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# Study on the Statistical and Dynamic Characteristics of Rainfall in the Philippines

by

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**Abstract**

Using Kalman filtering and generalized likelihood ratio techniques, four monthly mean rainfall time series typical of the four types of climate in the Philippines are analyzed for the presence of abnormal rainfall patterns. Proper transformation of the rainfall data results in a periodic-stochastic model with the stochastic component being uncorrelated and normally distributed. The abnormality detection index $\phi_*$ automatically and accurately estimates the time of occurrence and magnitude of the rainfall pattern abnormalities. Identified abnormal rainfall patterns are classified into three types. The application of the decile range method provides a better characterization of the three types of abnormal rainfall patterns in terms of the probability of occurrence of the residual. Abnormal patterns of similar or different types tend to occur in the same period at certain portions of the country or at certain types of climate. Some of them appear to continue for a few years. Three reported drought events are successfully identified as major rainfall pattern abnormalities. This study provides a basic understanding of the dynamic features of the rainfall sequence in the Philippines.

## 1. Introduction

In 1982 and 1983, the Philippines experienced two devastating droughts which caused severe crop damages, hydroelectric power failure, depleted irrigation water supply, alteration of normal agricultural and other human activities. According to the paper of Jose (1984)[1], the first one was the nine-month drought which persisted over Visayas and Mindanao and some portions of the Bicol Region during the second half of 1982 up to the first quarter of 1983 and the second one in Luzon during the remaining months of 1983. The Pantabangan Dam and Reservoir which is the Philippines' second largest reservoir (having a capacity of three billion cubic meters) dried up and became inoperational for some months as a result of these droughts. In order to minimize these undesirable effects of

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droughts, operation of the reservoir must be coupled with the application of forecasting model that can adapt at once to the abrupt changes in the hydrological system.

The fact that drought is a result of some abnormal rainfall behaviour has motivated this study to understand the basic dynamic features of the rainfall sequence in the Philippines. Specifically, the purpose of this study is to identify the abnormal patterns in a rainfall sequence in the country and to depict their spatial and temporal characteristics. Knowledge of the presence of abnormal patterns and their characteristics will be especially important in modelling for forecasting and simulation purposes. This is because the mere presence of an abnormal pattern may suggest that a parameter change model is operating in the system and may provide clue into the nature of the model.

Being the most useful single index of water supply[2)], rainfall has been the basis of many methods[1),2),3)] which are used to examine the occurrence and to delineate the extent of drought. One of these methods is the generalized monsoon index[1)] which has been found useful as a drought indicator for Philippine rainfall condition. However, this method being an empirical one lacks the mathematical explanation for the occurrence of rainfall abnormalities. The decile range system proposed as a drought indicator by Gibbs and Maher[2)] in 1967 suggests the use of a normally distributed rainfall. Its practicality for Philippine monthly rainfall data will be limited because many of these data or even their transformed values do not obey normality. Spectral analysis[3)] requires a lengthy record of rainfall data. Because of the meager rainfall data in the Philippines, information regarding the recurrence of drought will be almost impossible to extract. In practice it is expected that abnormal patterns become indiscernible and less easily delineated by simple visual inspection of the data. Examination of the rainfall data by any of these methods will do no better unless records show that rainfall abnormalities did occur at some certain dates. Also, these methods can not be used to explain the dynamic characteristics of the rainfall phenomenon.

Kalman filtering coupled with the generalized likelihood ratio technique does not only describe the dynamic behaviour of a system but also detect the time of occurrence and magnitude of any abnormality present in the system. These techniques have been applied in the detection and estimation of an abnormality occurring at an unknown point in a synthetically generated time sequence[4)], in problems such as estimations for tracking of vehicles capable of abrupt maneuvers[5)] and in an adaptive real-time runoff forecasting model which accounts for the presence of transient input errors[6)]. A mathematical procedure that utilizes these techniques is presented in this paper to identify the abnormal patterns in a rainfall sequence.

Four monthly mean rainfall series typical of the four types of climate in the Philippines are analyzed. The time of occurrence and magnitude of the abnormalities are effectively estimated by the presented mathematical procedure and hence proper characterization of these abnormal patterns is made possible.

## 2. Detection of Abnormal Rainfall Patterns

Details of the mathematical theory underlying the detection of abnormality utilizing Kalman filtering and generalized likelihood ratio techniques are given in a number of papers[4),5),6)]. However, this paper is based on the work of Ueda, et. al. (1984)[4)] who proposed a new and simple method for on-line detection of the time of occurrence of abnormality. This section presents the methodology used to identify the abnormal patterns in the four rainfall time series.

Since the variation of meteorological elements, such as rainfall, is closely connected with the changes of the seasons, the annual variations of these elements can be regarded as periodic[7]. As Brooks and Carruthers (1953)[7] pointed out, this is so, because the astronomical seasons, being connected with the movements of the heavenly bodies, recur systematically after fixed periods of time. Sen (1980)[8] considered that any continuous hydrologic time series observed over an extensive time period show periodicity and random fluctuations about it. Hence, the system model is conceived as having two independent components: periodic and stochastic. The general periodic-stochastic model may be written in the form

$$y(k)=M_y+\sum_{i=1}^{q}(A_i\sin 2\pi f_i k+B_i\cos 2\pi f_i k)+w(k) \tag{1}$$

where $y(k)$ is the periodic-stochastic hydrologic variable at a time instant $k$; $M_y$ is the mean of the sequence; the Fourier series with necessary finite harmonics is the periodic component; $q$ is the number of significant frequency components; $f_i$ is the frequency component; $A_i$ and $B_i$ are the Fourier coefficients; and $w(k)$ is the stochastic component which is assumed to be white Gaussian noise with zero mean and variance $W(k)$. The maximum entropy method (MEM) is used to find the necessary finite harmonics to account for periodicity in equation (1).

When the rainfall data are not normally distributed, it is necessary to make transformations. The reasons for transforming the series is to result in a model with the stochastic component being uncorrelated and normally distributed and to provide a guarantee for the analysis of the data by standard least-square methods[9].

The system parameters $M_y$, $A_i$ and $B_i$ in equation (1) are identified using the Kalman filter. The system and observation equations for the Kalman filter formulation are:

$$x(k+1)=\Phi(k)x(k)+\Gamma(k)u(k) \tag{2}$$

$$y(k)=H(k)x(k)+w(k) \tag{3}$$

where $x(k)$ is the $n$-dimensional state vector of the system at time $k$; $\Phi(k)$ is known state transition matrix of order $n\times n$; $\Gamma(k)$ is known system noise matrix of order $n\times p$; $y(k)$ is the $m$-dimensional observation vector $(m\leqq n)$; $H(k)$ is known observation matrix of order $m\times n$; $u(k)$ is independent, zero mean, white Gaussian $p$-dimensional system noise vector with known covariance matrix $U(k)$; and $w(k)$ is independent, zero mean, white Gaussian $m$-dimensional observation noise vector with known covariance matrix $W(k)$. The problem of identifying the parameters $M_y$, $A_i$ and $B_i$ corresponds to the case of the Kalman filter where the observation vector's dimension $m=1$ (i.e., $y(k)$ is scalar), the system state vector $x(k)=[M_y A_1 B_1 \cdots A_q B_q]^T$, the transition matrix $\Phi(k)=I$ (identity matrix), and the observation matrix $H(k)=[1 \sin 2\pi f_1 k \ \cos 2\pi f_1 k \ \cdots \ \sin 2\pi f_q k \ \cos 2\pi f_q k]$.

To detect the presence of an abnormal pattern in a given rainfall time series, the transformed generalized likelihood ratio, $\phi_*(k,l)$, defined as the abnormality detection index[4], is calculated recursively at each time instant $k$ from a finite series (of length $l$) of innovations, $\nu(k+1)$, $\nu(k+2)$, $\cdots$, $\nu(k+l)$, as follows:

$$\phi_*(k,l)\triangleq\sqrt{\phi^T(k,l)\,\mu^{-1}(k,l)\,\phi(k,l)} \tag{4}$$

where

$$\phi(k,l)\triangleq\sum_{i=1}^{l}A^T(k,k+i)\,V^{-1}(k+i)\,\nu(k+i) \tag{5}$$

$$\mu(k,l) \triangleq \sum_{i=1}^{l} A^T(k,k+i)\, V^{-1}(k+i) A(k,k+i) \tag{6}$$

$$A(k,k+i) \triangleq H(k+i)\, \Psi(k,k+i) \tag{7}$$

$$\Psi(k,k+i) \triangleq \begin{cases} \Phi(k+i-1)[I-K(k+i-1)H(k+i-1)] & \\ \cdot\, \Psi(k,k+i-1) & i \geqq 2 \\ I & i=1 \\ 0 & i \leqq 0 \end{cases} \tag{8}$$

$$\begin{aligned} V(k+i) &\triangleq E[\nu(k+i)\, \nu^T(k+i)] \\ &= H(k+i)P(k+i|k+i-1)H^T(k+i) + W(k+i) \end{aligned} \tag{9}$$

where $K(k)$ is the Kalman gain matrix of order $n \times m$; $\nu$ is the step 1 prediction residual vector of $m$-dimension, called innovation, which resulted from the Kalman filter calculations; $l$ is the number of innovations; and the symbols $^T$, $\triangleq$, $I$ and $E[\ ]$ denote the transpose of a matrix, equal by definition, an identity matrix of order $n \times n$, and an expectation operator respectively.

The gain matrix $K(k)$ at time $k$ is computed from the following recursive equations:

$$\begin{aligned} P(k|k-1) = {} & \Phi(k-1)P(k-1|k-1)\Phi^T(k-1) \\ & + \Gamma(k-1)\, U(k-1)\Gamma^T(k-1) \end{aligned} \tag{10}$$

$$\begin{aligned} K(k) = {} & P(k|k-1)H^T(k) \\ & \cdot [H(k)P(k|k-1)H^T(k) + W(k)]^{-1} \end{aligned} \tag{11}$$

$$P(k|k) = [I-K(k)H(k)]P(k|k-1) \tag{12}$$

where $P(k|k-1)$ is the estimation error covariance matrix at time $k$, given observations up to time $k-1$ and $P(k|k)$ is the estimation error covariance update matrix at time $k$.

The detection procedure works like passing a "window" of width $l$ through the given rainfall time series. Once this window encounters an abnormal rainfall pattern at time $k$, the $\phi_*(k,l)$−function will peak. It will decrease once the abnormal pattern is outside the range of this window. Hence, the peaks on the time series plot of a $\phi_*(k,l)$−function give the time of occurrence and magnitude of abnormalities.

The length of the finite series of innovations used for the four monthly mean rainfall time series is 15 (months). The choice of $l$ is based on these considerations: 1) $l$ should be greater than or equal to the dimension of the system state vector; this is to ensure the matrix $\mu(k,l)$ will be full rank, thereby making the calculation of its inverse $\mu^{-1}(k,l)$ possible[4]; and 2) It should be selected to provide a more realistic duration for the occurrence of abnormal pattern. Other considerations such as quicker detection or more accurate estimation of abnormality are given in other papers[5),6)].

## 3. Basic Characteristics of Rainfall in the Philippines

The rainfall data together with the other information[10] on Philippine climate were provided by the Philippine Atmospheric, Geophysical and Astronomical Services Administration (PAGASA).

The Philippines is located in the tropics and the climate prevailing in any particular place in the country is influenced by its geographical position and wind system prevalent in different localities at certain times of the year. The prevailing wind systems over the country are as follows: the northers or northeast monsoon (December to January), trade wind (April) and southwest monsoon (July, August and September). The driest of these is the trade wind season, while the wettest is the southwest monsoon season. The classification of Philippine climatic conditions is based on the characteristics of the distribution of rainfall received in a locality during the different months of the year. On the basis of this classification, four types of climate are adopted. The climatological map[11] of the country is shown in Figure 1. It should be noted in this figure that the dividing lines between different climatic types are mountain ranges which are high enough to cause variations in rainfall distribution.

The data used in the analysis are four monthly rainfall time series (details are given in Table 1) typical of the four types of climate in the Philippines. The missing data are

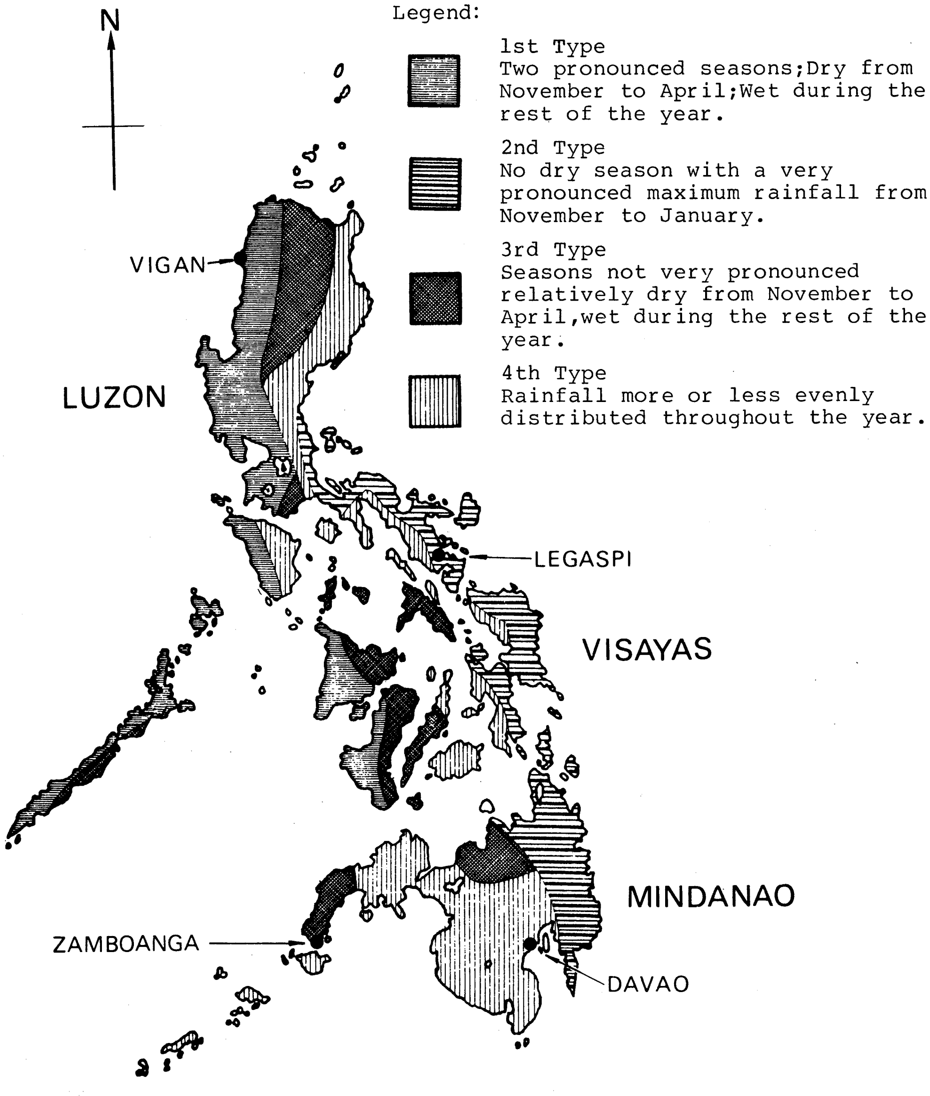


**Fig. 1** Climatological map. (After "Philippines Water Resources" 1976). Vigan, Legaspi, Zamboanga and Davao are the stations selected for analysis.

**Table 1** Stations selected for analysis.

| Station name | Latitude N | Longitude E | Period of record (year) | Dates with missing data |
|---|---|---|---|---|
| Vigan | 17°34′ | 120°23′ | 1951–1983 | July 1974; Aug–Oct 1975; Nov 1977; Jan, Sept, Dec 1980; July–Dec 1983 |
| Legaspi | 13°08′ | 123°44′ | 1951–1983 | Jan–Feb 1978; Feb, Mar, June, Aug 1979; June–Nov 1980 |
| Zamboanga | 6°54′ | 122°05′ | 1952–1983 | July–Aug 1975; Oct–Dec 1976; June–July 1978; Jan–Apr, Nov 1979; Aug 1980 |
| Davao | 7°04′ | 125°36′ | 1951–1983 | Aug 1974; Feb–Mar 1981 |

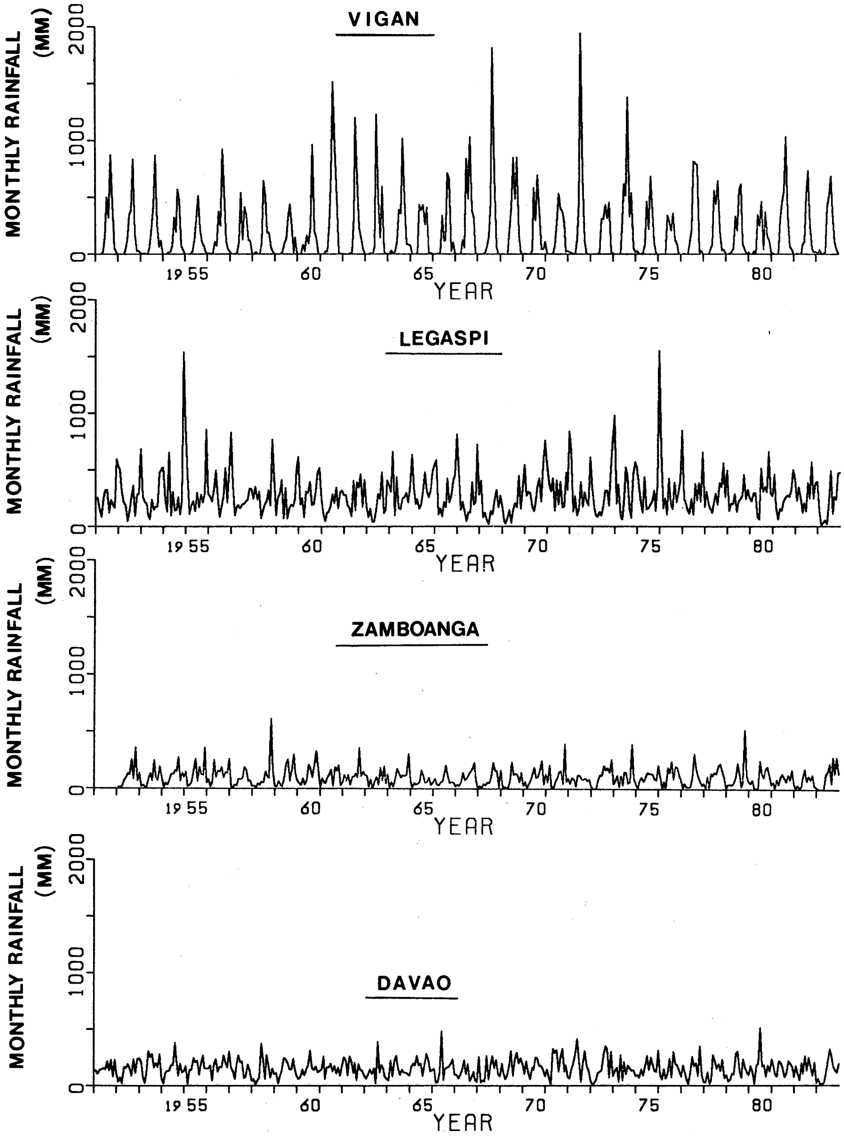


**Fig. 2a** Time series plot of the monthly rainfall data of each station.

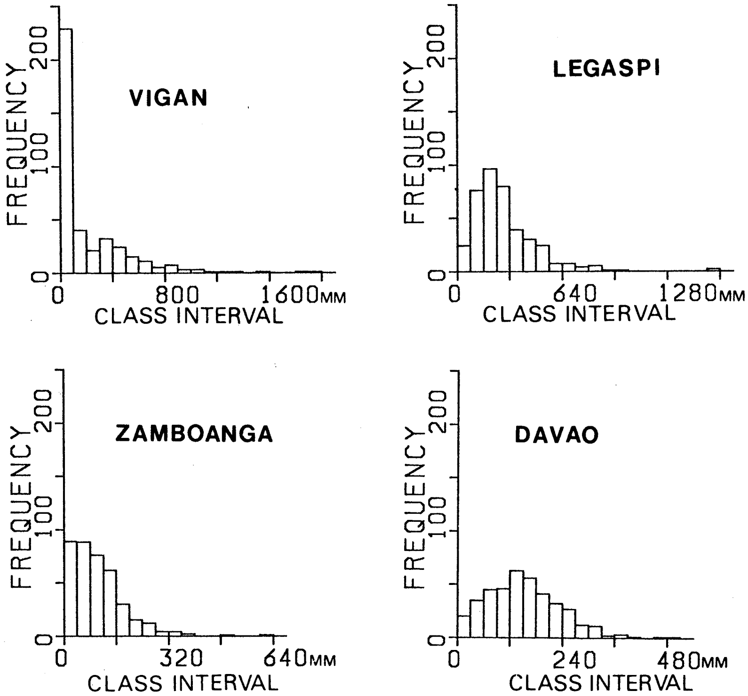


**Fig. 2b** Histogram of the monthly rainfall data of each station.

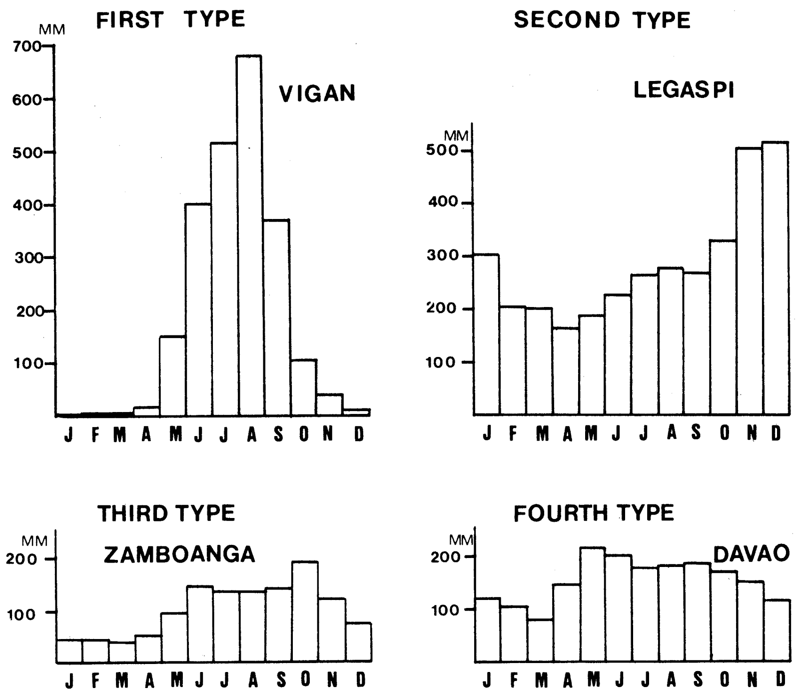


**Fig. 3** Mean monthly rainfall. First type, second type, third type and fourth type are the types of climate in the Philippines.

replaced by the mean values. Figure 1 also shows the locations of the four selected stations. The time series plots and histograms of the monthly rainfall data are shown in Figure 2. The frequency distributions of rainfall at the four stations are obviously not normal and are of common occurrence in meteorology [7].

The mean monthly rainfall at each station selected for analysis is shown in Figure 3. Vigan receives large rainfalls during the southwest monsoon season and is dry from November to April. Vigan belongs to the first type of climate which has two pronounced seasons and is shielded from the northeast monsoon and even to a good extent from the trade wind by mountain ranges. It is open only to the southwest monsoon and cyclonic storms. Legaspi is typical of the second type which has no dry season with a very pronounced maximum rain period from November to January. Legaspi is along the eastern coast and is sheltered neither from the northeast monsoon and the trade wind nor from

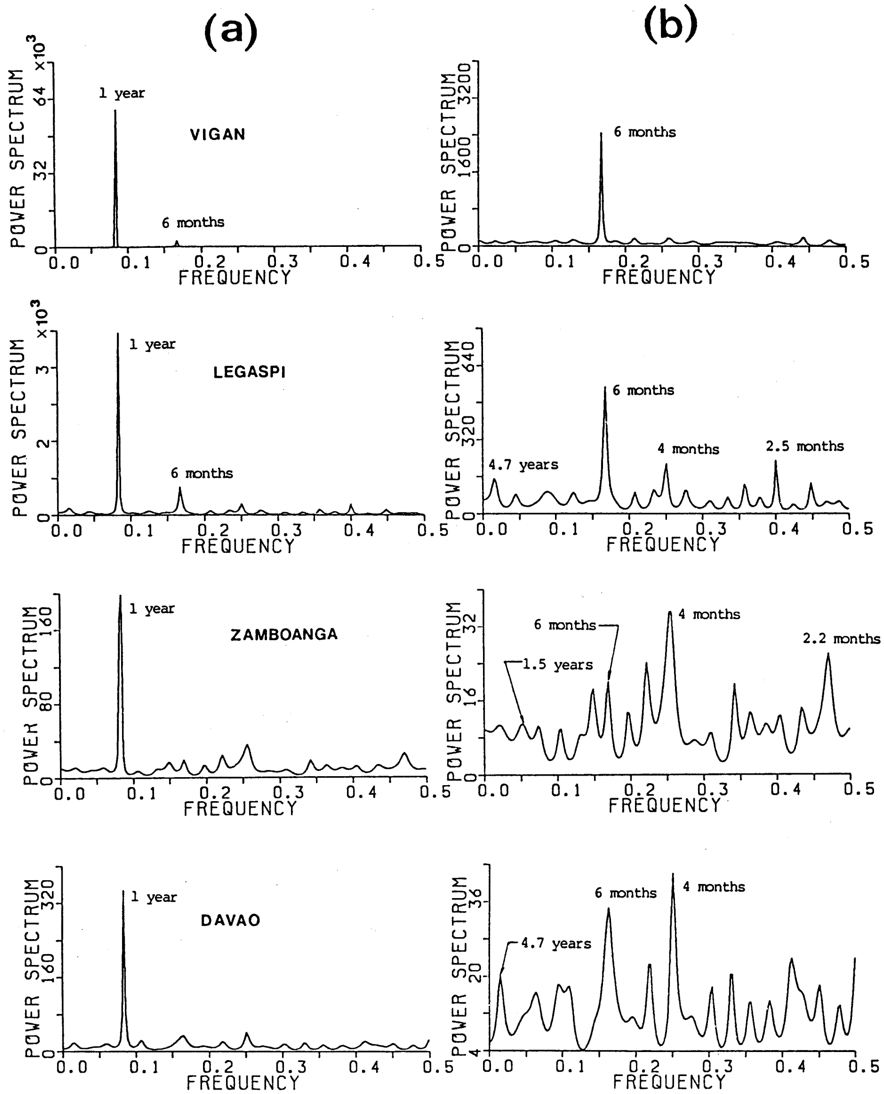


**Fig. 4** a) MEM power spectrum of monthly mean rainfall of each station; b) one-year harmonic removed. Power spectrum is in $(mm/day)^2$-month and frequency is in cycles/month.

cyclonic storms. Zamboanga is of the third type; localities with similar type are only partly sheltered from the northers and trade winds and open to the southwest monsoon or at least to frequent cyclonic storms. Zamboanga has seasons that are not very pronounced: relatively dry from November to April and wet during the rest of the year. Davao represents a more or less even distribution throughout the year and characterizes the fourth type of climate. It is interesting to note that over 50% of the rainfall in the Philippines is associated with typhoons and tropical storms which are formed in the Pacific Ocean.

The detection of periodicities for the derivation of the periodic-stochastic models for the four rainfall time series provides the basic spectral properties of Philippine rainfall.

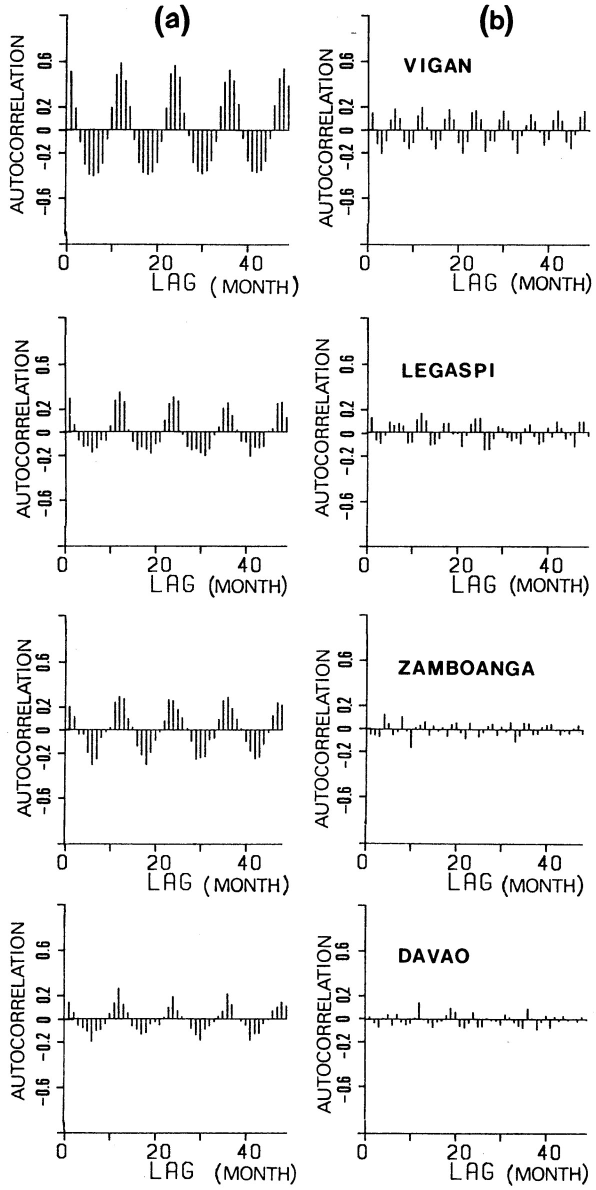


**Fig. 5** a) Correlogram of each station; b) one-year frequency component removed.

Figures 4 and 5 show two sets of power spectra and correlograms, respectively: one (left hand side) includes all the harmonic components in the time series and the other (right hand side) excludes the one-year harmonic to emphasize the effect of the next dominant harmonic in the periodogram and correlogram, according to the procedure reported by Quimpo (1968)[12].

The power spectra of the monthly mean rainfall series at Vigan, Legaspi, Zamboanga and Davao reveal two (annual and semi-annual), three (one-year, six- and four-month), one (annual) and one (annual) significant peaks respectively. These periodicities are accepted as real after performing significance test for amplitudes obtained by harmonic analysis, in accordance with the procedure described by Brooks and Carruthers (1953)[7].

The presence of these periodicities is well supported by the correlograms of these series (see Figure 5). After removing the one-year cyclicity, the correlograms for Vigan and Legaspi show significant autocorrelations at lags 6, 12, 18, . . . and at lags 3, 9, 15, . . . indicating a strong six-month cycle for these series. However, the four-month rhythm in the correlogram for Legaspi, after subtracting one-year and six-month cycles, does not occur at regular intervals. One interpretation for the presence of six-month cycle is that there are two rain periods within a geophysical year: one below and one above the average rainfall level. The presence of very pronounced maximum and minimum rain periods in Vigan and Legaspi stations explains the presence of the six-month cycle, while the absence of the two pronounced rain periods in Zamboanga and Davao series accounts for the insignificant six-month periodicity. Since the data used in this study only dates from 1951, it is not surprising that no statistically significant frequency component of lower than one-year is found.

## 4. Statistics of the Residuals

The data used in this analysis are the four transformed monthly mean rainfall time series. For Vigan, Lagaspi and Zamboanga time series, cube root transformation is employed. Square root transformation is found appropriate for Davao data.

**Table 2** Estimated model parameters by least-square method and Kalman filter.

| Station name | $n$ | Method used | Estimated Parameters | | | | | | | | | | | $W$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | $M_y$ | $A_1$ | $B_1$ | $A_2$ | $B_2$ | $A_3$ | $B_3$ | $A_4$ | $B_4$ | $A_5$ | $B_5$ | |
| | | | | (1/12) | | (1/6) | | (70/396) | | (132/396) | | | | |
| Vigan | 9 | L-S | 1.26 | −0.93 | −0.88 | 0.18 | 0.06 | −0.06 | −0.07 | −0.13 | 0.04 | | | 0.19 |
| | | KF | 1.26 | −0.93 | −0.88 | 0.18 | 0.06 | −0.06 | −0.07 | −0.13 | 0.04 | | | 0.22 |
| | | | | (7/396) | | (1/12) | | (1/6) | | (99/396) | | (160/396) | | |
| Legaspi | 11 | L-S | 2.01 | 0.08 | 0.02 | −0.19 | 0.24 | −0.01 | 0.15 | −0.07 | 0.05 | −0.03 | 0.05 | 0.13 |
| | | KF | 2.01 | 0.08 | 0.02 | −0.19 | 0.24 | −0.01 | 0.15 | −0.07 | 0.05 | −0.03 | 0.05 | 0.15 |
| | | | | (21/384) | | (1/12) | | (1/6) | | (96/384) | | (178/384) | | |
| Zamboanga | 11 | L-S | 1.38 | 0.04 | 0.01 | −0.34 | −0.13 | −0.08 | 0.06 | −0.01 | −0.09 | −0.08 | −0.02 | 0.09 |
| | | KF | 1.38 | 0.04 | 0.01 | −0.34 | −0.13 | −0.08 | 0.06 | −0.01 | −0.09 | −0.08 | −0.02 | 0.12 |
| | | | | (7/396) | | (1/12) | | (1/6) | | (99/396) | | | | |
| Davao | 9 | L-S | 2.15 | 0.11 | 0.04 | −0.27 | −0.26 | −0.12 | 0.10 | 0.14 | −0.05 | | | 0.31 |
| | | KF | 2.15 | 0.11 | 0.04 | −0.27 | −0.26 | −0.12 | 0.10 | 0.14 | −0.05 | | | 0.31 |

Note: Figures in the parentheses are the identified significant harmonics in cycles/month.
L-S = Least-square
KF = Kalman filter
$W$ = variance of the residuals
$n$ = number of parameters

The recursive applications of the Kalman filter algorithm require initial conditions for the state vector $\hat{x}(0|0)$, covariance matrix $P(0|0)$, system noise $U$ and measurement noise $W$. A least-square approach is used in the initialization of the Kalman filter. Table 2 indicates the necessary number of parameters in each model, the necessary harmonics (given in cycles/month) identified from the power spectrum of each transformed monthly mean rainfall time series and the values of the parameters estimated by the least-square method (L-S). These parameter estimates are used as the initial values of the state vector $\hat{x}(0|0)$. By doing this, the filter estimates of the state variable will rapidly converge within a few time steps. On the other hand, the diagonal elements of the covariance matrix $P(0|0)$ are all taken as ten in this study and off-diagonal elements as five. The

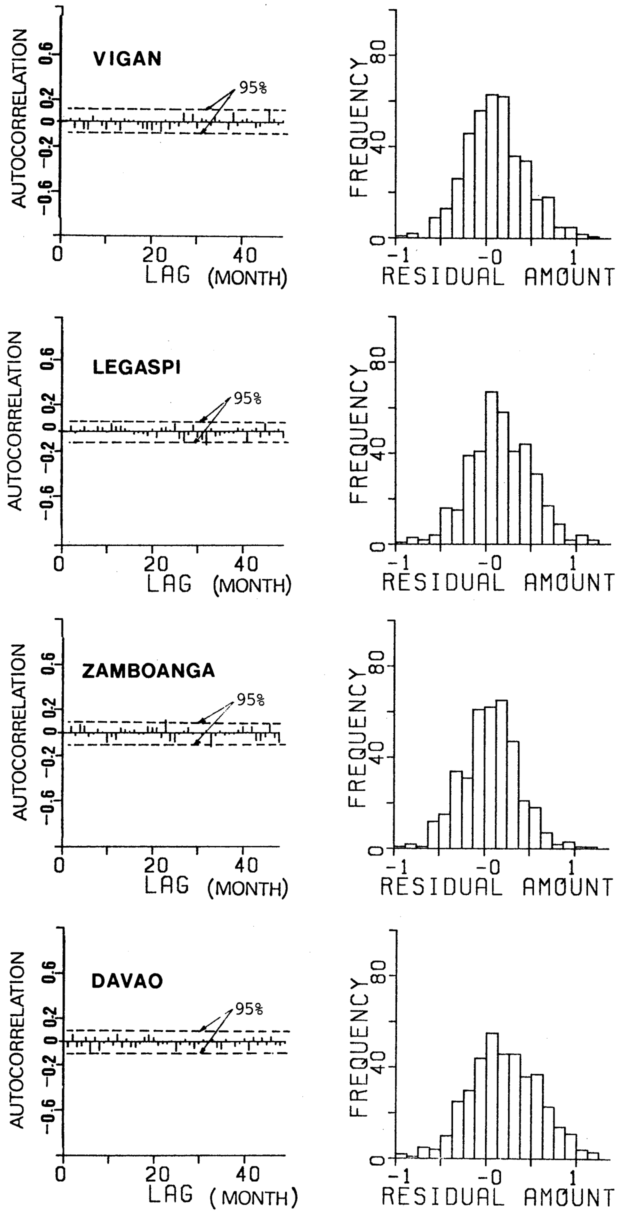


**Fig. 6** Autocorrelation function and histogram of the residual series of each station.

system noise $U$ is taken as zero. The measurement noise $W$ is assumed equal to the variance of the residuals which resulted from the least-square fit of the model to the given observed rainfall time series (see Table 2 for the values of $W$). This gives a relatively high signal-to-noise ratio, allowing a satisfactory detection of abnormalities.

With the abovementioned initial values, the Kalman filter algorithm is executed, and finally yields the parameter estimates presented in Table 2 (KF). Note that the Kalman filter and least-square estimates of the system parameters are equal.

At every time step, the predicted monthly rainfall value by Kalman filter is subtracted from the observed value, yielding the residual value. Hence, a sequence of residuals, constituting the stochastic component of the original data, is obtained at the end of the calculations. Figure 6 shows the autocorrelation functions (ACF) and histograms of the residual series for the four rainfall stations. Confidence limits from a simplified form of Bartlett's formula are shown in the ACF plots to indicate that the ACF coefficients are effectively zero, ACF coefficients being within the 95% confidence limits. Though ACF coefficients for lags 46, 32 and 23 and 33 for Vigan, Legaspi and Zamboanga, respectively, are outside of the confidence limits, the residuals (for each station) as a set are considered to be time-independent, because the calculated chi-squared value results in less than the critical value at 5% level of significance after performing the Ljung-Box test, as presented in Table 3. Bartlett's formula and Ljung-Box test are obtained from Pankratz (1983)[13]. Furthermore, the histogram for each station also shows an almost normal distribution for the residual series. To verify this notion, a test of the residual series for normality by performing a chi-square goodness-of-fit test[14] is done for each station. Test results in Table 3 show that the four residual series obey normality at the 5% level of significance. Therefore, it can be concluded from Figure 6 and the results of the tests in Table 3 that the validity of our assumption of a Gaussian white noise stochastic component with zero mean is verified.

**Table 3** Results of the tests for time-independence and for normality of the residuals.

| Station name | Time–Independence | | Normality | | Residual Statistics | |
|---|---|---|---|---|---|---|
| | Chi-square values | d.f. | Chi-square values | d.f. | Mean | S.D. |
| Vigan | 38.78(55.8) | 40 | 15.21(27.59) | 17 | −0.002 | 0.471 |
| Legaspi | 36.93(53.4) | 38 | 18.34(27.59) | 17 | 0.008 | 0.388 |
| Zamboanga | 41.56(52.2) | 37 | 19.02(27.59) | 17 | −0.014 | 0.349 |
| Davao | 30.83(55.8) | 40 | 15.31(27.59) | 17 | −0.036 | 0.598 |

Note: Figures in parentheses are the critical values of the chi-square distribution $\chi^2_{5\%(\mathrm{d.f.})}$;
where d.f. = degrees of freedom.
S.D. = standard deviation

## 5. Characteristics of the Abnormal Rainfall Patterns

The abnormality detection index, $\phi_*(k, l)$, is computed at every time instant $k$; the time series plots of the $\phi_*(k, l)$-function for the four stations are shown in Figure 7. Threshold values, $\eta$, for $\phi_*(k, l)$ are set at $\eta = 4.2$ for Zamboanga station and at $\eta = 3.8$ for the rest of the stations. The consideration for these choices of the threshold value is mentioned later in this section. The peaks above the threshold value identify the time

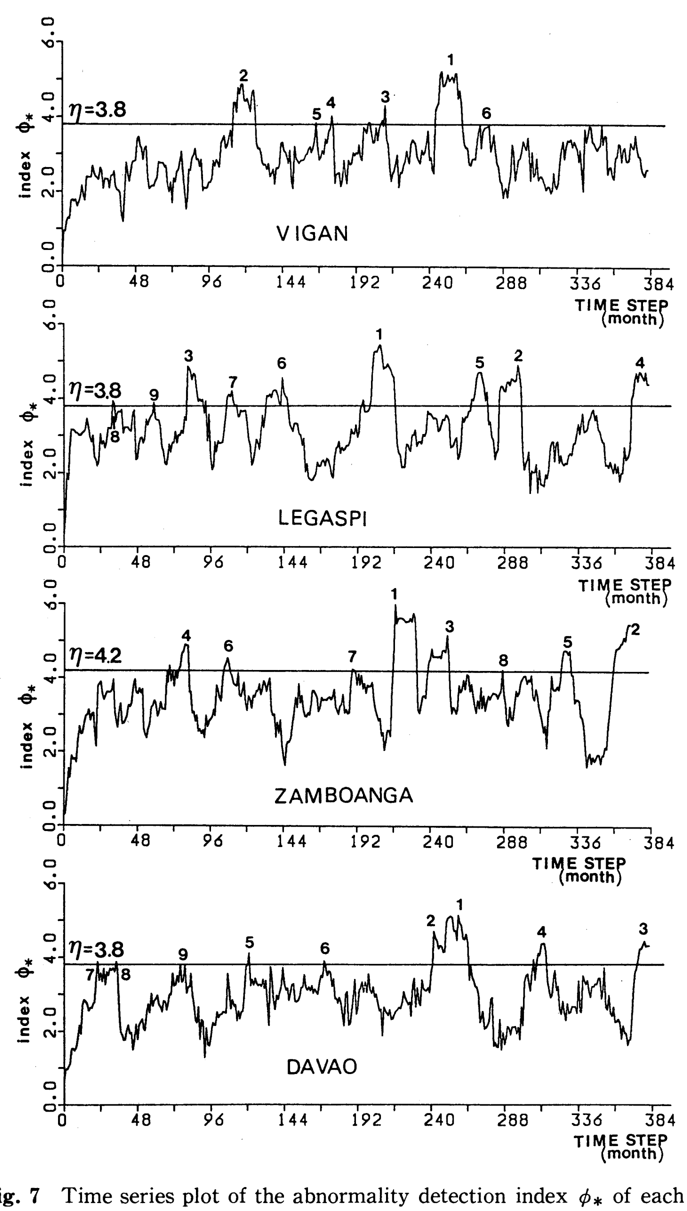


**Fig. 7** Time series plot of the abnormality detection index $\phi_*$ of each station. Numbers indicate the order of the abnormalities.

position and magnitude of the abnormalities.

The time of occurrence of peak $\phi_*$ indicates the time of the initiation of the rain period with identified abnormal pattern. The duration of this rain period is 15 months which is the length of the finite series of innovations, $l$. The magnitude of peak $\phi_*$ is the quantitative description of the pattern's degree of abnormality. These abnormal patterns are arranged in order of magnitude of the peak $\phi_*$ (order one being the highest of the magnitudes of peak $\phi_*$), as presented in Table 4. This table also illustrates the approximate dates of the onset of the detected abnormal patterns.

Figure 8 shows the observed monthly mean rainfall time series plots of the four stations, indicating the positions of the identified abnormal patterns. (This figure also shows the plots of the monthly mean values, full lines, and the monthly "mean plus/minus standard deviations", broken lines). Note that in Figure 8a the overlapping of two abnormal patterns (from December of 1964 to December of 1966) is due to the detection of the second abnormal pattern within the first abnormal rain period and due to the abnormal rain period actually lasted for two years. In Figure 8a-d, by simple visual inspection of the pattern of the observed monthly rainfall depths within the identified abnormal rain

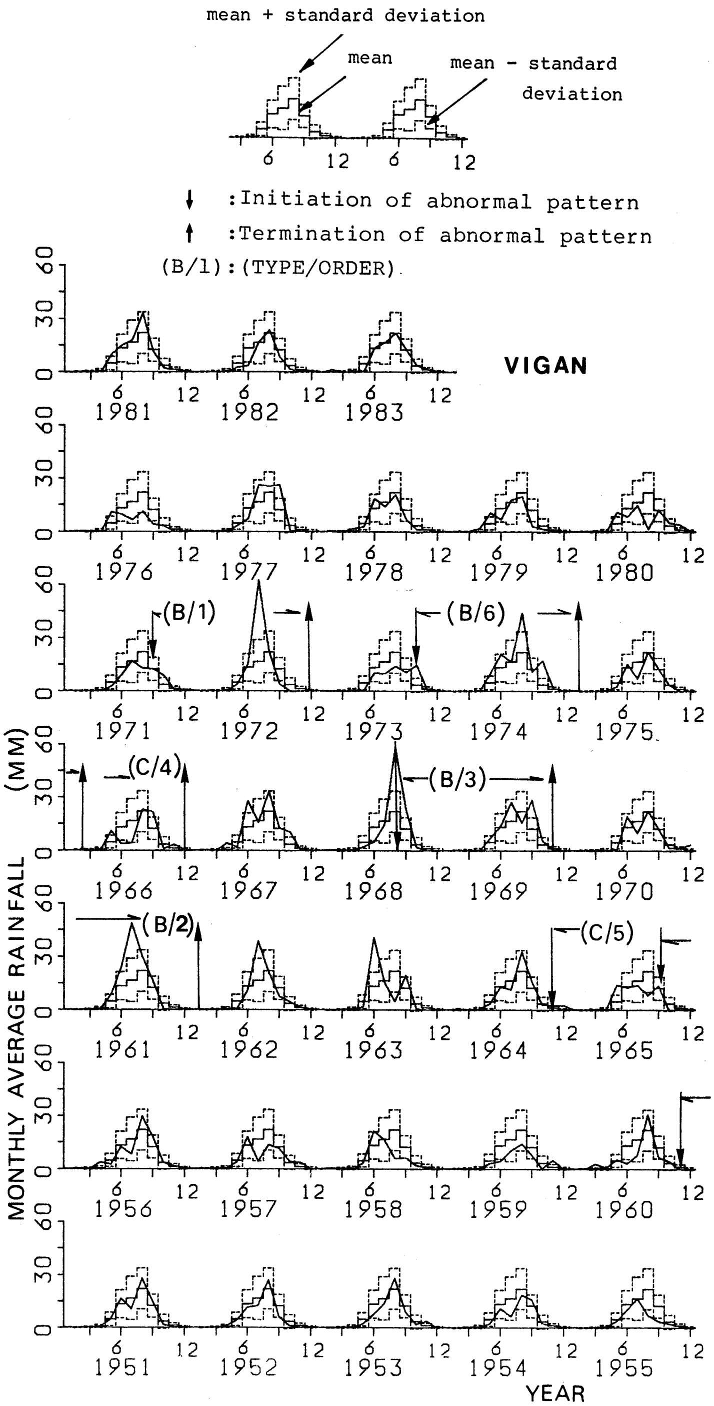


**Fig. 8a** Abnormal rainfall patterns at Vigan station.

period relative to the pattern of the average monthly mean values, it can be concluded that there are three types of abnormal patterns in rainfall sequences in the Philippines: 1) Type A which is characterized by the dominance of rainfall depths of below the mean values; 2) Type B which is typified by the dominance of rainfall depths of above the

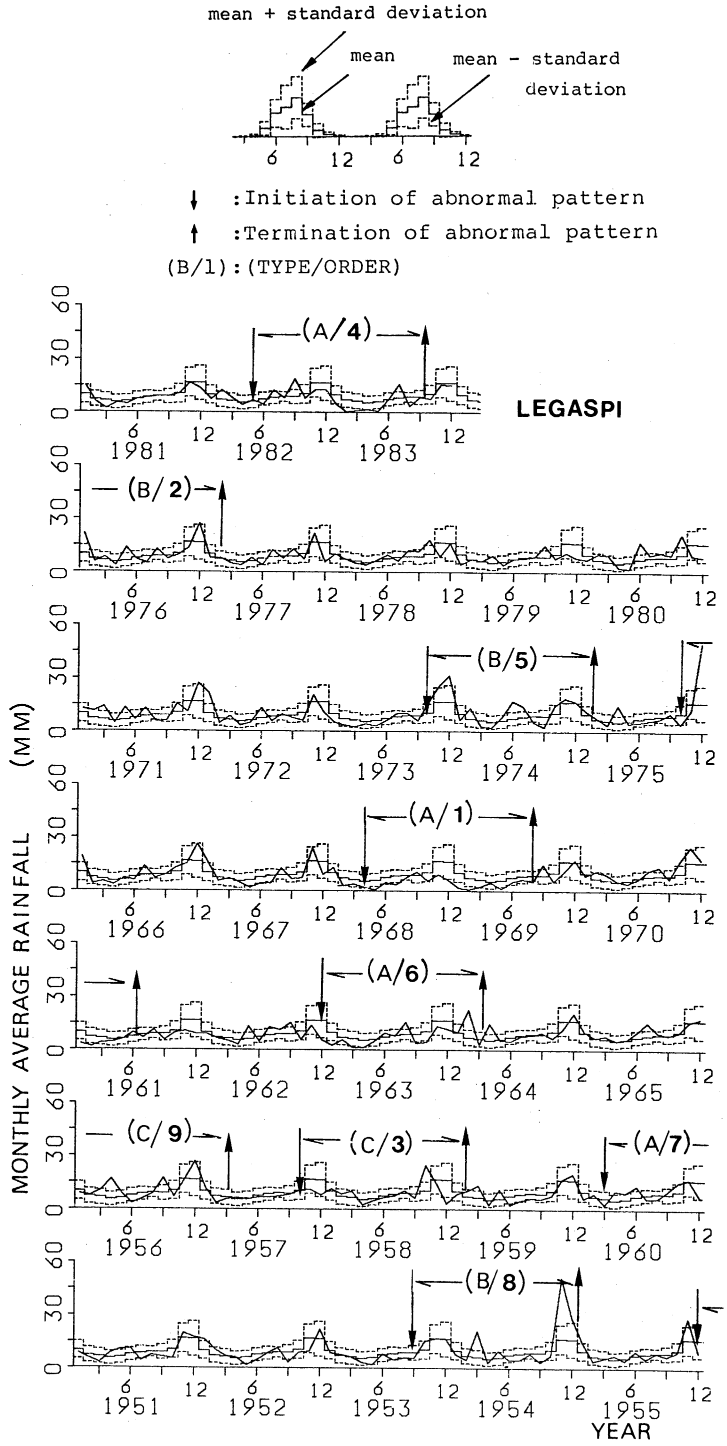


**Fig. 8b** Abnormal rainfall patterns at Legaspi Station.

mean values; and 3) Type C which is usually characterized by short-lived high fluctuations of rainfall. Also, a close examination of these periods reveals the existence of maximum and minimum rainfall depths occurring in the historical record.

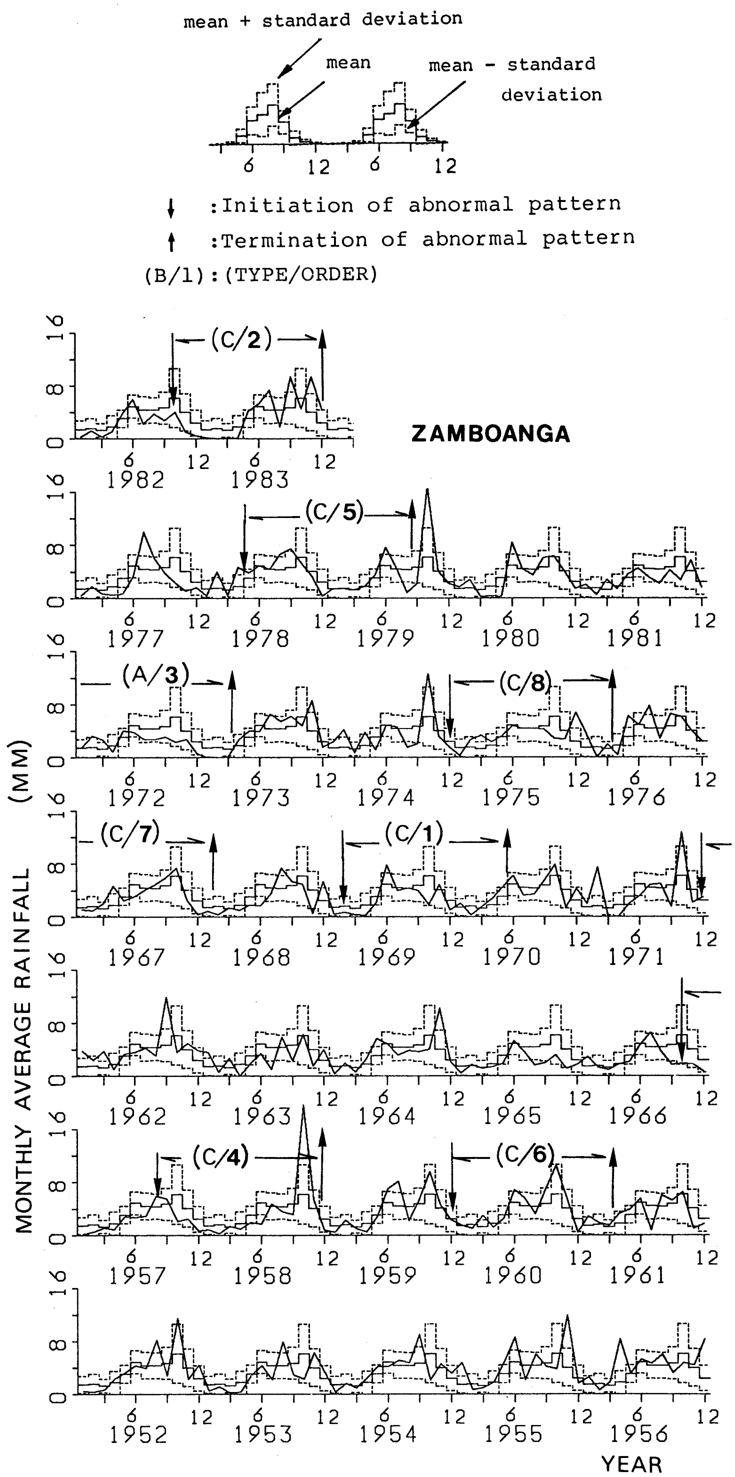


**Fig. 8c** Abnormal rainfall patterns at Zamboanga station.

To show the effectiveness of the method in detecting abnormal patterns and a clearer picture of the characteristics of the three types of abnormal patterns, a non-parametric method of describing rainfall, which has been advocated by Gibbs and Maher[2)] as drought

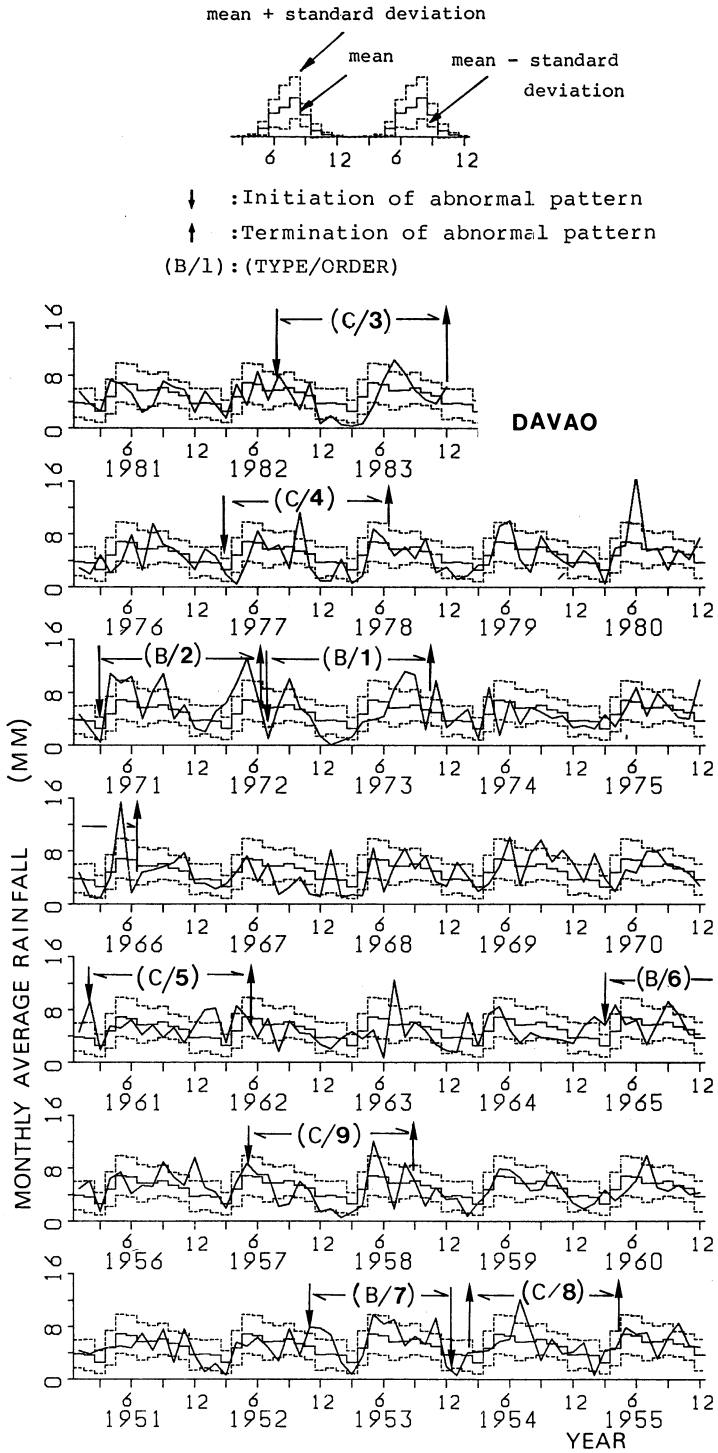


**Fig. 8d** Abnormal rainfall patterns at Davao station.

indicator for Australia, is adopted. This method suggests the use of a Gaussian or normal distribution of rainfall occurrence. Since given the mean and the variance, they completely describe the distribution and with these two parameters it is possible to calculate the probability of occurrence of values within any given range. However, the distributions of the monthly rainfall totals or their transformed values at the four stations show a marked departure from the normal curve (see Figure 2b). For this reason the four residual series are used, which were shown earlier to be normally distributed. The use of the residual amounts, which is the basis of the detection techniques, works equally well.

The method uses the limits of each ten per cent (or decile) of the distribution. Thus the *first decile* is that residual amount which is not exceeded by ten per cent of totals, the *second decile* by twenty per cent and so on. The *fifth decile* or *median* is the amount not exceeded on 50 per cent of occasions. The *decile ranges* are the ranges of values between deciles. This idea is illustrated in Figure 9. The decile ranges used in assessing residual at a particular station are given in the same figure. The decile range in which a particular residual falls give a useful indication of its departure from "average". Thus, decile range one suggests abnormally dry and decile range ten abnormally wet conditions.

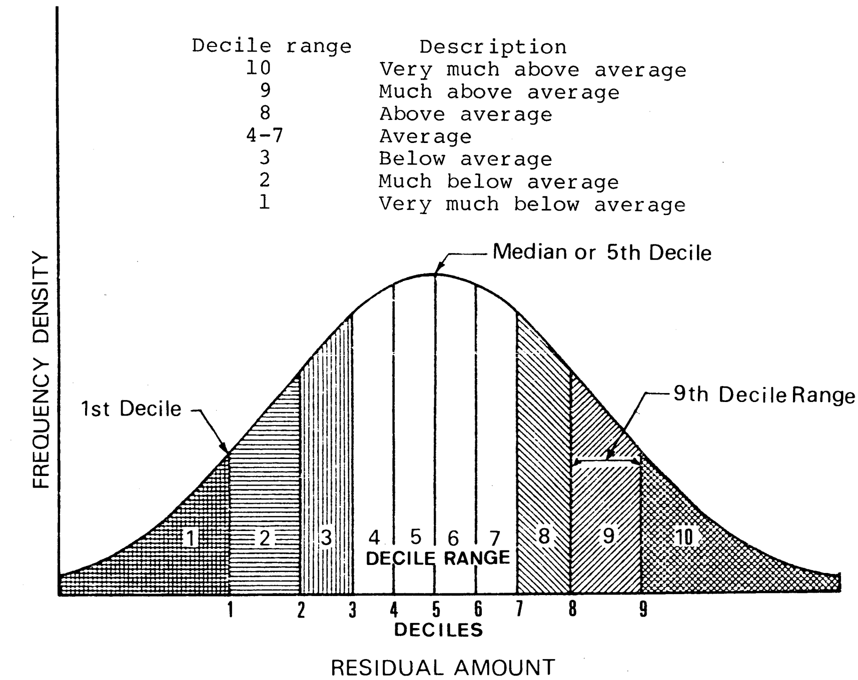


**Fig. 9** Decile range method. (After Gibbs 1975)

The threshold values, $\eta$, are set such that there is the tendency for the residual values (within the abnormal rain period) to occur most often in either range one or ten.

The monthly residual values in the periods with detected abnormal patterns are evaluated and their distribution in the ten decile ranges are illustrated in Table 4. As shown in this table, high frequency of occurrence of residual values in range one characterizes Type A, reflecting the presence of abnormally dry months in this type of abnormal pattern. By contrast, the figures for Type B exhibit a dominance of residuals in ranges nine and ten. This suggests that abnormally wet conditions exist in Type B abnormal patterns. Concentrations of the residuals in Type C appear in three ways: 1) more or less evenly distributed throughout the ten decile ranges; 2) high in range one; and 3) high in range ten. The occurrences of abnormally high (or low) rainfall depths in Type C are characterized by strong recovery of rain of average or below (or above) average

**Table 4** Characteristics of the abnormal patterns at the four selected stations.

| Station name | Peak $\phi_*$ Order | Date of Occurrence | Magnitude | Decile Range 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | Type |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Vigan | 1 | Sept. 1971 | 5.24 | 2 | 2 | | 2 | 1 | 2 | 2 | 1 | | 4 | B |
| | 2 | Nov. 1960 | 4.88 | 2 | 1 | 3 | | 1 | | 2 | 1 | 4 | 2 | B |
| | 3 | Aug. 1968 | 4.32 | 2 | | 3 | 2 | 1 | | 1 | 1 | 4 | 1 | B |
| | 4 | Sept. 1965 | 4.03 | 3 | 2 | 1 | 2 | | 2 | 1 | 2 | 2 | 1 | C |
| | 5 | Nov. 1964 | 3.85 | 1 | 2 | 2 | 1 | 3 | 3 | | 1 | 2 | 4 | C |
| | 6 | Oct. 1973 | 3.80 | | | 1 | 2 | 2 | 2 | 2 | 1 | 2 | 4 | B |
| Legaspi | 1 | April 1968 | 5.43 | 6 | 4 | 1 | 3 | 1 | | | 1 | | | A |
| | 2 | Nov. 1975 | 4.90 | 1 | 1 | 2 | 1 | 3 | 2 | | 1 | 1 | 4 | B |
| | 3 | Oct. 1957 | 4.84 | 3 | 1 | | 1 | 2 | 2 | 2 | 2 | 2 | 1 | C |
| | 4 | June 1982 | 4.73 | 4 | 2 | | 2 | 2 | 1 | 1 | 1 | 2 | 1 | A |
| | 5 | Oct. 1973 | 4.70 | 2 | 2 | 2 | | 2 | 1 | | | 3 | 4 | B |
| | 6 | Dec. 1962 | 4.55 | 5 | 2 | | 2 | 2 | 1 | 1 | 1 | | 2 | A |
| | 7 | March 1960 | 4.20 | 4 | 1 | 1 | 1 | 2 | 1 | 1 | 3 | 1 | 1 | A |
| | 8 | Sept. 1953 | 3.94 | | | 4 | 2 | 1 | 1 | 1 | 3 | 1 | 3 | B |
| | 9 | Dec. 1955 | 3.88 | 1 | 2 | 2 | 2 | 1 | | 2 | 1 | 3 | 2 | C |
| Zamboanga | 1 | Feb. 1969 | 6.00 | 2 | 2 | | 3 | | | 2 | 4 | 2 | 1 | C |
| | 2 | Oct. 1982 | 5.48 | 6 | | 2 | | | 1 | | 2 | 1 | 3 | C |
| | 3 | Dec. 1971 | 5.18 | 2 | 2 | | 2 | 2 | | 2 | 4 | | 2 | A |
| | 4 | Aug. 1957 | 4.90 | 2 | 1 | 2 | 1 | 1 | 3 | 1 | | 3 | 2 | C |
| | 5 | May 1978 | 4.77 | 3 | 2 | | | 1 | 3 | 3 | | 2 | 2 | C |
| | 6 | Dec. 1959 | 4.54 | 3 | | | 1 | 1 | 1 | 2 | 2 | 3 | 3 | C |
| | 7 | Oct. 1966 | 4.26 | 2 | 3 | 2 | 1 | 1 | 2 | 2 | 1 | 1 | 1 | C |
| | 8 | Dec. 1974 | 4.25 | 1 | 2 | | 1 | 2 | 1 | 3 | 3 | 1 | 2 | C |
| Davao | 1 | July 1972 | 5.13 | 3 | 2 | 2 | 1 | 1 | 1 | 1 | 1 | | 4 | B |
| | 2 | Mar. 1971 | 4.70 | 1 | | 1 | 3 | | | 1 | 1 | 4 | 5 | B |
| | 3 | Aug. 1982 | 4.43 | 4 | 3 | 1 | 1 | 2 | 1 | 1 | | 2 | 1 | C |
| | 4 | March 1977 | 4.37 | 4 | 2 | 1 | 2 | | | 2 | 2 | 2 | 1 | C |
| | 5 | Feb. 1961 | 4.10 | | | 5 | | 2 | 3 | 1 | 1 | | 4 | C |
| | 6 | March 1965 | 3.89 | 2 | 1 | | 2 | 2 | 1 | 2 | 1 | 2 | 3 | B |
| | 7 | Nov. 1952 | 3.88 | 3 | 2 | 2 | 1 | 1 | 1 | 1 | 1 | 4 | | B |
| | 8 | Jan. 1954 | 3.88 | 4 | 1 | | 2 | 2 | 1 | 2 | 1 | 2 | 1 | C |
| | 9 | May 1957 | 3.81 | 4 | 1 | 3 | 1 | | 2 | 2 | 1 | | 2 | C |

depths. It is observed that the occurrence of two or more successive months of abnormally low and high rainfall amounts are most common in Type A and Type B respectively, while less usual in Type C, depicting the high variability of rainfall. The use of the decile range method utilizing the normally distributed residual series results in a more detailed description of rainfalls in the detected abnormal pattern in terms of the probability of occurrence of the residuals.

As illustrated in Table 4 and in Figure 8, there are six, nine, eight and nine abnormal patterns that have occurred in the 33-year rainfall records (32 years for Zamboanga) at

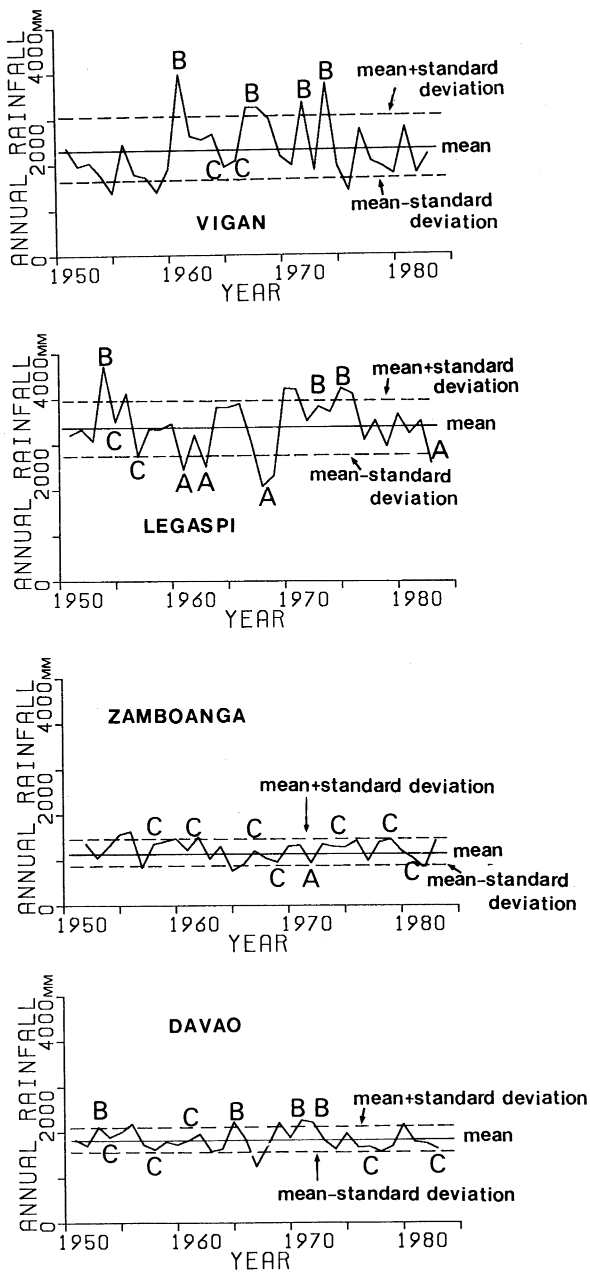


**Fig. 10** Annual rainfall sequence of each station. A, B and C are the types of abnormal patterns.

Vigan, Legaspi, Zamboanga and Davao stations, respectively. Vigan series has four of Type B and two of Type C; Legaspi has four of Type A, three of Type B and two of Type C; Zamboanga has one of Type A and seven of Type C; and Davao has four of Type B and five of Type C. Order one falls on Type B, A, C and B for Vigan, Legaspi, Zamboanga and Davao stations, respectively.

Figure 10 shows the plot of the annual rainfall time series, indicating the positions of the occurrence of abnormal patterns. The observations that can be made regarding this figure are as follows. The years with abnormally low and high rainfall amounts took place in the detected rain periods with Type A and Type B abnormal patterns respectively. Those years falling in Type C appear normal. This is so, because of the nature of Type C abnormal pattern i. e. strong recovery of rain after the occurrence of short-lived abnormally low (or high) rainfall amounts. Furthermore, the occurrence of Type C abnormal patterns can not be discerned from the annual time series.

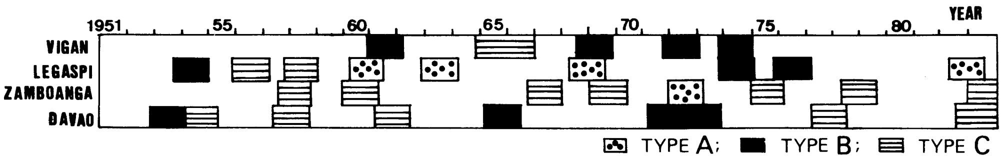


**Fig. 11** Distribution of the abnormal patterns.

Figure 11 shows the distribution of the abnormal rainfall patterns in 1951–1983 for the four selected rainfall stations. A close inspection of this figure reveals the following features. The 1957–58 Type C abnormal patterns disclose that one type of abnormality may occur more or less in the same period at different climatic regimes. Different areas of the country or types of climate may experience abnormal episodes of different types in one instance. This is shown by the abnormal patterns for the periods 1960–61, 1968–69 and 1982–83 in the four stations. Successions, at gaps of less than a year, and overlappings of abnormal periods of similar types reveal the fact that abnormalities may continue for a few years. Abnormal periods 1956–58 and 1974–76 in Legaspi series, 1964–66 in Vigan series and 1971–73 in Davao series illustrate this observation. There is one occasion (period 1953–55 in Davao series) that two different types of abnormal pattern occurred successively.

A 1969-drought episode which caused crop failure in the Bicol region where Legaspi station is situated was also reported by Jose (1984)[1]. This drought event is identified as the most abnormal pattern (being order one) at Legaspi station. This Type A abnormal pattern which initiated in April of 1968 is characterized by the persistence of below average monthly rainfall amounts for the whole 15-month period, as shown in Figure 8b. A complete failure of the northeast monsoon rains in the period between October of 1968 and March of 1969 aggravated the situation. This is substantiated by the respective residual values having a decile range pattern of 2, 2, 1, 1, 1, 2 for those months.

The two significant droughts in 1982 and 1983 are successfully detected as the occurrence of Type A and Type C abnormal rainfall patterns in Legaspi and Zamboanga and Davao, respectively. They are not detected in Vigan because the data from July to December of 1983 at this station are missing. Figure 8b shows that as early as October of 1982 the rainfall depths of less than the mean monthly levels already existed in Legaspi. From January to May of 1983, the rainfall situation became severe: monthly rainfall depths deep lower outside of the standard deviation. Monthly rainfall depths in Zamboanga (see Figure 8c) fell below the "mean minus standard deviation" levels from November of 1982 to April of 1983. In Davao (Figure 8d), month-to-month rainfall depths fluctuated about the mean since the start of 1982 and became persistently below the "mean minus standard deviation" levels from December of 1982 to April of 1983. Notice the strong recovery of rain after the dry spell in Zamboanga and Davao stations; this kind of recovery in the performance of rain is typical of Type C abnormal pattern. In terms of the decile range method, the residual values in those months with severe rainfall conditions are all in range one, indicating an abnormally dry months had existed.

Note the orders of these abnormal patterns as shown in Table 4: four, two and three in Legaspi, Zamboanga and Davao respectively. These orders suggest that these two destructive drought events resulted from major rainfall pattern abnormalities.

It can not be ascertained whether drought events took place or not in other detected rain periods with identified abnormal patterns due to inavailability of information. However, the successful detections of the three drought events that occurred in the country has shown the potential use of the abnormality detection procedure which is presented in this paper as a drought detector.

## 6. Conclusion

The presence of abnormal patterns in the four rainfall time series representative of the four types of climate in the Philippines has been successfully identified by the presented procedure which utilizes the Kalman filtering and generalized likelihood ratio techniques. The abnormality detection index $\phi_*$ has allowed an automatic and accurate estimations of the time of occurrence and magnitude of abnormality. This has made it possible to have a proper characterization of the abnormal patterns and hence an understanding of the basic dynamic behaviour of the rainfall sequence in the Philippines. On the basis of the results discussed in the previous sections, the presented methodology in general and the abnormality detection technique in particular appear promising for rainfall analysis.

## Acknowledgement

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