rainfall patterns in Indonesia, as also found by Supari et al. (2017) and Tangang et al. (2020), who emphasize the importance of local analysis in understanding regional climate dynamics.

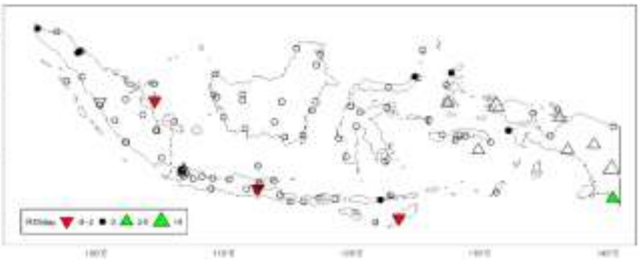

Figure 6. As Figure 5 except for RX5day

The RX5day trend analysis (Figure 6), which measures maximum rainfall on five consecutive days, shows diverse patterns in different regions of Indonesia. Three stations in Papua and Maluku—Tanah Merah, Domine Eduard Osok, and Mozez Kilangin—showed positive trends, indicating the potential for an increase in the intensity of extreme rainfall. However, all three are not statistically significant, so they cannot be concluded to be consistent climate change. In contrast, two stations in the western and southern regions of Indonesia—Dabo and Eltari—showed significant negative trends, signaling a decrease in the intensity of extreme rainfall for five consecutive days. These findings reinforce the results of a study by Misnawati and Perdanawanti (2019), which showed that most stations in Sumatra experienced a positive trend of RX5day, but only a significant fraction. Meanwhile, Kiki et al. (2024) noted that the RX5day trend is strongly influenced by local climate types, with savannah areas such as Kupang tending to decline.

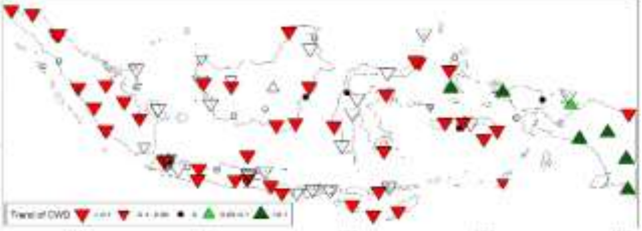

Figure 7. As Figure 5 except for CWD and unit is in days

Analysis of the trend of the CWD (Consecutive Wet Days) index (Figure 7) shows that there are differences in patterns between regions in Indonesia. Three stations—Mozez Kilangin, Domine Eduard Osok, and Oesman Sadik—showed positive trends, with two of them statistically significant, indicating a trend of increasing the number of consecutive wet days. In contrast, three stations in the Nusa Tenggara region—Eltari, Tardamu, and Gewayantana—showed negative trends, with two of them significant, signaling a decrease in the duration of continuous rainfall. This pattern reflects the influence of local climate types, where tropical savanna areas such as Kupang and its surroundings tend to experience a decrease in CWD due to the influence of global climate variability such as ENSO and IOD. These findings are in line with a study by Misnawati and Perdanawanti (2019), which showed a downward trend in CWD in most parts of Sumatra, as well as a study by Kiki et al. (2024) that identified a downward trend in savannah areas and an increasing trend in tropical rainforest areas such as Kalimantan and Papua.

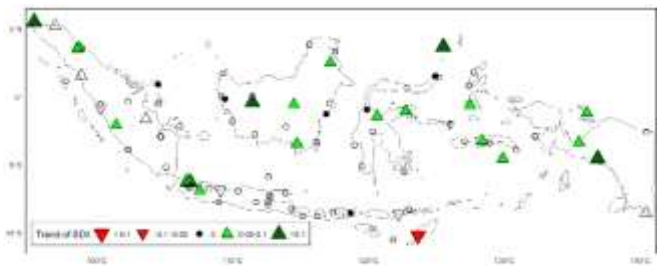

Figure 8. As Figure 5 except for SDII and unit is in mmday^{-1}

Table 3. Stations with the highest and lowest of SDII

Station	Slope	P-value	Significance
Mozez Kilangin	0.16	0.01	Yes
Sultan Iskandar M.	0.14	0.00	Yes
Halim P. Kusuma	0.12	0.03	Yes
Eltari	-0.11	0.00	Yes
Tegal	-0.06	0.11	No
Francis X. Seda	-0.05	0.07	No

Analysis of the SDII (Simple Daily Intensity Index) trend (Figure 8 and Table 3) showed that three stations—Mozez Kilangin, Sultan Iskandar Muda, and Halim Perdana Kusuma—experienced a significant increase in the average daily rainfall intensity, with a slope >0.1 and a p-value of < -0.1), indicating a decrease in the intensity of daily rainfall. The other two stations (Tegal and Seda) showed a negative trend but were not statistically significant. These findings are in line with a study by Misnawati & Perdanawanti (2019) which showed that SDII tends to increase in most parts of Sumatra, as well as a study by Kiki et al. (2024) which found an increasing pattern of extreme rainfall in the tropics of Indonesia, especially in the daily intensity index.

Figure 9. As Figure 5 except for R95p index

Trend analysis of the R95p index (Figure 9), which measures the amount of rainfall from days with extreme rainfall (above the 95th percentile), shows a divergent pattern between stations. Three stations in eastern Indonesia—Mozez Kilangin, Tanah Merah, and Domine Eduard Osok—showed a fairly high positive trend, but not statistically significant. This indicates the potential for an increase in the frequency of extreme rainfall, although it is not yet strong enough to be categorized as real climate change. In contrast, the other three stations showed a negative trend, with Dabo Station being the only statistically significant one (p-value 0.03), signaling a marked decrease in the incidence of extreme rainfall. These findings are in line with a study by Kiki et al. (2024) which showed that the R95p trend in Indonesia is strongly influenced by local climatic characteristics and regional variability, with the western region tending to show a decline and the eastern region showing an increase that has not yet been significant. In addition, Misnawati and Perdanawanti (2019) also found that most stations in Sumatra showed a positive trend in R95p, although not all of them were statistically significant.

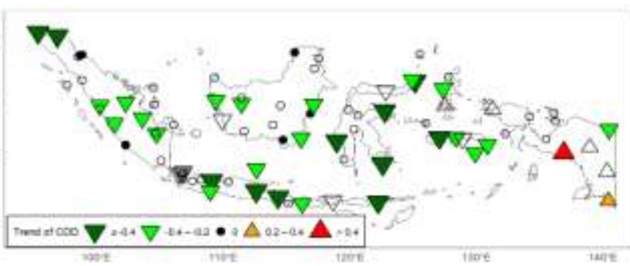

Figure 10. As in Figure 5 except for CDD and the unit is in days

Analysis of the trend of the CDD (Consecutive Dry Days) index (Figure 10 and Table 4) shows a contrasting pattern between regions. Three stations—Mozez Kilangin, Francisco Xaverius Seda, and Beto Ambari—show significant trends, but in different directions. The Kilangin Mozez has seen a significant increase in the number of consecutive dry days, which could indicate the potential for a longer drought in the region. In contrast, Seda and Beto Ambari show a significant decrease, which could mean an increase in the frequency of rainfall or a reduction in dry periods. The other three stations showed insignificant trends, although the slope direction still gave an indication of changes in local climate patterns. Research by Misnawati and Perdanawanti (2019) also noted that most regions of Sumatra show a positive trend in CDD, although it is not always statistically significant. When compared to the findings of Supari et al. (2017), the trend of extreme rainfall indices such as SDII, R95p, and CDD, the results of this study show a more spatially diverse pattern.

Table 4. Stations with the highest and lowest of CDD

Station	Slope	P-value	Significance
Mozez Kilangin	0.44	0.00	Yes
Domine Eduard Osok	0.32	2.09	No
Oesman Sadik	0.28	1.25	No
Francis Xaverius Seda	-1.07	-2.67	Yes
Beto Ambari	-0.8	-1.99	Yes
Syukur Aminudin A	-0.66	0.00	Yes

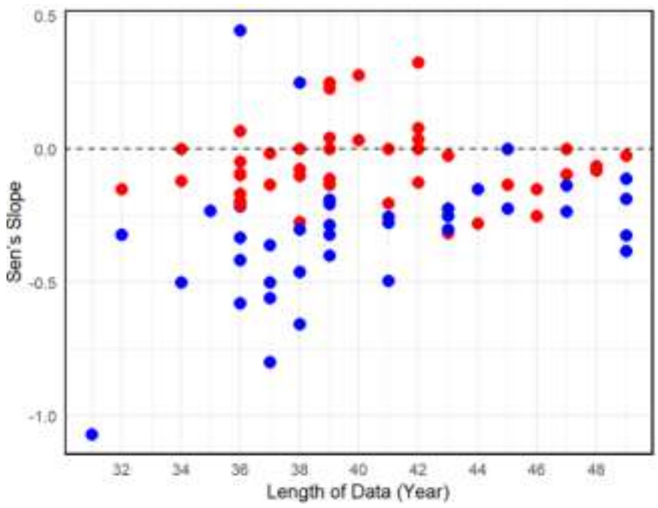

Figure 11. Relationship of slope, length of data, and their significance on the CDD parameter, the blue (red) color is statistically significant (not) significant based on the p-value.

Based on the Figure 11, the relationship between the length of the data, the value of the slope, and its significance on the CDD (Consecutive Dry Days) parameter shows that most stations have a negative slope, which indicates a decreasing tendency to the length of the dry period in the range of observation data. However, the blue dots that represent statistically significant results (p-value < 0.05) are relatively fewer compared to the insignificant red dots. This means that although in general a downward trend of dry periods is observed, most of those trends are not strong enough to be statistically significant. Data length (between ±33 to 47 years) is not necessarily directly related to significance, but trends tend to be more stable in longer data series. Overall, these results confirm the importance of considering aspects of statistical significance in determining extreme climate trends, as not all apparent slope shifts actually represent consistent climate change.

Figure 12. The average of CDD for each BMKG station

Table 5. Stations with the highest and lowest of CDD

Station	CDD mean
Umbu Mehang Kunda	**58.29**
Sultan M. Kaharuddin	56.54
Sultan M. Salahuddin	50.36
Nabire	**1.5**
Banjarnegara	2.86
Bukit Koto Tabang	3.75

Understanding the average number of consecutive dry days (CDD) is crucial for assessing drought risk and water resource vulnerability, especially in regions with pronounced seasonal variability. It serves as a key indicator of prolonged dry spells that can impact agriculture, ecosystems, and local livelihoods. The average of CDD mean shown in Figure 12 and their three highest and lowest values in Table 5 show very striking spatial variations, reflecting the local climatic characteristics of each region. The Umbu Mehang Kunda Meteorological Station in East Sumba and the Sultan Muhammad Kaharuddin Station in Sumbawa recorded very high CDDmean values, at 58.29 and 56.54 days, respectively. This indicates the dominance of a long dry season and the lack of rainfall during a certain period, this is consistent with the characteristics of the semi-arid climate in the Nusa Tenggara region. In contrast, stations such as Geophysics Nabire (1.5 days), Geophysics Banjarnegara (2.86 days), and Bukit Koto Tabang (3.75 days) showed very low CDD values, reflecting a more even distribution of rainfall and high humidity throughout the year.

These results are in line with the results of the study of Supari et al. (2018), which showed that the eastern regions of Indonesia tend to experience an increase in the number of consecutive dry days, especially during the El Niño phase. In the study, El Niño was shown to prolong the dry season in regions such as NTT and NTB, while La Niña increased the number of wet days in western regions such as Sumatra and Papua. Therefore, high CDD values in Sumba and Sumbawa can be attributed to the influence of atmosphere-ocean dynamics that reinforce regional dry conditions. In contrast, the low CDD values in Nabire and Bukit Koto Tabang indicate that these regions are more affected by tropical wet circulation and have a natural resistance to extreme drought.

Overall, this CDD mean analysis not only strengthens the understanding of the spatial distribution of drought in Indonesia, but also confirms the importance of the ETCCDI index-based approach in detecting and mapping extreme climate risks. These results can serve as a basis for the development of early warning systems and more focused adaptation strategies, especially in regions vulnerable to prolonged drought.

Table 6. Summary comparison with previous study

Indices	This study	(Supari et al., 2017)
PRCPTOT	-29.64 - 101.02	−140.31 - 449.26
SDII	-0.11 - 0.16	−0.33 - 2.02
CDD	-1.07 - 0.44	−3.00 - 16.25
CWD	-1.97 - 0.44	−1.74 - 2.67
R5Xday	-4.20 - 7.41	−17.91 - 36.04
R95p	-14.59 - 51.56	−117.36 - 205.38

The trend is expressed in index units: per decade Comparison of the results of the extreme rainfall index analysis between this study and the existing study (Table 6) shows that despite the similar trend direction, the range of slope values in this study tends to be narrower. The annual total rainfall index (PRCPTOT) in this study ranged from −29.64 to 101.02 mm/decade, much lower than the range of −140.31 to 449.26 mm/decade reported by Supari et al. This may reflect differences in spatial coverage or analysis period. The daily rainfall intensity index (SDII) also showed lower values in this study (−0.11 to 0.16 mm day^{-1} $decade^{-1}$), compared to −0.33 to 2.02 mm day^{-1} $decade^{-1}$ in the previous study, indicating that the daily rainfall intensification may not be as strong as detected in the long-term data. For the dry and wet duration indices, CDD and CWD in this study showed a more moderate downward trend compared to Supari et al., who recorded a decrease of up to −3 days/decade for CDD and −1.74 days/decade for CWD. This decline is important because it might has a direct impact on the risk of drought and flooding. Meanwhile, extreme rainfall indices such as RX5day and R95p also showed a lower trend in the study, with RX5day ranging from −4.20 to 7.41 mm/decade and R95p ranging from −14.59 to 51.56 mm/ decade, compared to a much higher range in the Supari et al. study (−17.91 to 36.04 mm/decade for RX5day and −117.36 to 205.38 mm/decade for R95p). These differences can be caused by variations in station locations, statistical methods, or different regional climatic influences. Overall, the results of this study show that extreme rainfall trends are more moderate than the previous study but still indicate a significant change in rainfall patterns in Indonesia.

As this study uses longer periode of data, the substantial differences in trend values between this study and Supari et al. (2017), particularly for PRCPTOT, can be largely attributed to the different data periods used. This study analyzes the period 1971–2020, whereas Supari et al. (2017) use a shorter range (1983–2012). In addition, the inclusion and relative position of extreme climate events, especially the strong 1997 El Niño, play a crucial role in shaping long-term rainfall trends. The sharp decline in rainfall during 1997 significantly influences any trend calculation. When this extremely dry year lies near the beginning of the analysis period, the resulting trend often appears strongly increasing; conversely, when the same year occurs near the end of the data series, the trend may appear decreasing. This phenomenon reflects the sensitivity of non-parametric trend analysis to the temporal placement of anomalies within the dataset. Supari et al. (2017) emphasize that the timing of extreme events within the data range can substantially affect the magnitude and direction of detected trends. Therefore, variations in time span and the position of major ENSO-related anomalies are key factors explaining the differing PRCPTOT trend ranges observed between the two studies.

The analysis of extreme rainfall trends in Indonesia provides crucial insights into the changing characteristics of precipitation under a warming climate. Previous studies have highlighted the importance of evaluating rainfall variability and extremes using both observational data and regional climate model outputs to understand spatial and temporal dynamics (Aminoto et al., 2024). In particular, the application of ensemble modeling and weighted mean approaches has been shown to improve the accuracy of rainfall simulations across the CORDEX-SEA domain (Aminoto et al., 2024a). Moreover, recent investigations comparing regional trends using CORDEX-SEA and ERA5 datasets indicate a consistent increase in the intensity and frequency of extreme rainfall events in several parts of Southeast Asia, including Indonesia (Aminoto & Faqih, 2024). These findings emphasize the significance of continuous monitoring and model-based assessments of rainfall extremes to support climate adaptation and disaster mitigation strategies in the region.

Integrating the results of this study into physics education can be aligned with existing frameworks that incorporate environmental and climate issues into science and physics learning. At the university level, particularly in physics education programs, extreme rainfall indices (e.g., R95p, RX1day, RX5day, CDD, and CWD) and trend analysis using the Mann–Kendall trend test and Sen's slope estimator can be used as practical materials for data analysis and environmental physics courses. Students can analyze Indonesian rainfall time series and relate the results to environmental hazards such as floods, landslides, and droughts, in line with the view that physics plays a significant role in understanding and modeling environmental processes and climate change (Alexander et al., 2019; Edilbekovich, 2025).

A project-based learning approach that integrates physics with environmental issues has been shown to enhance creativity and learning effectiveness, particularly when the context involves climate change and environmental disasters (Lestari et al., 2024). At the senior high school level, findings on trends in extreme rainfall indices can be incorporated into the environmental “hidden curriculum” within Grade XI physics topics, such as heat, fluids, and waves. Through this approach, students learn core physics concepts while simultaneously developing environmental literacy using real-world examples such as floods, droughts, and global warming in Indonesia (Yusliani & Desnita, 2021; Marzuki & Desnita, 2023).

The environmental curriculum integration matrix that has been developed for high school physics can also be expanded by including extreme rainfall indicators as learning contexts and data-based project assignments, such as interpreting trend graphs and linking them to flood events in students’ local regions (Yusliani & Desnita, 2021; Marzuki & Desnita, 2023). Studies on integrating environmental education into physics teaching at the secondary school level indicate that systematically incorporating environmental issues increases student engagement, fosters positive attitudes, and encourages greater environmental awareness (Azzouzi et al., 2023). In addition, physics projects focusing on climate and environmental issues can significantly improve students’ creativity and positive responses to learning (Lestari et al., 2024).

Therefore, the findings of extreme rainfall index studies can serve as scientific content that supports the integration of environmental hidden curricula, data-based physics projects, and the strengthening of environmental literacy in both senior high schools and university-level physics education programs (Yusliani & Desnita, 2021; Lestari et al., 2024; Edilbekovich, 2025; Azzouzi et al., 2023; Marzuki & Desnita, 2023).

Conclusion

This study examined how the intensity, frequency, and duration of extreme rainfall events in Indonesia have changed over the past 3 to 5 decades (1971–2020). Daily rainfall observations from 172 weather stations across the country were assessed for quality and homogeneity using a consistent methodology. Of these, 101 station time series met the required criteria (>30 years) and were used to calculate a selection of extreme rainfall indices, based on a subset of the ETCCDI indices. A comparison of extreme rainfall indices between this study and earlier work indicates that, although the overall trend directions are consistent, the slope ranges here are generally narrower. For instance, PRCPTOT varied from −29.64 to 101.02 mm/decade, substantially lower than the −140.31 to 449.26 mm/decade reported by Supari et al., likely due to differences in study period. Similarly, SDII trends were weaker (−0.11 to 0.16 mm day^{-1} $decade^{-1}$) compared to −0.33 to 2.02 mm/day in the previous study, suggesting less pronounced intensification. The dry- and wet-spell indices (CDD and CWD) also exhibited more moderate declines, which are critical for drought and flood risk assessment. Extreme indices such as RX5day (−4.20 to 7.41 mm/decade) and R95p (−14.59 to 51.56 mm/decade) followed the same pattern, with narrower ranges than earlier findings. Such discrepancies may be attributable to differences in station distribution, statistical approaches, or regional climatic variability. Overall, the results of this study show that extreme rainfall trends are more moderate than the previous study but still indicate a significant change in rainfall patterns in Indonesia. The "moderation trend" finding may be influenced by the distribution of stations remaining after quality selection. It is important to note that a narrower range does not inherently signify a more moderate trend. Such a pattern may result from reduced variability or fewer outliers in the dataset. Therefore, the interpretation of trend intensity should rely on the mean slope value rather than the range itself. In addition, the use of longer period up to 2020 period (which was the period of the most intense global warming) may capture a stronger anthropogenic signal but with more stable variability than periods involving climate transitions before the 1990s. These findings support the importance of ongoing monitoring of extreme climate indices to support climate change adaptation and mitigation policies at the local and national levels.

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Conflicts of Interest
The authors declare that they have no conflict of interest.

References

Aditya, F., Gusmayanti, E., & Sudrajat, J. (2021). Rainfall trend analysis using Mann–Kendall and Sen's slope estimator test in West Kalimantan. IOP Conference Series: Earth and Environmental Science, 893(1), 012006. https://doi.org/10.1088/1755-1315/893/1/012006

Agbo, E.P., Nkajoe, U. & Edet, C.O. (2023). Comparison of Mann–Kendall and Şen's innovative trend method for climatic parameters over Nigeria's climatic zones. *Clim Dyn* 60, 3385–3401. https://doi.org/10.1007/s00382-022-06521-9

Aldrian, E., & Budiman, M. K. (2011). Climate change adaptation and mitigation in Indonesia. Jakarta: Ministry of Environment.

Aldrian, E., & Djamil, Y. S. (2008). Spatio-temporal climate variability over Indonesia and its relation to ENSO. *International Journal of Climatology*, 28(4), 435–448. https://doi.org/10.1002/joc.1040

Alexander, L., Fowler, H., Bador, M., Behrangi, A., Donat, M., Dunn, R., Funk, C., Goldie, J., Lewis, E., Rogé, M., Seneviratne, S., & Venugopal, V. (2019). On the use of indices to study extreme precipitation on sub-daily and daily timescales. *Environmental Research Letters*, 14. https://doi.org/10.1088/1748-9326/ab51b6

Aminoto, T., & Faqih, A. (2024). Tren curah hujan di asia tenggara berdasarkan model CORDEX-SEA dan data ERA5. Journal online of physics, 10(1), 7-13.

Aminoto, T., Faqih, A., Koesmaryono, Y., & Dasanto, B. D. (2024). A Comparison of the Performance of the Weighted Ensembles Means in CORDEX-SEA Precipitation Simulations. Agromet, 38(1), 19-35.

Aswad, F. K., Yousif, A. A., & Ibrahim, S. A. (2020). Trend analysis using Mann-Kendall and Sen's slope estimator test for annual and monthly rainfall for Sinjar District, Iraq. Journal of Duhok University, 23(2), 41–50.

Avia, L. Q., & Sofiati, I. (2018, June). Analysis of El Niño and IOD phenomenon 2015/2016 and their impact on rainfall variability in Indonesia. In *IOP conference series: earth and environmental science* (Vol. 166, No. 1, p. 012034). IOP Publishing.

Azzouzi, A., Elachqar, A., & Kaddari, F. (2023). Integrating Environmental Education Into Physics

Instruction: Insights From Teachers Regarding Students' Engagement. *Randwick International of Education and Linguistics Science Journal*. https://doi.org/10.47175/rielsj.v4i3.787

Calma, J., & Fajardo, S. M. (2022). Climate trend analysis using Mann-Kendall and Sen's slope estimator tests in Central Luzon, Philippines. Interdisciplinary Research Review.

Calma, J., & Fajardo, S. M. (2025). Climate Trend Analysis Using Mann-Kendall and Sen's Slope Estimator Tests in Central Luzon, Philippines. *Interdisciplinary Research Review*, 20(1).

Chanzi, G., Bushesha, M., Munishi, S., & Karia, A. (2023). Application of Mann-Kendall and Sen's Slope Estimator in Trend Analysis of Historical and Future Precipitation and Temperature in the Kilombero River Basin. *Huria Journal*, 30(2), 45–60.

Chervenkov, H., & Slavov, K. (2020). ETCCDI climate indices for assessment of the recent climate over Southeast Europe. In *Advances in High Performance Computing* (pp. 398–412). Springer. https://doi.org/10.1007/978-3-030-55347-0_34

Ding, Y., Cheng, B., & Jiang, Z. (2008). A newly-discovered GPD-GEV relationship together with comparing their models of extreme precipitation in summer. *Advances in Atmospheric Sciences*, 25(3), 507–516.

Donat, M. G., Alexander, L. V., Yang, H., Durre, I., Vose, R., & Caesar, J. (2013). Global land-based datasets for monitoring climatic extremes. *Bulletin of the American Meteorological Society, 94*(7), 997–1006. https://doi.org/10.1175/BAMS-D-12-00109.1

Edilbekovich, O. (2025). The role of physics in the formation of ecological education of schoolchildren. *International Journal of Pedagogics*. https://doi.org/10.37547/ijp/volume05issue01-28

Fitria, W., & Pratama, M. S. (2013). The Effect of the 1997 El Niño Phenomenon and the 1999 La Niña on Rainfall in Biak. *Journal of Meteorology and Geophysics*, 14(2), 121–130. https://jmg.bmkg.go.id/jmg/index.php/jmg/article/view/156/142

Frimpong, B. F., Koranteng, A., & Molkenthin, F. (2022). Analysis of temperature variability utilising Mann–Kendall and Sen's slope estimator tests in the Accra and Kumasi Metropolises in Ghana. *Environmental Systems Research*, 11(24). https://doi.org/10.1186/s40068-022-00269-1

Gupta, L. K., & Verma, S. (2023). Rainfall and temperature trend analysis using Mann-Kendall and Sen's slope estimator test in Kharun watershed, Chhattisgarh, India. Current Journal of Applied Science and Technology, 42(22), 1–9. https://doi.org/10.9734/cjast/2023/v42i234174

Hamed, K.H., & Rao, A.R. 1998. A modified Mann-Kendall trend test for autocorrelated data. *Journal of Hydrology*, 204, 182–196. doi:10.1016/S0022-1694(97)00125-X

Juda, I. W. A., Sudiarta, I. W., & Suryawan, I. W. 2020. Comparison of the Impact of Strong El Niño 2015/16 and 1997/98 on Rainfall in Bali Province. *Megascience*, 11(2), 28–35.https://megasains.gawbkt.id/index.php/megasains/article/download/13/12/92

Karl, T. R., Nicholls, N., & Ghazi, A. (1999). CLIVAR/GCOS/WMO workshop on indices and indicators for climate extremes: Workshop summary. *Climatic Change, 42*(1), 3–7. https://doi.org/10.1023/A:1005491526870

Kiki, K., Fauzi, M. A., Nurhayati, N., & Khairani, K. N. A. (2024). Study of extreme rainfall index in Indonesian region. *Megasains*, 15(1), 8–17.

Lestari, N., Susanti, F., Madlazim, M., Hariyono, E., & Uulaa, R. (2024). Integrated environmental education physics project to enhance student creativity. *Momentum: Physics Education Journal*. https://doi.org/10.21067/mpej.v8i1.9054

Marzuki, Y., & Desnita, D. (2023). Mapping Environmental Hidden Curriculum in Physics Learning. *Jurnal Penelitian Pendidikan IPA*. https://doi.org/10.29303/jppipa.v9i1.2127

Mulsandi, A., Koesmaryono, Y., Hidayat, R., Faqih, A., & Sopaheluwakan, A. (2024). On the interannual variability of Indonesian monsoon rainfall: A literature review of the role of its external forcing. *Jurnal Meteorologi dan Geofisika*, 25(1), 1–15.

Nabilah, F., Prasetyo, Y., & Sukmono, A. (2017). Analysis of the Influence of El Niño and La Niña Phenomena on Rainfall in 1998–2016 Using ONI Indicators (Case Study: West Java Province). *Journal of Undip Geodesy*, 6(4), 402–412. https://ejournal3.undip.ac.id/index.php/geodesi/article/view/18170

Peterson, T. C., Folland, C., Gruza, G., Hogg, W., Mokssit, A., & Plummer, N. (2001). *Report on the activities of the Working Group on Climate Change Detection and Related Rapporteurs 1998–2001*. World Meteorological Organization.

Putra, D. P., Sari, R. K., & Nugroho, H. (2021). Adaptation to hydrometeorological disasters in Indonesia: A review of community policies and approaches. *Journal of Environmental Science*, 19(2), 123–134. https://doi.org/10.14710/jil.19.2.123-134

Ruminta, R., Herlina, D., & Prasetyorini, N. (2018). Shifts in rainy and dry seasons in Indonesia due to climate change. *Journal of Geography*, 10(2), 101–112.

Sa'adi, Z., Shahid, S., Ismail, T., Chung, E.-S., & Wang, X.-J. (2017). Trends analysis of rainfall and rainfall extremes in Sarawak, Malaysia using modified

Mann–Kendall test. *Meteorology and Atmospheric Physics*, 131(2), 263–277.

Sillmann, J., Kharin, V. V., Zwiers, F. W., Zhang, X., & Bronaugh, D. (2013). Climate extremes indices in the CMIP5 multimodel ensemble: Part 1. Model evaluation in present climate. *Journal of Geophysical Research: Atmospheres*, 118(4), 1716–1733.

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

Supari, S., Tangang, F., Salimun, E., Aldrian, E., Sopaheluwakan, A., & Juneng, L. (2018). ENSO modulation of seasonal rainfall and extremes in Indonesia. *Climate Dynamics*, 51, 2559–2580. https://doi.org/10.1007/s00382-017-4028-8

Tangang, F., Chung, J.X., Juneng, L. et al. (2020). Projected future changes in rainfall in Southeast Asia based on CORDEX–SEA multi-model simulations. *Clim Dyn*, 55, 1247–1267. https://doi.org/10.1007/s00382-020-05322-2

Trend of Extreme Precipitation over Sumatera Island for 1981–2010. (2019). *Agromet*, 33(1), 41. https://doi.org/10.29244/j.agromet.33.1.41-51

Venegas-Quiñones, H. L., Thomasson, M., & Garcia-Chevesich, P. A. (2019). Trend analysis of precipitation, groundwater level and flow rate data using Mann-Kendall and Sen's slope estimator statistical tests. American Journal of Environmental Sciences, 15(4), 180–187.

Whitfield, P. H., Burn, D. H., Hannaford, J., Higgins, H., Hodgkins, G. A., Marsh, T., & Looser, U. (2021). The spatial extent of hydrological and landscape changes in the streamflow record. *Hydrology and Earth System Sciences, 25*, 2513–2541. https://doi.org/10.5194/hess-25-2513-2021

Yusliani, E., & , D. (2021). Mapping environmental curriculum in physics learning at senior high school grade X semester 2. *Journal of Physics: Conference Series*, 1876. https://doi.org/10.1088/1742-6596/1876/1/012040

Zhang, X., & Yang, F. (2004). *RClimDex (1.0) user manual*. Climate Research Division, Environment Canada.

Zhang, X., Alexander, L., Hegerl, G. C., Jones, P., Klein Tank, A., Peterson, T. C., ... & Zwiers, F. W. (2005). Trends in Middle Latitude Daily Temperature and Precipitation Indices. *Journal of Geophysical Research*, 110(D5).

Zhang, X., Alexander, L., Hegerl, G. C., Jones, P., Tank, A. K., Peterson, T. C., Trewin, B., & Zwiers, F. W. (2011). Indices for monitoring changes in extremes based on daily temperature and precipitation data. *WIREs Climate Change, 2*(6), 851–870. https://doi.org/10.1002/wcc.147