Spatiotemporal Pattern of Extreme Rainfall Events in Indochina Peninsula

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Abstract

Rainfall is the most influential weather parameter affecting human lives, besides being a natural resource that is needed by humans it can also be a source of disasters if it gets to its extreme. This extreme rainfall is a big problem for the society, thus the analysis of extreme rainfall is needed to design mitigation strategies. This study describes the extreme rainfall phenomena based on statistics that focused on the existence of trends in Consecutive Dry Days (CDD) and Consecutive Wet Days (CWD) and characteristic of its distribution. The trends were obtained from high-quality grid precipitation data compiled by Asian Precipitation-Highly-Resolved Observational Data Integration towards Evaluation of Water Resources (APHRODITE) over Indochina Peninsula (4°-25°N and 90°-112°E). This analysis were selected from the list of climate change indices recommended by World Meteorological Organization-Commission for Climatology (WMO-CCI) and the research program on climate variability and predictability (CLIVAR). Linear trends were calculated by least squares fitting and significant or non-significant trends were identified using Mann-Kendall test. The result revealed contrasting trends of each index in the eastern and western Indochina Peninsula. In the eastern Indochina Peninsula mostly indicated positive trends in CWD and negative trends in CDD with some grids showing significant trends, contrary to western Indochina Peninsula. The percentages of positive and negative significant trends of CDD are 10.88% and 2.41% respectively, while for CWD index are 6.85% and 14.51% respectively from a total of 248 grids.

Keywords: Indochina Peninsula, Extreme Rainfall, CDD, CWD, Trends

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1. Introduction

Weather is the most important geographical parameter affecting human lives, while rainfall is the most influential weather parameter. Rainfall is a natural resource that is needed by humans, but it can be a source of disasters if it gets to its extreme. Extreme rainfall events often damage the environment, because they are often followed by floods, lightening, and strong winds [1]. As a result of extreme weather and climate, some areas are vulnerable to disaster such as floods, landslides, and severe drought.

The impacts of climate change and extreme weather events are the most serious problems for society [2]. Extreme events will be more frequent, more widespread and will increase in intensity in the 21st century [3]. Various problems that arise due to extreme weather and climate change range from disease outbreaks, health problems, fishermen dare not go to sea due to high waves, farmers can not do harvest and also social vulnerability.

Lately, extreme rainfall events are getting a serious attention in the community, because of their great impact on nature and a great loss for the community. In rural areas, these extreme rainfall events often cause damages to agricultural crops and livestock, while in urban areas they can cause floods because of inability of drainage systems to accommodate high rainfall [4].

Indochina Peninsula is a region in Southeast Asia, including Thailand, Cambodia, Laos, Vietnam, Myanmar, and some parts of Malaysia. Some disaster events that caused extreme rainfall in the region include in Thailand; long floods in the year 2011 that started in June and ended in mid-January 2012. The flooding affected the provinces of northern, northeastern and central Thailand along the Mekong and Chao Phraya river basins, as well as parts of the capital city of Bangkok [5].

In Myanmar, rainfall caused flooding in several places at the end of July 2013. The flash initially displaced over 38.300 people, leaving six dead and one person missing, and damaged residential buildings, roads and bridges [6]. On the other hand extreme rainfall also occurs annually in the Upper Mekong countries of China, Laos, Myanmar and Thailand, where these events greatly impact on the environment and society [7]. While in Malaysia floods triggered by extreme rainfall in northeastern, central and southern parts of Malaysia killed 33, and affected 158,000 in December 2007[5].

The statement of World Meteorological Organization (WMO) based on the analysis of extreme events [2], says that the development of the economy depends on our ability to deal with some risks that are caused by extreme events. The knowledge of extreme events is necessary, because our lives depend on food, water, energy, and transportation which are very sensitive to extreme events. It is a priority to use advancement in scientific knowledge of extreme rainfall to develop solutions to the water-related challenges faced by the society [8]. It is therefore important to study the information and knowledge of extreme weather and climate change. By knowing the pattern of extreme weather and climate change, the impacts of extreme events can be anticipated as early as possible.

2. Research Methodology

The steps of this study include determining the data, QC and homogeneity data, data processing, and data analysis as follows:

2.1 APHRODITE Datasets

In this study, the indices of extreme rainfall events were generated using series data. Period of data is crucial in determining extreme rainfall events [9]. Long period of time is needed to estimate the frequency and intensity of extreme rainfall events [2] because it would eliminate the effect of bias [10]. On the other hand, the used data should have a high resolution at least daily data [2].

The data in this study was obtained from Asian Precipitation-Highly-Resolved Observational Data Integration towards Evaluation of Water Resources (APHRODITE) datasets for 48 year period from 1960 to 2007, this grid data was extracted from the station data that had been collected by the APHRODITE team. The station data from various sources such as National Hydro-Meteorological Service (NHMS) in each country such as Thai Meteorological Agency and the Royal Irrigation Department in Thailand, Department of Hydrology and Meteorology in Myanmar, Ministry of Water Resources and Meteorology in Cambodia, and National Hydro-Meteorological Service in Vietnam. This data was also collected from Precompiled datasets by other projects such as the Global Energy and Water Cycle Experiment (GEWEX) Asian Monsoon Experiment and-Tropics (GAME-T) and from Global Telecommunication Systems (GTS) report based global datasets such as the Global Surface Summary of the Day (GSOD) [11].

2.2 Quality Control and Homogeneity Test of APHRODITE Datasets

This study used APHRODITE dataset, which the selection of this data was based on APHRODITE daily rainfall data in the grid form that was extracted from the station data. The data was ready to be processed because it has been through a long quality control (QC) process. Automated QC system developed in this APHRODITE datasets basically designed to detect errors in daily rainfall station data such as recording errors, clerical errors and so on.

There were 14 steps that had been developed to process APHRODITE QC data such as; QC for errors in station metadata, errors identified in single station records such as; erroneous values inherent to particular data, values exceeding national/regional records, contamination with different weather elements, repetition of constant values, duplication of monthly or sub-monthly records, outliers, homogeneity test, and also errors identified in multiple station records such as; spatiotemporally isolated values, errors in units of measurement, and ambiguity in recorded date [12].

2.3 Methods for Identification of Extreme Rainfall

Adapted from WMO [2], the analysis of extreme rainfall events were determined by several indices that are widely used in determining extreme weather events. The indices were selected from the list of climate change indices recommended by World Meteorological Organization-Commission for Climatology (WMO-CCI) and the research program on Climate Variability and Predictability (CLIVAR). Table 1 explains the definition of Consecutive Dry Day (CDD) and Consecutive Wet Day (CWD) that were used in this study.

Table 1: Definition of CDD and CWD

Indices	Indices Name	Indices Calculation	Definition	Unit
CDD	Consecutive Dry days	$RR_{ij} < 1_{mm}$	Maximum number of consecutive days with rainfall (RR) <1 mm	Day
CWD	Consecutive Wet days	$RR_{ij} \geq 1_{mm}$	Maximum number of consecutive days with RR >1 mm	Day

RR=Rainfall on consecutive days

In this study, the rainfall data was processed using the RClimDex software package to calculate indices and trends, a R-language software package that was developed by CCI-CLIVAR Expert Team for Climate Change Detection, Monitoring and Indices (ETCCDMI) with the main focus for detection and monitoring the extreme climate events using daily data. This RClimDEX software packages are available at http://cccma.seos.uvic.ca.

2.4 Methods for Temporal Trend Analysis

Man-Kendall test is a statistical test widely utilized for the analysis of trend in climatology [13-16]. The benefit of Man-Kendall test; it is non parametric statistic and does not require a normally distributed data, and has a low sensitivity to empty data due to non homogeneity data. Null hypothesis (H_0) states that data is no trend (the data is independent and randomly ordered), and this is tested against the alternative hypothesis (H_1) which assumes that there is trends. Kendall's statistic (S) is computed as follows:

2.4.1 Man-Kendall Statistical Calculation

The computational procedure of Mann-Kendall test considers the time series of n data points and x_j and x_k as two subsets of data which j =1,2,3,…n and k = $j+1$, $j+2$, $j+3$ …, n. The data values are evaluated as an ordered time series. Each data value is compared with all subsequent data value. The initial value is assumed with zero (0) or no trend, if the value of the data from the later time period is greater than the earlier time period, therefore S is added by 1, on the other hand, if the value of the data in later time period is less than the earlier time period, therefore S is reduced by 1. The end result of the addition and subtraction is final value of S .

The formula to calculate the S is:

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} sign\,(x_j - x_k)\,, \tag{3.1}$$

where:

$$sign(x_j - x_k) = \begin{cases} 1, \text{ if } & x_j - x_k > 0 \\ 0, \text{ if } & x_j - x_k = 0 \\ -1, \text{ if } & x_j - x_k < 0 \end{cases}, \tag{3.2}$$

where x_j and x_k are the annual values in years j and k , $j > k$, respectively. If $n < 10$, the value of $|S|$ is compared directly to the theoretical distribution of S derived by Mann and Kendall. The two tailed test is used. At certain probability (H_0) is rejected in due to (H_1) if the absolute value of S equals or exceeds a specified value of $S_{\alpha/2}$, where $S_{\alpha/2}$ is the smallest S which has the probability less than $\alpha/2$ to appear in case of no trend. A positive (negative) value of S indicates an upward (downward) trend. For $n > 10$, the statistics S is approximately normally distributed with mean and variance as follows:

The variance of S is given by

$$\sigma^2 = \frac{n(n-1)(2n+5) - \sum t_i (i)(i-1)(2i+5)}{18} \tag{3.3}$$

which t_i denotes the number of ties to extent i . The summation term in the numerator is used only if the data series contains tied values.

2.4.2 The Standard Test Statistics Z_c Calculation

The standard test statistics Z_c is calculated as follows:

$$Z_C = \begin{cases} \dfrac{s-1}{\sqrt{\sigma}}, \; if \;\; S > 0 \\ 0, \; if \;\; S = 0 \\ \dfrac{s-1}{\sqrt{\sigma}}, \; if \;\; S < 0 \end{cases} \tag{3.4}$$

Positive values of Z_c indicates an upward trend while negative Z_c shows downward trend. When testing either upward or downward trends at a significance level α , the null hypothesis was rejected for absolute value of Z_c greater than $Z_{\alpha/2}$. In this study, significance level α of 0.05 was applied.

2.4.3 To Compute the Probability Associated with This Normalized Test Statistics Expressed in P-Value.

The probability density function for a normal distribution is given by the following equation:

$$f(z) = \frac{1}{\sqrt{2}} e^{\frac{z^2}{2}}\,, \tag{3.5}$$

$$p-value = 1 - f(z)\,,$$

$$\text{when} \; \begin{matrix} p-value < \alpha = significant \\ p-value > \alpha = non\;significant \end{matrix} \tag{3.6}$$

2.4.3 Decide level of Significant (α=5%*typically*)

Conclude the trend using this criterion, the trend is said to be downward if z is negative and is said to be upward if the z is positive. The trend is statistically significant if *p-value* is less then α and non-significant if *p-value* is greater than α.

2.5 Methods for Spatial Analysis

Since rainfall is not distributed proportionally, therefore the spatial patterns analysis is needed because topography affects the rainfall in some regions. In this study, mean climatology of annual indices is executed using interpolation methods of Radial Basis Function. Spatial analysis of temporal trends is done with thematic maps using dots (.) and plus (+) signs, where the plus (+) sign indicates a positive trend and a dot (.) sign indicates a negative trend. The color indicates the significant of changes, the blue color indicates significant trends, and the red color indicates non-significant trends. And the gradient of plus (+) or dot (.) sign indicates how significant the trend is.

3. Research Result and Discussion

The results of this study include mean climatology of annual indices, temporal trends analysis, and spatial pattern analysis of CDD and CWD index, as follows:

3.1 Mean Climatology of Annual Indices

The annual indices in this study were calculated based on annual block that means only one value per year. Thus, in this study with period from 1960 to 2007 there would be 48 values for each grid. To analyze the spatial patterns of each extreme rainfall indices, each index was averaged to obtain the mean value of each grid of climatology.

The mean climatology of consecutive dry day or consecutive days without rainfall (CDD) in Indochina Peninsula ranged from 8 to 110 days each year (Fig. 1). The lowest number of consecutive days without rainfall is on grid Lon 101.25 and Lat 4.25 with total 8 days, while the greatest number of consecutive days without rainfall is on grid Lon 95.25 and Lat 18.25 with total 110 days. The area with the greatest number of consecutive days without rainfall is mostly situated on the West coast of Indochina Peninsula; in most of Myanmar, central and northern Thailand, most of Cambodia, some part of Laos, and southern Vietnam. While the East coast of the Indochina peninsula, extending from southern China to Vietnam, southern Thailand, eastern and northern Laos and a part of Malaysia include small part of Indonesia experienced a lower number of consecutive days without rainfall.

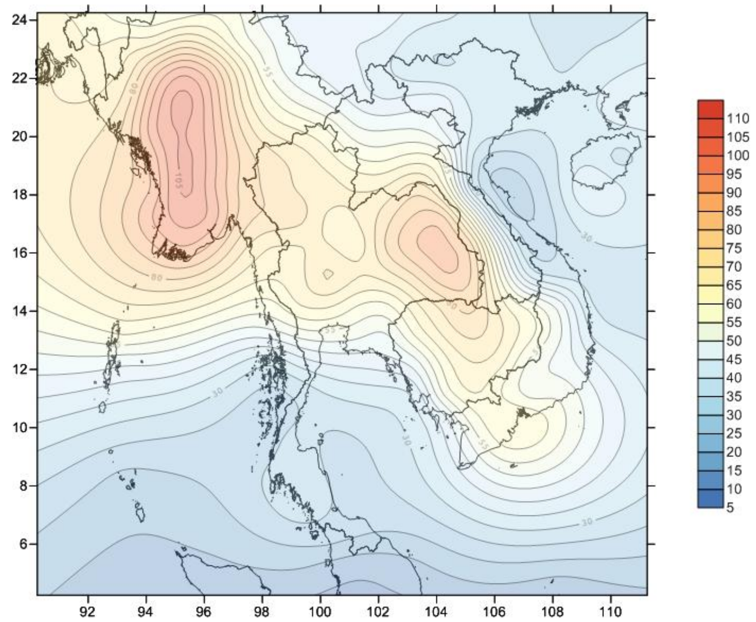

Figure 1: Mean climatology of CDD index

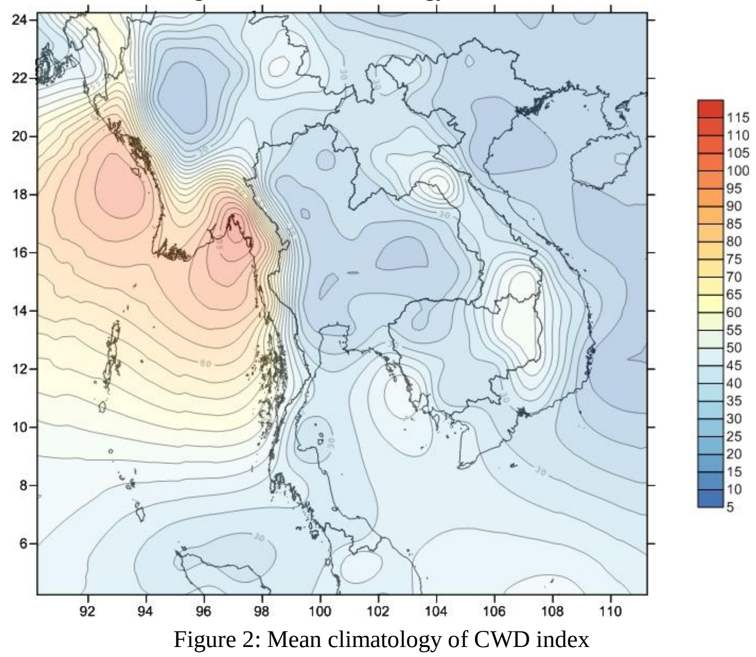

Figure 2: Mean climatology of CWD index

Figure 2 shows the spatial pattern of mean number of consecutive wet days or consecutive rainy days (CWD) in Indochina Peninsula that ranged from 11 to 111 days each year. The lowest number of consecutive rainy days is on grid Lon 106.25 and Lat 20.35 with a total 11 days, while the greatest number of consecutive rainy days is on grid Lon 97.25 and Lat 17.35 with total 111 days. This figure shows that most of the Indochina Peninsula covering the whole territory of Vietnam, Thailand, Laos, and Cambodia has a consecutive rainy days on average from 11 to 40 days, and a bit different in the coastal areas of Myanmar which has a consecutive rainy day on average more than 55 days.

3.2 Temporal Trends of Extreme Rainfall

Trends in extreme rainfall indices are calculated using statistical software RClimDex R-based language program. The positive (negative) values indicate upward (downward) trends. This study uses a significance level (α) of 5%. The slope represents the magnitude of the variable changes each year.

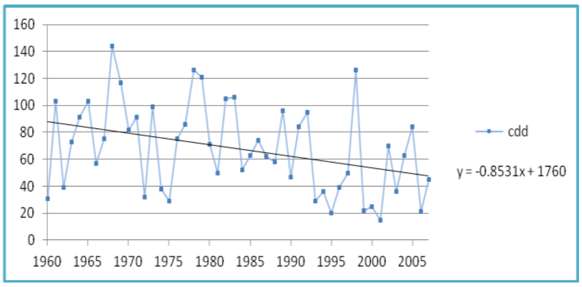

Figure 3: Significant negative trend of CDD index on grid Lon 107.25 and Lat 10.25

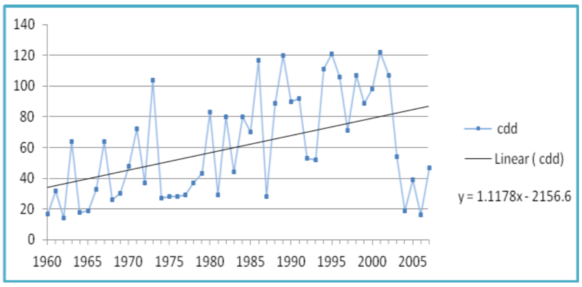

Figure 4: Significant positive trend of CDD index on grid Lon 105.25 and Lat 17.25

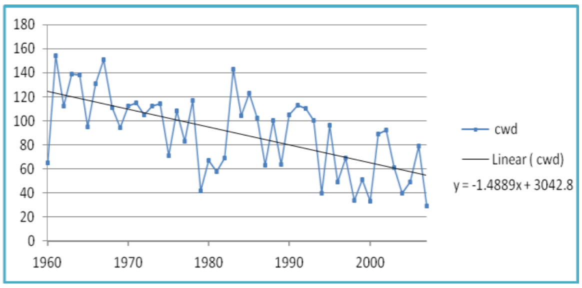

Figure 5: Significant negative trend of CWD index on grid Lon 95.25 and Lat 16.25

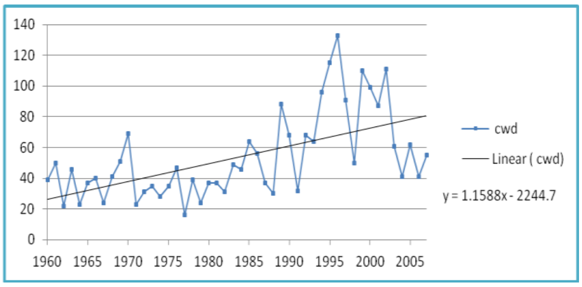

Figure 6: Significant positive trend of CWD on grid Lon 104.25 and Lat 18.25

Consecutive days without rainfall (CDD) index was the first to be processed, the results show that non-significant trend changes dominate the study area. From a total of 248 grids, there are 215 grids showing non-significant trends which 65.72% shows positive trends and 20.96% shows negative trends of the overall number of grids. While 32 of other grids demonstrate significant trends which 10.88% shows positive trends and 2.41% shows negative trends of the overall number of grids. Figures 3 and 4 show the most significant of positive and negative trends of CDD index. The most significant of positive trends is on the grid Lon 105.25 and Lat 17.25 with the slope 1.117, while the most significant of negative trends is on grid Lon 107.25 and Lat 10.25 with the slope -0.853.

The next calculated index is consecutive rainy days (CWD) index, the results indicate 194 grids showing non-significant trends which 36.29% shows positive trends and 41.93% shows negative trends of the total grids. While 53 of other grids demonstrate significant trends which 6.85% shows positive trends and 14.51% shows negative trends of the total grids. Figures 5 and 6 indicate the most significant of negative and positive trends of CWD index. The most significant of positive trend is on grid Lon 104.25 and Lat 18.25 with the slope 1.1588, while the most significant of negative trend found on grid Lon 95.25 and Lat 16.25 with a slope -1.488. Here Table 2 shows the percentages of significant and non-significant trends.

Table 2: Percentage of Significant and non-significant trends

Index	Positive Significan t Trend (%)	Positive Non Significan t Trend (%)	Negative Significan t Trend (%)	Negative Non Significan t Trend (%)
CDD	10.88	65.72	2.41	20.96
CWD	6.85	36.29	14.51	41.93

3.3 Spatial Pattern of Detected Trends

The purpose of the spatial patterns analysis of extreme precipitation trends is to identify which areas are experiencing a positive (negative) significant (non-significant) trend, whether the resulting pattern is a random pattern, spread, or to form a particular pattern. This study used a point pattern analysis by plotting each grid into Indochina Peninsula Map.

The spatial pattern of consecutive days without rainfall (CDD) index and consecutive rainy days (CWD) index are shown in Figure 7 and Figure 8. In the CDD index, the pattern shows that most of the eastern coast of the Indochina Peninsula covering the East coast of Vietnam and the East coast of southern Thailand experienced negative trends with some grids show significant trends. Otherwise, a unique pattern occurred in the West coast of the Indochina Peninsula, most grids experienced positive trends with some grids show a significant trend. While for CWD index, the positive trends occurred in the eastern Indochina peninsula along the East coast of Vietnam and the East coast of southern Thailand with some grids show significant trends. While the West coast of the Indochina Peninsula shows negative trends with some grids show significant trends. This became a unique pattern because it shows the opposite pattern between the eastern and western Indochina Peninsula.

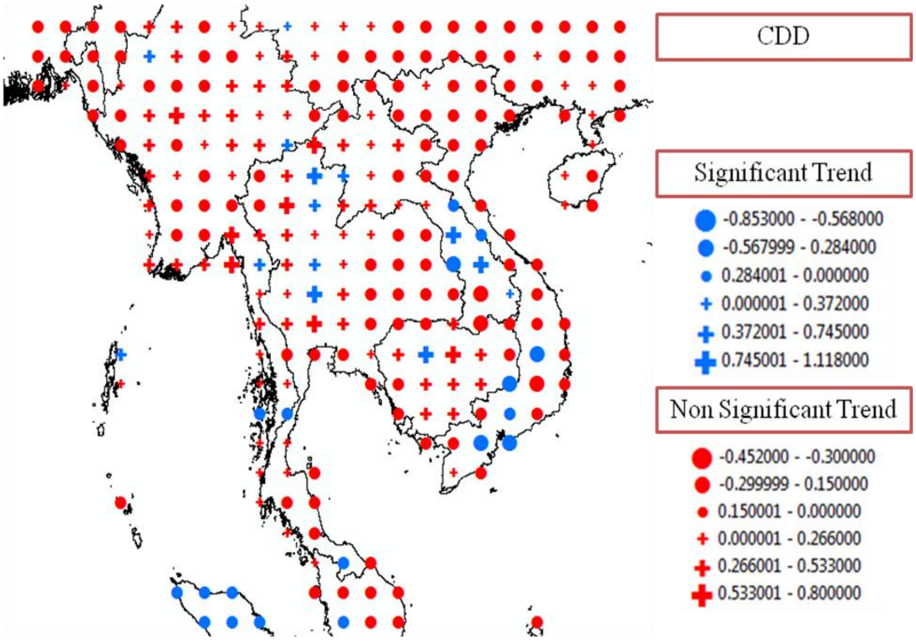

Figure 7: Spatial analysis of CDD index over Indochina

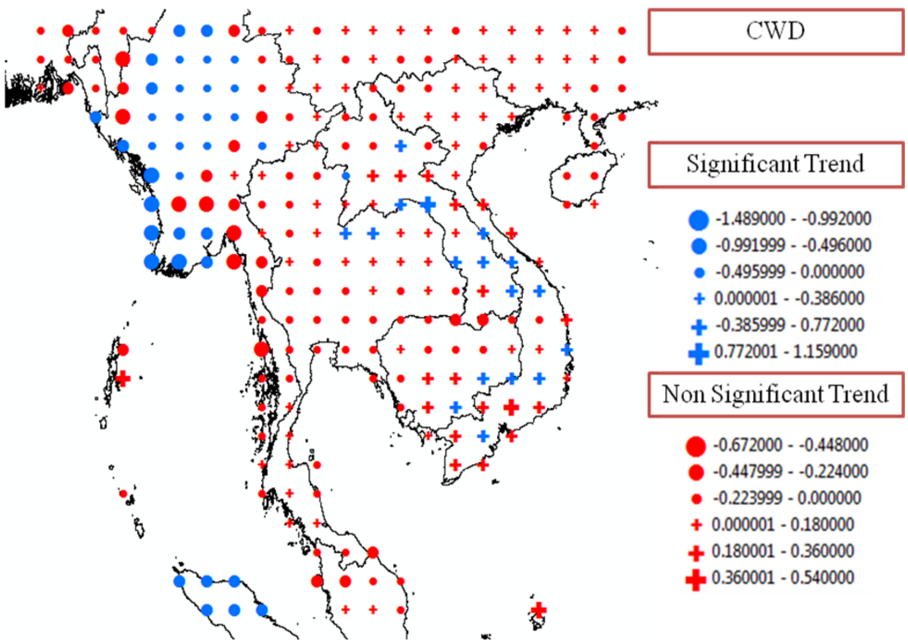

Figure 8: Spatial analysis of CWD index over Indochina Peninsula

4. Conclusion

Some remarkable findings can be concluded from this study. Data analysis and homogeneity data become very important because they can affect the resulting trends and will cause a bias interpretation, hence the selection of high quality data should be considered very important before doing research on trend changes of extreme rainfall indices. This study used APHRODITE datasets with high quality data that has been through long QC process.

Overall, the pattern of the mean climatology of each index can be well described. These two indices have a pattern and specificity to the geographic location of this area. The highest mean climatology was noticed in two indices situates in the coast of North Myanmar, North Vietnam, and southern Thailand (border with Malaysia). While other regions have mean climatology from medium to lower that dominated in the central Indochina Peninsula.

This study also found that the Indochina peninsula is dominated by non-significant trends that spread evenly across it with the percentage of positive and negative significant trends respectively, 10.88% and 2.41% for CDD index, 6.85% and 14.51% for CWD index.

For CDD and CWD indices show a unique pattern that contrasted between West and East Indochina Peninsula. In the CDD index, the pattern shows that most of the eastern coast of Indochina Peninsula covering the East coast of Vietnam and the East coast of southern Thailand experienced negative trends with some grids show significant trends. Otherwise, for CWD index, which the negative trends occurred in the West coast of the Indochina Peninsula with some grids show significant trends.

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