Memoirs of the Faculty of Engineering, Kyushu University, Vol. 46, No. 4, December 1986

Characterization of Rainfall Fluctuations in the Philippines by the Adaptive Kalman Filter

by

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(Received September 6, 1986)

Abstract

Our approach to the identification of rainfall fluctuations is to determine whether or not the occurrence of a short-duration rainfall pattern anomaly will cause an abrupt change in rainfall characteristics, i.e., the rainfall characteristics within a period will be terminated by a rather instantaneous shift to another period with different rainfall characteristics. We explore the recent (1951–1983) monthly rainfall data of four stations representative of the four types of climates in the Philippines to determine if rainfall in the country shows such kinds of fluctuations. We use the adaptive Kalman filter (AKF) to identify these kinds of fluctuations in a rainfall sequence by directly linking them with the abrupt changes in the parameters of the periodic-stochastic model of the rainfall time sequence. These abrupt changes in the model parameters, which are identified by AKF, occur in the short intervals with rainfall pattern anomalies and divide the time sequence into rainfall periods. We characterize the rainfall fluctuations based on the behaviour of the individual model parameter estimated by AKF. Finally, fluctuations of $\pm 10\%$ or more in average rainfall and statistically significant changes in rainfall characteristics are detected between two nonoverlapping adjacent periods.

1. Introduction

The biggest problem besetting the water resource management planners in the Philippines is the scarcity of hydrological data. According to the report prepared by the Philippine National Water Resources Council (1976)[1], there are 369 rain gaging stations in the country as of 1976; 66% of this number have less than ten years of record. To complement the rain gaging network, there are 496 stream gaging stations, and some 20 % of this number have been abandoned or discontinued. Less than 20% of the 496 stations have more than 20 years of record. Also the density of the existing data collection network is insufficient to meet the needs for long-range development planning.

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Potential users of the short records of data must be warned that careless use of these data may lead to wrong assumptions on some parameters, which may cause some undesirable consequences in the future. This is so because of the inherent fluctuations in rainfall characteristics, and the data may belong to a period with rainfall characteristics *significantly* different from the previous or succeeding periods. In this case, a reservoir designed using data belonging to a *much* rainfall period will be vulnerable if that period is terminated abruptly by another period characterized by *less* rainfall. Hence, in order to minimize the risk involved in using short records of data in the design and operation of water resource system, the rainfall fluctuations in the country must be identified and their characteristics fully understood.

Moderate climate variations have been considered as possibilities (although with different probabilities) of moderate average cooling in different latitudes with a maximum decrease of 1°C, moderate average warming with an increase of 1°C and a maximum of 3°C, and corresponding changes in average precipitation of ±10%; in the case of warming, precipitation may increase or decrease in different latitudes by 25%. Nemec (1985)[2] has adopted these values (namely changes in temperature of ±1°C, +3°C and variations in precipitation of ±10% and ±25%) as scenarios and used subsequently to examine the sensitivity of water resources systems and their design to climate variations. He has simulated as significant the influence of moderate climate variations on the runoff regime, and the serious impact of runoff changes on storage design further substantiates the need for consideration of climate-change impact on the design and operation of water resource system.

Since we limit our study to rainfall fluctuations by disregarding completely the variations of other climate elements such as temperature and evapotranspiration, we have to emphasize that this study offers the first step towards the identification of recent climate changes in the country. To put it in perspective, however, climates of the Philippines are based upon rainfall since temperature differences in the archipelago are really very slight and rainfall differences are, on the contrary, important and decidedly variant due to combined influence of topography and air stream direction[3]. For this reason, the basic climate element of rainfall takes priority for the identification of climate fluctuations.

In this paper, we explore the recent (1951–1983) monthly rainfall data of four stations representative of the four types of climates in the Philippines to determine if rainfall in the country shows fluctuations of ±10% or more in the mean between two nonoverlapping adjacent periods. This value (namely changes in precipitation of ±10%) has been considered in defining moderate climate variations as mentioned above. This search would not only provide the information needed to anticipate the impacts of future rainfall fluctuations but also contribute towards a better understanding of the basic dynamic characteristics of rainfall in the Philippines. Specifically, we identify and characterize the occurrences of rainfall fluctuations by analyzing the dynamic characteristics of the monthly rainfall time sequence utilizing the adaptive Kalman filter (AKF)[4].

2. Identification of Rainfall Fluctuations

In a rainfall sequence, there are intervals of shorter or longer duration when rainfall amounts seem to be in excess or in deficit[5]. Practically, we expect that these intervals become less easily delineated by simple visual inspection of the data. In a previous study[6], the ordinary Kalman filter (OKF) is used to detect these intervals in the monthly rainfall records of the stations considered in the present study. OKF identifies first the average rainfall pattern and then estimates the abnormality detection index ϕ_*[4] from the difference in rainfall amounts between the observed and average patterns. The occurrence of a peak ϕ_* identifies interval with abnormal rainfall pattern, and its value determines quantitatively the pattern's magnitude of abnormality. This leads to the identification of three types of abnormal patterns present in a rainfall time series: Type A which is characterized by the dominance of monthly rainfall depths of below the mean values and presence of abnormally dry months, Type B which is typified by the dominance of rainfall depths of above the monthly mean values and existence of abnormally wet months, and Type C which is characterized by both abnormally dry and wet months occurring more or less alternately. A close examination of these intervals reveals the existence of maximum and minimum rainfall depths occurring in the historical record. However, we refer the reader to the previous paper[6] for more detailed descriptions of these types of abnormal rainfall patterns. It is interesting to note that the two significant droughts in the country in 1982 and 1983, which were felt across a wide spectrum of human activities (agriculture, water supply, hydropower generation, etc.), have been identified as the occurrences of Type A and Type C abnormal patterns.

Our approach to the identification of recent rainfall fluctuations is to determine whether or not the occurrence of a short-duration rainfall pattern anomaly described above will cause an abrupt change in rainfall characteristics, i.e., the rainfall characteristics within a period will be terminated by a rather instantaneous shift to another period with different rainfall characteristics. We design the identification for fluctuations in this way because we believe that it is often important to have the identification not only to detect when a rainfall fluctuation has occurred, but also to know when rainfall is about to change or is in the process of changing its characteristics. In this way, we explore the possibility of early detection of moderate climate change, which is especially important in the operation of water resources systems.

We treat the identification of such rainfall fluctuations as a system identification problem involving detection of abrupt changes in the output of a dynamic system. In particular, we regard the rainfall time sequence as an output of a dynamic system. We use AKF to identify and characterize the rainfall fluctuations by directly linking them with the abrupt changes in the parameters of the periodic-stochastic model of the rainfall time sequence. These abrupt changes in the model parameters, which are identified by AKF, occur in the short interval with abnormal rainfall pattern. They divide the time sequence into parameter regimes, where each parameter regime corresponds to one rainfall period. The estimates of the parameters (such as the mean and the amplitudes of the periodic components) in a period describe the rainfall characteristics of that period and the occurrences of abnormal rainfall patterns. Also the occurences of the abnormal patterns in a period characterize the rainfall of that period. Here the behaviour of the model parameters determines the dynamic properties of the rainfall sequence.

In the absence of prior information on parameter change, it is only possible to make valid inferences, however, if great care is to be taken in the interpretation of any parameter change[7]. Chosen for reason of its simplicity, the analysis of covariance test (referred to as 'Chow test') proposed by Chow (1960)[8] is used for testing each pair of nonoverlapping adjacent rainfall periods for the presence of two parameter regimes. However it must be emphasized that, in this study, this test of significance of two parameter regimes is used for the purpose of highlighting the differences in characteristics between two adjacent rainfall periods.

The adaptive Kalman filter follows the method of Willsky and Jones (1976)[9] on detection and estimation of jumps in the state of linear systems. Technique similar to their method has been applied to rainfall-runoff models by Kitanidis and Bras (1980)[10] and AKF to the analysis of long-term pattern fluctuations in a precipitation sequence by Kawamura, et al. (1985)[11].

Short-duration rainfall pattern anomalies do not happen at regular interval and, like droughts and floods, should be expressed in terms of return period. Hence we feel that the most appropriate recurrence interval for such anomalies would be the one related to the design and operation of water resource systems. For instance, Japan's Ministry of Construction[12] has recommended the use of a return period of 10 years for drought occurrence in designing reservoir capacity. Thus we consider the period in years *on the average* of about a decade during which rainfall fluctuations can be expected to recur.

Table 1 gives the details of the four monthly rainfall time series used in this study. Here the missing data are replaced by the mean values. Figure 1 shows the climatological map of the country and the locations of the four selected stations, namely Vigan (Type I), Legaspi (Type II), Zamboanga (Type III) and Davao (Type IV). In the previous paper[6], we have described in detail the four types of climates in the Philippines.

Table 1 Stations selected for analysis.

Station	Latitude N	Longitude E	Period of record (year)	Dates with missing data
Vigan	17°34′	120°23′	1951–1983	July 1960 ; 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	06°54′	122°05′	1952–1983	July-Aug 1975 ; Oct-Dec 1976 ; June-July 1978 ; Jan Apr, Nov1979 ; Aug 1980
Davao	07°04′	125°36′	1951–1983	Aug 1974 ; Feb-Mar 1981

3. Adaptive Kalman Filter Formulation

Since rainfall time series is a periodic-stochastic process, the rainfall time series model conceived in this study is given in the form:

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

where $y(k)$ is the transformed monthly mean rainfall at time instant k; M_y is the mean of the transformed sequence; q is the number of significant frequency components; f_i is the frequency component; A_i and B_i are the periodic coefficients; and $w(k)$ is the stochastic component which is assumed to be white Gaussian noise with zero mean and variance $W(k)$. To result in a periodic-stochastic model with the stochastic component $w(k)$ being uncorrelated and normally distributed, transformation of the four rainfall time sequences becomes essential. The transformations of the four rainfall records are discussed in the previous paper[6]. In order to detect whether there have been significant rainfall fluctuations in Vigan, Legaspi, Zamboanga and Davao stations, fluctuations associated with abrupt

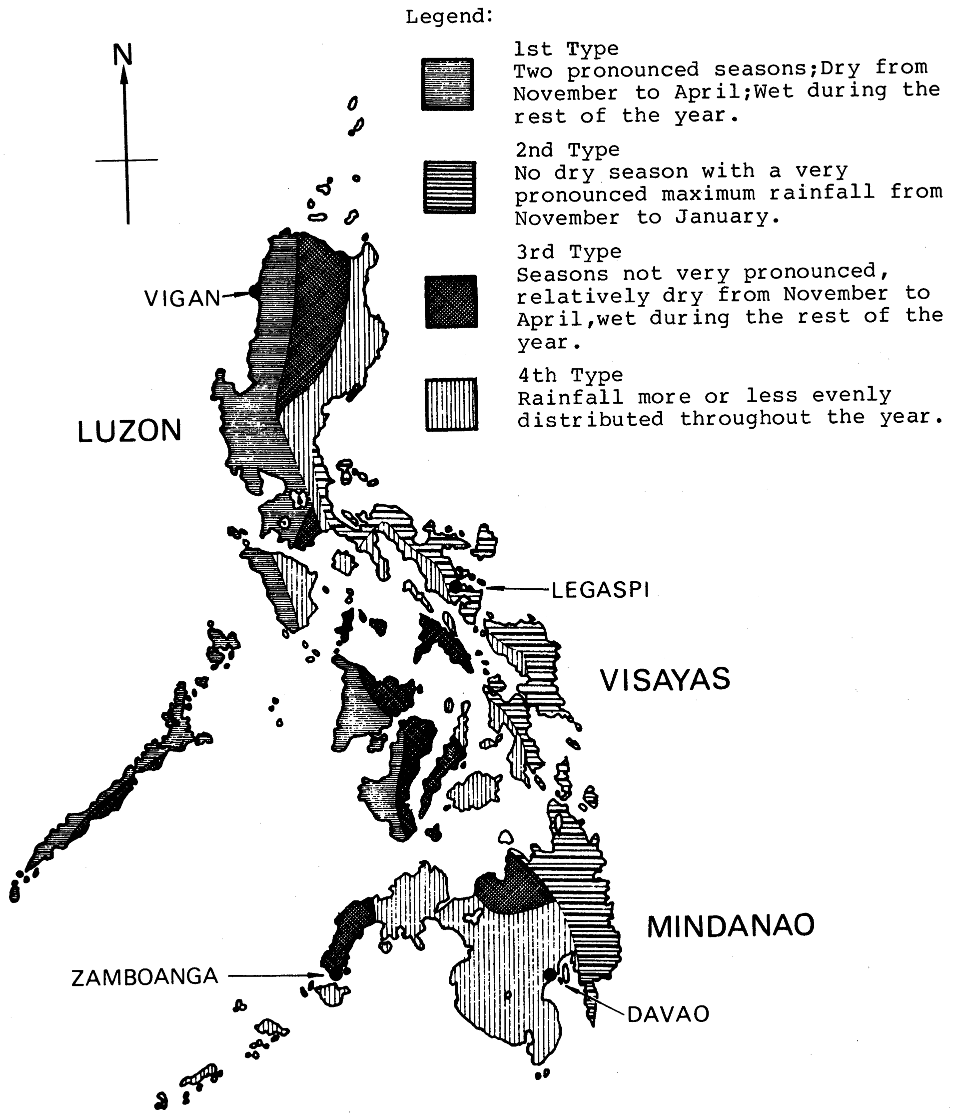

Fig. 1 Climatological map of the Philippines. (After "Philippine Water Resources" 1976). Vigan, Legaspi, Zamboanga and Davao are the stations selected for analysis.

changes in the parameters M_y, A_i and B_i of the periodic-stochastic model (1) provide a suitable approach. This assumes, however, that f_i are known.

The adaptive Kalman filter detects whether an abrupt change in the system state variables occurs or not by evaluating the innovations (step-one prediction residuals) sequence using generalized likelihood ratio test (GLRT). When such abrupt change is detected, its time of occurrence and magnitude are estimated quantitatively, and the state variables are appropriately corrected according to the magnitude of this abrupt change. Note that the state variables are the model parameters M_y, A_i and B_i. We refer the reader to the work of Ueda, et al. (1984)[4] for details of the derivation of AKF.

The AKF formulation considers the following system and observation equations.

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

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

where k denotes time instant; x is the $(n\times 1)$ system vector; Φ is the known $(n\times m)$ state transition matrix; Γ is the known $(n\times p)$ system matrix; u is the independent, zero mean, white Gaussian $(p\times 1)$ system noise vector with known covariance matrix U; G is the unknown $(n\times 1)$ abnormality vector; θ is the unknown time instant when the abnormality occurred; $\delta_{k\theta}$ is the Kronecker's delta ($\delta_{k\theta}=1$ if $k=\theta$ and $\delta_{k\theta}=0$ if $k\neq\theta$); y is the $(m\times 1)$ observation vector $(m\leqq n)$; H is the known $(m\times n)$ observation matrix; and w is the independent, zero mean, white Gaussian $(m\times 1)$ observation noise vector with known covariance matrix W. Here the system equation (2) is composed of the system equation for the OKF and the term $\delta_{k\theta}G(k)$ for the magnitude of abrupt change in the state variables. With this equation, two hypotheses can be made: H_0 is the hypothesis that no abrupt change has occurred and H_1 is the hypothesis that an abrupt change occurred at time $k=\theta$. Under H_0 hypothesis, equation (2) is reduced to OKF formulation. In this study, the observation equation (3) is the periodic-stochastic model (1).

The problem of identifying the parameters M_y, A_i and B_i which may change abruptly and randomly at an unknown time corresponds to the case of the ordinary Kalman filter where the observation vector's dimension $m=1$ (i.e., $y(k)$ is scalar), $x(k)=[M_yA_1B_1\cdots A_qB_q]^T$, $\Phi(k)=I$ and $H(k)=[1\ \sin2\pi f_1k\ \cos2\pi f_1k\cdots\sin2\pi f_qk\ \cos2\pi f_qk]$.

The maximum likelihood estimate $\hat{\theta}$ of the time of occurrence of abrupt change θ is given as

$$\hat{\theta}=\{k|\max\phi_*(k,l)\} \tag{4}$$

which means that $\hat{\theta}$ is the time step k when $\phi_*(k,l)$ is maximum. The transformed generalized likelihood ratio $\phi_*(k,l)$ which is referred to as the abnormality detection index[4], as it expresses quantitatively the system abnormality, is calculated recursively at each time step k from a finite series (of number l) of innovation vectors, $\nu(k+1)$, $\nu(k+2)\cdots,\nu(k+l)$, as follows:

$$\phi_*(k,l)\triangleq\sqrt{\phi^T(k,l)\mu^{-1}(k,l)\phi(k,l)} \tag{5}$$

where

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

$$\mu(k,l)\triangleq\sum_{i=1}^{l}A^T(k,k+i)V^{-1}(k+i)A(k,k+i) \tag{7}$$

$$A(k,k+i)\triangleq H(k+i)\Psi(k,k+i)\qquad (m\times n\ \text{matrix}) \tag{8}$$

$$\Psi(k,k+i)\triangleq\begin{cases}\Phi(k+i-1)[I-K(k+i-1)H(k+i-1)]\Psi(k,k+i-1) & i\geqq 2\\ I & i=1\\ 0\qquad (n\times n\ \text{matrix}) & i\leqq 0\end{cases} \tag{9}$$

$$\begin{aligned}V(k+i)&\triangleq E[\nu(k+i)\nu^T(k+i)]\\ &=H(k+i)P_0(k+i|k+i-1)H^T(k+i)+W(k+i)\end{aligned} \tag{10}$$

where $\phi(k,l)$ is an $n\times 1$ vector and $\mu(k,l)$ is an $n\times n$ matrix. Here the symbols $\triangleq$, ^{T} and I denote equal by definition, transpose of a matrix, and $(n\times n)$ identity matrix respectively; ν is the $(m\times 1)$ innovations (step-one prediction residuals) vector; l is number of cumulative innovations; K is the $(n\times m)$ Kalman gain matrix; $P_0(k+i|k+i-1)$ is P at time $k+i$, given observations up to time step $k+i-1$, and is calculated by OKF under H_0 hypothesis; and P is the $(n\times n)$ estimation error covariance matrix of x.

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

$$P(k|k-1)=\Phi(k-1)P(k-1|k-1)\Phi^T(k-1)+\Gamma(k-1)U(k-1)\Gamma^T(k-1) \tag{11}$$

$$K(k)=P(k|k-1)H^T(k)[H(k)P(k|k-1)H^T(k)+W(k)]^{-1} \tag{12}$$

$$P(k|k)=[I-K(k)H(k)]P(k|k-1) \tag{13}$$

where $P(k|k-1)$ is P at time k, given observations up to time $k-1$, whereas $P(k|k)$ is P at time k, given observations up to time k.

To detect whether an abrupt change exists or not, an equivalent GLRT[4)] is performed utilizing $\hat{\theta}$ through the following equation

$$\phi_*(\theta, l) \underset{H_0}{\overset{H_1}{\gtrless}} \eta \tag{14}$$

Thus the equivalent GLRT compares the value of $\phi_*(\theta, l)$, defined by equation (5), with a threshold value η. If $\phi_*(\theta, l)$ is greater than η, H_1 hypothesis is accepted; otherwise, H_0 hypothesis is accepted.

When the equivalent GLRT leads to the inference that H_1 hypothesis is true at time step $\theta+i$, the state variables are corrected at the same time step to allow the filter to adjust to the new system. Using the maximum likelihood estimate $\hat{G}(\theta)$ of the magnitude of abrupt change $G(\theta)$ given as

$$\hat{G}(\theta)=\mu^{-1}(\theta, l)\phi(\theta, l) \tag{15}$$

which utilizes $\hat{\theta}$, the estimate of the state vector and its error covariance matrix are compensated at $\theta+i$ as

$$\hat{x}_{\overline{new}}(\theta+i|\theta+i)=\hat{x}_{old}(\theta+i|\theta+i)+\Delta(\theta, \theta+i)\hat{G}(\theta) \tag{16}$$

$$P_{\overline{new}}(\theta+i|\theta+i)=P_0(\theta+i|\theta+i)+\Delta(\theta, \theta+i)\mu^{-1}(\theta, l)\Delta^T(\theta, \theta+i) \tag{17}$$

where

$$\Delta(\theta, \theta+i)\triangleq[I-K(\theta+i)H(\theta+i)]\Psi(\theta, \theta+i) \qquad (n\times n \text{ matrix}) \tag{18}$$

Here $\hat{x}_{old}(\theta+i|\theta+i)$ and $P_0(\theta+i|\theta+i)$ are the estimate of $x(\theta+i)$ and its error covariance matrix respectively prior to compensation, which are calculated recursively by OKF.

Ueda, et al. (1984)[4)] have proposed a new and simple method for on-line estimation of θ through equation (4), in which l is set constant. The maximum ϕ_* is searched in the range from k_η to $j_\eta-1$ ($l-1$ time-steps), and its time of occurrence in this range is regarded as $\hat{\theta}$. Here k_η is the time step at which the magnitude of ϕ_* calculated at the present time step j_η is greater than η for the first time; k_η and j_η are l time-steps apart. The search is done in this range because the abrupt change has been detected to be present, through ϕ_* at k_η, in the innovations from $k_\eta+1$ to j_η. Specifically, the search for maximum ϕ_* works as follows. The ϕ_* at $k_\eta+1$ is calculated at the next present time step $j(=j_\eta+1)$, denoted as ϕ_{*now} and compared with ϕ_* at k_η. The larger ϕ_* is kept and denoted as ϕ_{*max}. Similarly, the ϕ_* at $k_\eta+2$ is calculated at the next $j(=j_\eta+2)$, denoted as ϕ_{*now} and compared with ϕ_{*max}, and the larger one is retained as the new ϕ_{*max}. This procedure continues until all the ϕ_* within the time-range from k_η to $j_\eta-1$ are evaluated, i.e., at every forward move of the present time step j. Thus the time of occurrence of abrupt change is determined precisely through ϕ_{*max} at time step $j_\eta-1$ and is equal to the time of occurrence of this ϕ_{*max}. However, it is decided actually at the present time step $j=j_\eta-1+l$.

To decide the time of occurrence of an abrupt change quicker, a choice of smaller value of l would be better. However, l must be greater than or equal to the minimum number of cumulative data needed to make matrix $\mu(\theta, l)$ full rank, which ensures the calculation of its inverse required to estimate $G(\theta)$ and $\phi_*(\theta, l)$. Moreover, if l is too small, ϕ_* would be influenced much by noise such that the time of occurrence of maximum ϕ_* may not correspond to $\hat{\theta}$. Hence these considerations will dictate the choice of l.

For the recursive applications of the AKF algorithm, we use the following initial conditions: $x(0|0)$ is the least-square estimates shown in the last row of Table 3 (given in Section 5), and the diagonal elements of $P(0|0)$ are taken as ten and off-diagonal as five. We set $U=0$ and assume W equal to the variance of the residuals which resulted from the least-square fit of the model to the given transformed rainfall time series, i.e., W=0.19, 0.13, 0.09 and 0.31 for Vigan, Legaspi, Zamboanga and Davao respectively. With these values, we execute the AKF algorithm, finally yielding the parameter estimates presented in Table 3. Here q=4, 5, 5 and 4 and the state vector's dimension n=9, 11, 11 and 9 for Vigan, Legaspi, Zamboanga and Davao respectively. In executing the algorithm, we set l=15 and η=4.8 for Vigan, Legaspi, and Zamboanga and 4.3 for Davao (see Section 5 for the considerations on the choice of η). At these levels of η, two instantaneous shifts in system parameters are detected by AKF for each time series, resulting in three periods with average duration of 11 years. For each period, the parameters M_y, A_i and B_i are estimated by AKF as shown in the same table.

Table 3 also shows the dominant harmonics f_i present in each rainfall time sequence, which are detected using maximum entropy method. They are chosen optimally so as to satisfy the model parsimony and the requirement of normality and time-independence for the stochastic component of the periodic-stochastic rainfall time series model. Using century-long monthly rainfall records, Suppiah and Yoshino (1984)[13] have revealed the dominance of 13-16 months, 24 months, 3-4 years and quasi-five year oscillations in the rainfall variations in Sri Lanka. These long-term periodicities have also been detected as dominant in other parts of the equatorial Pacific region and most tropical stations. Being very close to those demonstrated in Sri Lanka, the chosen long-term oscillations for Legaspi (4.7 years), Zamboanga (1.5 years) and Davao (4.7 years) may be accepted as real. Also Vigan and Legaspi reveal statistically significant semiannual cycle[6].

4. Chow Test for Parameter Change

A separate regression model can be calculated for each rainfall period, and parameter estimation and residuals of each period can be compared to determine if significant parameter shifts have occurred. Chow test is based on the statistic

$$F=\frac{(M-N-P)/p}{(N+P)/(n+m-2p)} \tag{19}$$

where p is the number of parameters; n and m are the respective numbers of observations in the first and second rainfall periods being paired; M is the sum of squares of $n+m$ deviations of the dependent variable from the regression estimated by $n+m$ observations, with $n+m-p$ degrees of freedom; N is the sum of squares of n deviations of the dependent variable from the regression estimated by the first observations, with $n-p$ degrees of freedom; P is the sum of squares of m deviations of the dependent variable from the regression estimated by the m observations, with $m-p$ degrees of freedom. From equation (19), the ratio will be distributed as $F(p, n+m-2p)$ under the null hypothesis that both groups of observations belong to the same regression model. The proof that the statistic (19) follows an F distribution under null hypothesis may be found in Chow (1960)[8]. Table 4 (given in Section 5) provides the calculated F-statistic associated with each pair of rainfall periods.

5. Results and Discussion

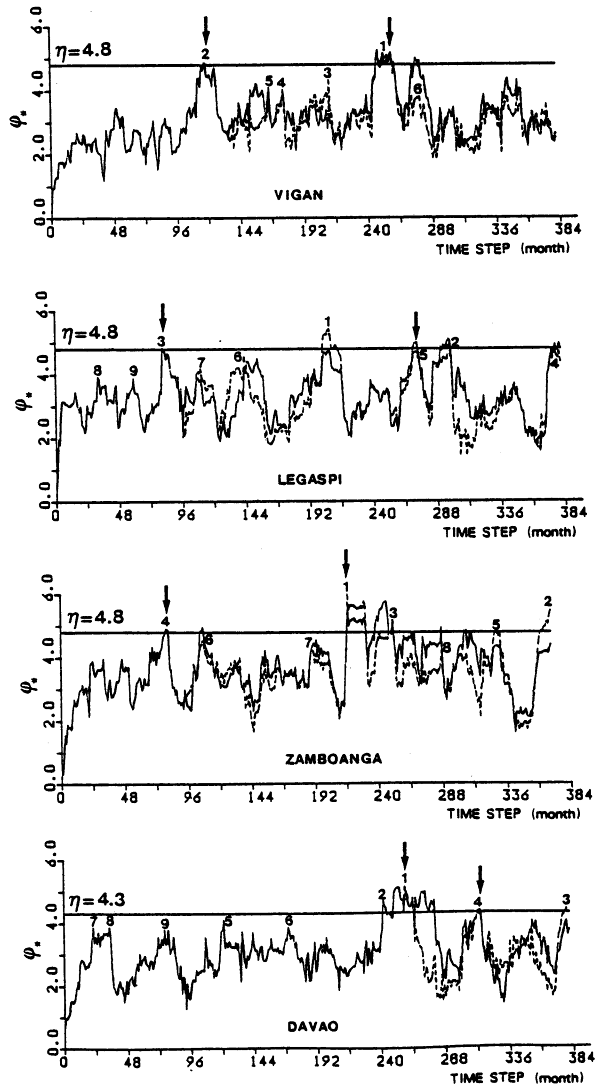

Fig. 2 Time series plots of the abnormality detection index ϕ_* as calculated by OKF (broken line) and by AKF (full line). Numbers indicate periods with abnormal rainfall patterns. Downward arrows indicate rainfall fluctuations.

Figure 2 illustrates the time series plots of $\phi_*(k, l)$ calculated by OKF[6] (broken line), assuming no abrupt change in system parameters, and by AKF (full line), implementing GLRT. The peaks shown with numbers in the figure identify the time positions and magnitudes of the abnormal rainfall patterns described in Section 2. The time of occurrence of a peak ϕ_* indicates the time of the initiation of the interval with identified abnormal pattern; the value of peak ϕ_* is the quantitative description of the pattern's magnitude of abnormality. These abnormal patterns may last for one or two years. Because of the relatively high noise levels, these intervals with abnormal rainfall patterns are expected to be indiscernible by simple visual inspection of the data. However, the use of OKF makes it possible to easily identify them.

In the same figure, the peaks (indicated by downward arrows) above η identify the time of occurrences of abrupt changes in rainfall characteristics. As can be observed in this figure, the rainfall fluctuations occur at the start of or within the short intervals with abnormal rainfall patterns. Table 2 shows the approximate dates of the onsets of the abnormal rainfall patterns identified with rainfall fluctuations and the dates of the occurrences of these rainfall fluctuations as estimated by AKF. Here we will not discuss about the precision of estimation of the time of occurrence of abrupt change as it is contained in the references cited[4),9)].

Table 2 Date of occurrence of peak ϕ_* as identified by OKF and AKF.

Station	OKF	AKF
Vigan	Nov 1960	Nov 1960
	Sep 1971	Jun 1972
Legaspi	Oct 1957	Oct 1957
	Oct 1973	Oct 1973
Zamboanga	Aug 1957	Aug 1957
	Feb 1969	Feb 1969
Davao	Jul 1972	Jul 1972
	Mar 1977	Mar 1977

In Figure 2, those threshold crossings immediately after the identified peak ϕ_* are mostly due to overcorrection (known as 'overshooting') of the parameters, where this overcorrection resulted from errors in $\widehat{G}(\theta)$. This overshooting of the parameters produces large innovations that yield increased estimates of ϕ_*. In the case of Zamboanga, other persistent crossings have to be disregarded to allow the estimates of the parameters to converge.

In this study, η is chosen in conjunction with the choice of the recurrence interval (of about 10 years) for rainfall fluctuations. If a higher η is chosen, however, only one fluctuation may be detected with a longer return period. If a lower η is opted, many rainfall fluctuations will be detected with shorter recurrence interval. Moreover, the basic assumption of the AKF is that abrupt changes in system parameters occur infrequently so that the filter will normally be operating under the assumption that no abrupt change in system parameters has occurred[9),10)].

Table 3 also gives the parameters identified by OKF for the whole series and by the least squares method (LS) for each period and for the whole series. Notice that AKF and LS estimates of the parameters are effectively equal, verifying the validity of the AKF estimates. This table illustrates that the parameters identified by AKF and LS do

Table 3 Model parameters estimated by AKF, OKF and least squares (LS) method.

Station	Method used	Period	Mean M_y	$f_1 = 1/12$ A_1	B_1	$f_2 = 1/6$ A_2	B_2	$f_3 = 70/396$ A_3	B_3	$f_4 = 132/396$ A_4	B_4
Vigan	AKF	I	1.23	−0.85	−0.81	0.08	0.02	−0.03	−0.02	−0.17	0.00
		II	1.29	−0.97	−0.95	0.21	0.04	−0.10	−0.18	−0.11	0.15
		III	1.24	−0.91	−0.88	0.23	0.12	−0.02	−0.01	−0.14	0.00
	OKF	I-III	1.26	−0.93	−0.88	0.18	0.06	−0.06	−0.07	−0.13	0.04
	LS	I	1.23	−0.85	−0.81	0.08	0.02	−0.03	−0.02	−0.17	0.00
		II	1.29	−0.99	−0.94	0.21	0.03	−0.10	−0.18	−0.09	0.13
		III	1.25	−0.93	−0.88	0.22	0.11	−0.02	−0.03	−0.13	−0.01
		I-III	1.26	−0.93	−0.88	0.18	0.06	−0.06	−0.07	−0.13	0.04

Station	Method used	Period	Mean M_y	$f_1 = 7/396$ A_1	B_1	$f_2 = 1/12$ A_2	B_2	$f_3 = 1/6$ A_3	B_3	$f_4 = 99/396$ A_4	B_4	$f_5 = 160/396$ A_5	B_5
Legaspi	AKF	I	2.05	−0.02	0.07	−0.10	0.35	−0.09	0.18	−0.12	0.15	−0.11	0.03
		II	1.99	0.14	0.00	−0.22	0.20	0.02	0.12	−0.07	0.03	−0.02	0.08
		III	2.04	0.05	−0.02	−0.26	0.21	0.01	0.17	−0.06	0.05	0.00	0.00
	OKF	I-III	2.01	0.08	0.02	−0.19	0.24	−0.01	0.15	−0.07	0.05	−0.03	0.05
	LS	I	2.05	−0.02	0.07	−0.10	0.35	−0.09	0.18	−0.12	0.15	−0.11	0.03
		II	1.99	0.13	0.01	−0.21	0.20	0.01	0.12	−0.07	0.03	−0.03	0.08
		III	2.04	0.05	−0.02	−0.24	0.22	0.01	0.17	−0.15	0.02	0.02	0.02
		I-III	2.01	0.08	0.02	−0.19	0.24	−0.01	0.15	−0.07	0.05	−0.03	0.05

Station	Method used	Period	Mean M_y	$f_1 = 21/384$ A_1	B_1	$f_2 = 1/12$ A_2	B_2	$f_3 = 1/6$ A_3	B_3	$f_4 = 96/384$ A_4	B_4	$f_5 = 178/384$ A_5	B_5
Zamboanga	AKF	I	1.40	−0.01	−0.04	−0.36	−0.12	−0.11	0.09	−0.01	0.08	−0.05	0.01
		II	1.38	0.05	0.03	−0.29	−0.11	−0.05	0.02	0.01	−0.11	−0.09	0.00
		III	1.36	0.09	0.03	−0.36	−0.14	−0.08	0.09	−0.01	−0.14	−0.11	0.00
	OKF	I-III	1.38	0.04	0.01	−0.34	−0.13	−0.08	0.06	−0.01	−0.09	−0.08	−0.02
	LS	I	1.40	−0.01	−0.04	−0.36	−0.12	−0.11	0.09	−0.01	0.08	−0.05	0.00
		II	1.38	0.04	0.02	−0.30	−0.12	−0.06	0.01	0.00	−0.12	−0.09	0.00
		III	1.37	0.10	0.03	−0.35	−0.14	−0.07	0.08	−0.02	−0.14	−0.09	−0.03
		I-III	1.38	0.04	0.01	−0.34	−0.13	−0.08	0.06	−0.01	−0.09	−0.08	−0.02

Station	Method used	Period	Mean M_y	$f_1 = 7/396$ A_1	B_1	$f_2 = 1/12$ A_2	B_2	$f_3 = 1/6$ A_3	B_3	$f_4 = 99/396$ A_4	B_4
Davao	AKF	I	2.16	0.08	0.10	−0.22	−0.23	−0.14	0.10	0.14	−0.03
		II	2.16	0.07	−0.10	−0.29	−0.24	−0.13	−0.09	0.14	0.06
		III	2.10	0.20	−0.06	−0.39	−0.31	−0.07	0.26	0.16	−0.22
	OKF	I-III	2.15	0.11	0.04	−0.27	−0.26	−0.12	0.10	0.14	−0.05
	LS	I	2.16	0.08	0.10	−0.22	−0.23	−0.14	0.10	0.14	−0.03
		II	2.17	0.06	−0.09	−0.31	−0.25	−0.10	−0.08	0.10	0.07
		III	2.11	0.21	−0.04	−0.39	−0.34	−0.09	0.24	0.16	−0.20
		I-III	2.15	0.11	0.04	−0.27	−0.26	−0.12	0.10	0.14	−0.05

differ from one period to another, suggesting that the rainfall time series may obey three separate parameter regimes. However, Table 4 shows that only pair I *vs* II of Vigan and Legaspi can be interpreted as obeying two different parameter structures at the 5% level

Table 4 Results of the Chow test for parameter change

Station	Pair of parameter regimes	F-statistic	Degrees of freedom (p, $n+m-2p$)
Vigan	I *vs* II	2.202 (1.92)	9, 239
	II *vs* III	1.110 (1.92)	9, 260
Legaspi	I *vs* II	2.218 (1.83)	11, 251
	II *vs* III	0.605 (1.82)	11, 293
Zamboanga	I *vs* II	1.487 (1.83)	11, 195
	II *vs* III	0.456 (1.83)	11, 283
Davao	I *vs* II	0.823 (1.91)	9, 296
	II *vs* III	1.266 (1.95)	9, 125

Note : Figures in parentheses are the critical values of the F-distribution at 5% level of significance.

of significance (by Chow test).

These results indicate that the on-line identification of the time of occurrence of parameter changes by AKF offers somehow an efficient way of dividing the series into different nonoverlapping segments for investigation of nonstationarity. Also the series over each period identified by AKF can be reasonably assumed stationary.

Figure 3 depicts the time series plot of the annual rainfall of each station. This figure is given for reason of convenience in presenting the three rainfall periods and the distribution of the abnormal patterns identified by OKF. In each time series plot, the short dotted horizontal lines represent the means of the three rainfall periods, the long solid horizontal line represents the mean of the whole series and the dashed lines represent the plus or minus standard deviation from the mean. Note that the division into three rainfall periods is done not in terms of the annual rainfall amounts, as we can discern other pairs of nonoverlapping adjacent periods which can give greater difference in the mean.

We propose the following discussion and conclusions regarding the fluctuations in rainfall characteristics on the basis of the behaviour of M_y and A_i and B_i which correspond to the periodicities (longer than one year, one year, and six months) accepted as real. For these, we refer the reader to Figure 3 and Tables 3 and 4.

The occurrence of Type B abnormal pattern in Vigan results in a period (II) abounded with abnormally high rainfalls as indicated by the presence of Type B and Type C abnormal patterns. This shift from period I to period II is reflected by the increased estimates of M_y and the coefficients A_1, B_1 and A_2 of the one-year and six-month harmonics. The abrupt change in M_y signifies an increase of 32.7% in actual monthly mean rainfall between period I to period II. This shift also corresponds to an increase of 854 mm (45.6 %) in annual rainfall that took place during the period 1961-72 compared to the previous ten years (1951–60). The occurrence of a Type B abnormal pattern results in the shift from period II to period III, in which this shift is characterized by decrease in M_y, A_1 and B_1 and increase in A_2 and B_2. Although F-statistic interprets these changes as not significant, the decrease of almost 700 mm in the annual total rainfall that occurred from 1961-72 to 1973-83 means a fluctuation of 25.4%.

In Legaspi station, the fluctuation from period I to period II is induced and marked by the occurrence of Type C abnormal pattern. The decrease in both M_y and amplitudes of one-year and six-month periodic components plus a remarkable increase in A_1 of the 4.7-year oscillation describe the fluctuation. Note that the amplitude of a frequency component f_i is computed as the square root of the sum of the squares of the coefficients A_i and

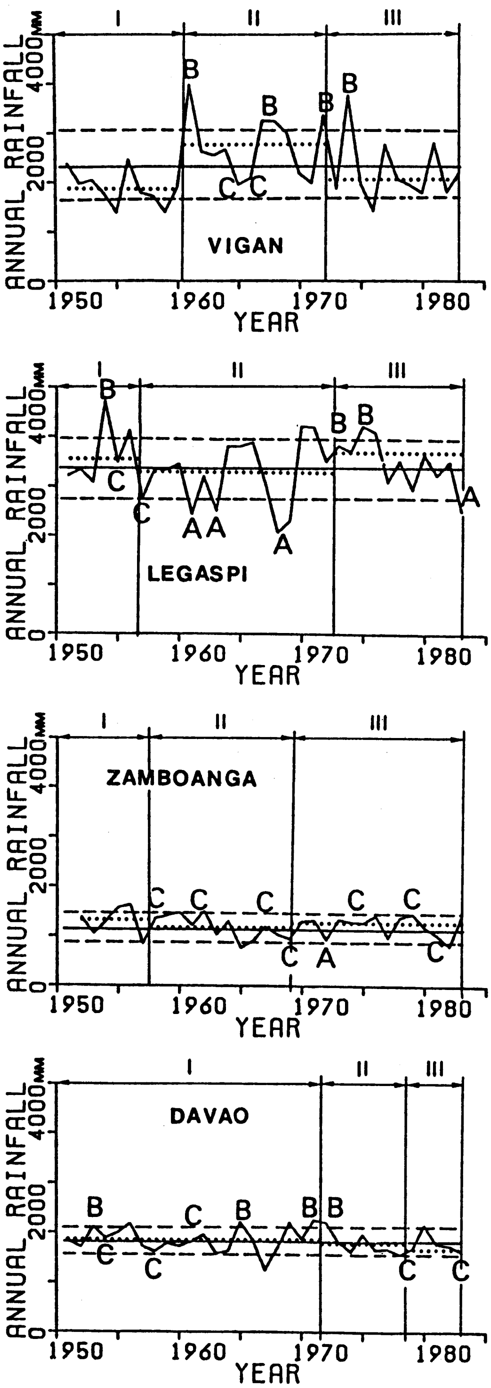

Fig. 3 Time series plot of the annual rainfall of each station, depicting two rainfall fluctuations and distribution of abnormal rainfall patterns (A, B and C).

B_i. This decrease in M_y reflects a drop of only 8.2% in actual monthly mean rainfall during period II from period I. In this shift, the presence of Type B and Type C abnormal patterns typifies period I and accounts for the above-average rainfall in this period, whereas

Type A abnormal pattern prevails in period II, which means the frequent occurrences of abnormally dry intervals in this period. On the other hand, the change from period II to period III is driven and characterized by the existence of Type B abnormal pattern. This shift is described by an increase in M_y, a decrease in the amplitude of the 4.7-year harmonic and increases in the amplitudes of the one-year and six-month components. The increase in M_y corresponds to an increase of 11.2% in the mean of the untransformed monthly mean rainfall data. Period III is depicted by the existence of Types A and B abnormal patterns.

In Zamboanga and Davao rainfall sequences, the occurrences of abnormal rainfall patterns, which resulted in abrupt changes in model parameters as detected by AKF, cause neither notable fluctuation in rainfall amounts nor statistically significant changes in paramater structures. This can be expected, since rainfalls in Zamboanga and Davao have much lower variances (therefore have much less fluctuation) than those in Vigan and Legaspi. Also, with this result, it appears that rainfall fluctuations would take place more easily at places with climates similar to those in Vigan and Legaspi than at localities with climates like those in Zamboanga and Davao.

A close examination of the behaviour of the model parameters (corresponding to the significant frequency components) of the four time series reveals the following three characteristics. The first one is that the amplitude of the oscillation longer than one-year is high in a period where Type A or Type C or both abnormal patterns are present. This characteristic is very evident in period II of Legaspi, where Type A abnormal pattern is frequent. It emerges also in period III of Zamboanga and Davao, where Types A and C abnormal patterns are existing. Note that these Type C abnormal patterns in period III of Zamboanga and Davao contain more dry months than those in periods I and II (see Medina, et al. (1985)[6)]). Landsberg (1975)[5)] and Kawamura, et al. (1985)[11)] have demonstrated a similar characteristic.

The second characteristic is that the amplitude of the one-year component is high when Type B abnormal patterns exist. This can be observed in periods I and II of Legaspi and period II of Vigan. The types of climates in Vigan and Legaspi are characterized by presence of two very pronounced maximum and minimum rain seasons (in a year). Excessive rainfall (as indicated by the presence of Type B abnormal patterns) during the maximum rain season obviously causes the amplitude of the one-year cycle to increase, as this rainfall also adds more power to the one-year frequency band in the spectra of Vigan and Legaspi rainfall sequences.

And, the third characteristic is that the amplitude of the one-year cycle increases when Type A or Type C or both abnormal patterns are existing. Period III, as compared with period II, of Zamboanga and Davao exemplifies this tendency. The type of climate in Zamboanga is characterized by not very pronounced maximum and minimum rain seasons, while that in Davao by a more or less even distribution of rainfall throughout the year. Hence, months with deficit rainfall create a pattern similar to the one having very pronounced maximum and minimum rain seasons (in which the power spectrum of the one-year frequency is characteristically high), resulting in an increased amplitude of the one-year cycle. The three characteristics may help in indicating the potential of water supply and possibility of occurrence of short interval of adverse rainfall in the present period.

While the shift in the mean is useful for the identification of significant rainfall fluctuations in this study, it is still not sufficient. This is illustrated by the fluctuations from period I to period II in Legaspi, where the shift in M_y exhibits less than 10% drop in actual monthly mean rainfall while the F-statistic shows significant changes in the parameter structures between these periods. In particular, the mean describes the average level. This parameter provides a vague description of just how poorly a water resource system might behave in the infrequent situation when flood or drought does occur. Although rainfall may be satisfactory in a decade, our concern should also be the short intervals of several months when water resources systems might be seriously 'depleted' (at least temporarlty). For example, our attention should not be focused exclusively on the ten-year low rainfall as things can be worse in critical parts of the system during several intervals of adverse rainfall. Period II of Legaspi, as shown in Figure 3, illustrate the inability of the mean by itself to define how severe and how frequent intervals of abnormally low rainfall may occur.

However, if rainfall is highly variable or if the consequences of intervals of abnormal rainfall are severe, then it is appropriate and desirable to consider the changes in the parameter structures which (unlike the shift in the mean) describe in clear and meaningful way what the character of fluctuations might be.

6. Conclusions

The AKF has given a useful procedure in the identification of the time of occurrence and magnitude of rainfall fluctuations. The AKF approach coupled with periodic-stochastic rainfall time series model has not only provided information on shifts in the mean but also automatically exposed hidden periodicities in a particular period, which have been found indispensable in probing for occurrences of adverse rainfall and rainfall fluctuations. In addition, we have shown the significance of AKF in time series analysis.

The fluctuations in rainfall characteristics have been described not only in terms of rainfall amounts but also in terms of the occurrences of adverse rainfall such as floods and droughts. The magnitude of changes in the annual and monthly means shown in Vigan and the high incidence of adverse rainfall in period II of both Vigan and Legaspi have demonstrated that the occurrence of a short interval with rainfall pattern anomaly may induce serious changes in rainfall characteristics. These kinds of severities of fluctuations in rainfall characteristics may serve as a basis for evaluation as to whether or not the existing and proposed water resource systems are robust, vulnerable or resilient. Nevertheless, the occurrence of an abnormal rainfall pattern, which resulted in abrupt changes in model parameters as detected by AKF, does not always mean that significant fluctuation in rainfall characteristics is happening or is going to happen. Zamboanga and Davao rainfall sequences have shown this result.

While the existence of rainfall fluctuations has been ascertained, it is obvious that the four stations involved are not sufficient to derive general and direct conclusions applicable to other stations of similar or different climatic conditions. With this number of stations, it is also difficult to examine the interrelationships among the four types of climates in the country regarding the spatial occurrence of rainfall fluctuations. Moreover, the shortness of records limits the interpretation of the results reported above. Also, three periods are not enough to draw complete characterization of the temporal occurrence of rainfall fluctuations.

On the basis of the results discussed above, the presented methodology in general and the AKF approach in particular appear promising for identification and characterization of moderate climate variations.

Acknowledgement

We would like to express our gratitude to the Philippine Atmospheric, Geophysical and Astronomical Services Administration (PAGASA) for providing us the rainfall data for this study.

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