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# COMPARATIVE STUDY OF DROUGHT PREDICTION TECHNIQUES FOR RESERVOIR OPERATION[1]

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ABSTRACT: Predicting the likelihood of a drought markedly enhances the efficiency of reservoir operations. This study applies the kriging method and time series analysis to predict inflows to Shihmen Reservoir in northern Taiwan. A subsequent reservoir operation simulation is employed to determine the drought lead time (DLT), the time before the onset of a drought. A more efficient reservoir operational strategy can be established with the aid of DLT and the probability of successful drought prediction (*Ps*). Simulation results of reservoir operation over a period of three decades demonstrate that, at one month DLT, the kriging approach achieves 0.86 of *Ps* for moderate droughts and 0.94 of *Ps* for severe droughts. The kriging approach generally outperformed the time series approach in terms of DLT, *Ps* of drought prediction, and the number of correctly predicted drought events.
(KEY TERMS: drought; drought lead time; kriging; time series analysis; modeling/statistics.)

## INTRODUCTION

Drought is a natural phenomenon. There have been many different definitions and identification methods of drought in the literature. Rossi *et al.* (1992) thoroughly reviewed the methodologies for estimating and analyzing regional drought. Droughts can generally be classified as: (1) a meteorological drought, which occurs when rainfall is far below the normal amount for a significant period of time; (2) an agricultural drought, which occurs when soil moisture is depleted to the extent that crop and pasture yields are significantly affected; and (3) a hydrological drought, which occurs when water resources cannot adequately supply established users under a given water management scheme. Bonacci (1993) applied three methods of drought identification, i.e., run analysis, a discrete Markov process, and the percentile method, to a series of monthly rainfall data.

Drought is also a continuous process, possibly lasting for a long or short period of time. Thus, during a drought, the waiting period before taking any remedial measures is of concern for reservoir operators. The timing associated with remedial actions must be clearly and precisely defined. For this purpose, an indicator of an approaching drought that will prompt immediate remedial actions is desired. Rouhani and Cargile (1989) proposed a geostatistical indicator for an approaching drought. Geostatistical estimation, also known as kriging, was employed to predict streamflows during low-flow periods in a drought prone area. Drought lead time (DLT), defined as the time length from the present to the onset of an approaching drought, was calculated and used as an indicator for drought management.

The average annual rainfall in Taiwan is abundant, i.e., 2,500 mm, as compared to the global average of 970 mm. However, over 75 percent of the annual rainfall occurs during the wet season (from May to October). Typhoons usually occur in July, August, and September, bringing much of the needed rainfall for the coming dry season (from November to April), during which an enormous amount of water is provided for irrigating rice paddies. Such a significant seasonal variation in annual rainfall makes reservoir operation complicated. The Shihmen Reservoir (located in northern Taiwan) is the major source of water supply for irrigation and domestic use; a hydraulic power plant operates as well. Since the beginning of its operation in 1957, it has experienced several

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severe drought events, particularly from August of 1983 to April of 1984. During that period, the drought lasted for 254 days and reservoir storage dropped to 1.56 percent of its full storage capacity.

The operation of Shihmen Reservoir is based on a set of three rule curves, the upper bound, the lower bound, and the extreme lower bound. Reservoir release is reduced from its normal release volume when the reservoir stage falls below the lower bound of reservoir rule curves. Thus, from the perspective of reservoir operations, the onset of a drought can be defined as the time when reservoir stage falls below the lower bound of the rule curves. DLT can also be considered as the period of time during which normal reservoir operations are maintained until the approaching drought occurs.

During a drought, water rationing and water share reallocation for different established users are common remedial measures. However, when and how to enforce these measures depends on knowing the DLT of an approaching drought. For example, cautionary measures such as prioritizing water users and reallocating their shares of water supply can be adopted for an impending drought. In this study, we not only compare two different approaches of drought prediction, but also assess their prediction accuracies.

## METHODOLOGY

This section describes the procedures employed in this study. These procedures include a reservoir inflow prediction model, a regression model of reservoir release prediction, and reservoir mass balance analysis. These three major components, although carried out in the same order as stated above, are briefly introduced in the subsequent subsections in a reverse order to better demonstrate their association.

### *Reservoir Mass Balance Analysis*

In Taiwan, a reservoir is operated on a ten-day-period basis according to its rule curves and the water demands of the downstream users. The mass balance equation of the reservoir is:

$$S(t+1) = I(t+1) - R(t+1) + S(t) \tag{1}$$

where $S(t)$ denotes the reservoir storage at the end of the $t^{th}$ period, $I(t+1)$ represents the total inflow to the reservoir during the $(t+1)^{th}$ ten-day-period, and $R(t+1)$ is the total losses from the reservoir during the $(t+1)^{th}$ ten-day-period including ground water seepage flow, reservoir evaporation, and downstream water supply needs. To simplify the expression, the ten-day-period is abbreviated TDP hereafter.

Reservoir operation is briefly described as follows. At the end of the $t^{th}$ TDP, reservoir operation personnel review the downstream water demands for the next TDP. The total release volume of the next TDP, $R(t+1)$, and shares for different users are determined on the basis of the available storage in the reservoir $S(t)$, the rule curve criterion, and reservoir management experiences. Thus, reservoir storage of the next TDP, $S(t+1)$, can be predicted if the inflow $I(t+1)$ is predicted, i.e.,

$$\hat{S}(t+1) = \hat{I}(t+1) - R(t+1) + S(t) \tag{2}$$

where $\hat{S}(t+1)$ and $\hat{I}(t+1)$ are predicted values of $S(t+1)$ and $I(t+1)$, respectively. Reservoir stage of the next TDP, $H(t+1)$, can then be determined with the assistance of the reservoir stage-storage relationship.

To extend the prediction even further, e.g., one month, releases from the reservoir for the $(t+2)$ and $(t+3)$ TDPs must also be predicted since reservoir storages $S(t+1)$ and $S(t+2)$ are not known at time t. Thus, the following equations are used to predict reservoir storage one month in advance:

$$\hat{S}(t+1) = \hat{I}(t+1) - R(t+1) + S(t) \tag{3a}$$

$$\hat{S}(t+2) = \hat{I}(t+2) - \hat{R}(t+2) + \hat{S}(t+1) \tag{3b}$$

$$\hat{S}(t+3) = \hat{I}(t+3) - \hat{R}(t+3) + \hat{S}(t+2) \tag{3c}$$

Notably, in Equation (3a), $R(t+1)$ is the real reservoir release of the $(t+1)$ TDP, while in Equations (3b) and (3c), predicted releases $\hat{R}(t+2)$ and $\hat{R}(t+3)$ are used. Prediction of reservoir release is described later.

### *Reservoir Inflow Prediction*

Reservoir inflow is predicted using two different approaches: kriging method and time series analysis. The kriging method of estimation, also known as the theory of regionalized variables or geostatistics, was originally proposed to deal with spatially distributed data (Matheron, 1971). Discussions of kriging include Huijbregts and Matheron (1971), Matheron (1971, 1973), Journel (1974), Journel and Huijbregts (1978), Mantoglou and Wilson (1981), Myers (1982, 1984), and Kitanidis (1983). In addition, many hydrologists have applied kriging to solve problems such as monitoring network design (Bastin *et al.*, 1984; Virdee and Kottegoda, 1984; Kassim and Kottegoda, 1991), piezometric surface estimation (Rouhani, 1986; Rouhani and Hall, 1989), and precipitation field simulation

(Chua and Bras, 1982). Delhomme (1978) introduced geostatistical applications to the hydrosciences. We briefly introduce the most widely used ordinary kriging in this section.

Let $Z(x)$ be a random variable at a spatial location $x$. We wish to estimate a value at $x_0$ using data values observed at neighboring locations $x_i$, $i = 1, 2, \ldots, n$, and combine them linearly with weights $\lambda_i$

$$\hat{z}(x_o) = \sum_{i=1}^{n} \lambda_i z(x_i). \tag{4}$$

The ordinary kriging assumes the following second-order stationary properties for the random field $\{Z(x), x \in \Omega\}$

$$E[Z(x)] = \mu_z \tag{5}$$

$$Var[Z(x)] = \sigma_z^2 \tag{6}$$

$$Cov[Z(x_i), Z(x_j)] = Cov(|x_i - x_j|) \tag{7}$$

$\forall x \in \Omega$, where $\Omega$ represents the domain of the study area. We require the kriging estimator to be unbiased and have minimum variance of estimation errors, i.e.,

$$E[\hat{Z}(x_0)] = E[Z(x_0)] \tag{8}$$

$$minimizing\ Var[\hat{Z}(x_0) - Z(x_0)]. \tag{9}$$

Under these two constraints, we solve the following ordinary kriging system for $\lambda_{io}$

$$\begin{cases} \sum_{j=1}^{n} \lambda_{io}\gamma_{ij} + \mu = \gamma_{io} \qquad i = 1,2,\ldots,n & (10a) \\ \sum_{i=1}^{n} \lambda_{io} = 1 & (10b) \end{cases}$$

where $\mu$ is a Lagrange multiplier and $\gamma_{ij} = \gamma(|x_i - x_j|)$ represents the semi-variogram of the random field $Z(x)$ and is defined as:

$$\gamma(|x_i - x_j|) = \frac{1}{2} E\left\{\left[Z(x_i) - Z(x_j)\right]^2\right\} \tag{11}$$

Although kriging was initially proposed for dealing with spatially distributed data, Rouhani and Cargile (1989) applied universal kriging, which is a Gaussian-Markovian interpolation method for nonstationary random variables, to monthly reservoir inflow (one-dimensional temporal data) prediction to yield an estimate of DLT for a given reservoir operation policy and initial conditions. In our study, the fact that reservoir storage is predicted only for the dry season accounts for why the mean of the random field is assumed constant and ordinary kriging approach is adopted herein.

Let $I(t)$ represent total volume of reservoir inflow of the $t^{th}$ TDP. Future reservoir inflow $I(t_k)$ can be estimated by using $n$ previously observed reservoir inflows $I(t_i)$, $i = 1,2, \ldots, n$.

$$\hat{I}(t_k) = \sum_{i=1}^{n} \lambda_{ik}\ I(t_i). \tag{12}$$

The weights $\lambda_{ik}$ being assigned to observed inflows can be determined by solving the ordinary kriging system of Equation (10) with $Z(x)$ being replaced by $I(t)$. The semi-variogram characterizes the spatial (in our case, temporal) variability of the random field and must be established before solving the above system. Notably, $\lambda_{ik}$ are weights used for predicting reservoir inflow volume at time $t_k (k > n)$ and are dependent on the time at which a prediction is to be made.

Our time series approach of reservoir inflow prediction involves building an Autoregressive–Moving-Average (ARMA) model (Box *et al.*, 1994) for $I(t)$. Prior to ARMA modeling, Fourier analysis is performed to determine the cyclic components embedded in $I(t)$. If significant cyclic components exist, $I(t)$ is expressed as:

$$I(t) = C(t) + \xi(t) \tag{13}$$

where $C(t)$ denotes the cyclic component and $\xi(t)$ represents the residual that will be modeled as an ARMA process. The cyclic component is the sum of several harmonic components and is expressed as:

$$C(t) = \alpha_0 + \sum_{p=1}^{N_p} \sum_{k=1}^{N} \alpha_{pk} \cos(\omega_p kt) + \beta_{pk} \sin(\omega_p kt) \tag{14}$$

where $N_p$ denotes the number of peaks in the periodogram of $I(t)$, $\omega_p$ are their angular frequencies, and $N$ represents the number of harmonic components.

The ARMA$(k,l)$ model of a stationary random process $X(t)$ has the form of

$$X(t) = \sum_{i=1}^{k} \phi_i X(t-i) + \varepsilon(t) + \sum_{j=1}^{l} \theta_j \varepsilon(t-j) \tag{15}$$

where $\varepsilon(t)$ are white noise with zero mean and variance $\sigma_\varepsilon^2$, and $\phi_i$'s and $\theta_j$'s are the autoregressive and moving average parameters, respectively. If $\theta_j = 0$ for $j = 1,2, \ldots l$, we say that we have an autoregressive or AR($k$) model, whereas if $\phi_i = 0$ for $i = 1,2, \ldots ,k$, we have a moving average or MA($l$) model. The readers are referred to Priestley (1981) and Shih and Cheng (1989) for detailed description of the modeling. As assumed herein, polynomial trend does not exist in $\xi(t)$.

### *Reservoir Release Prediction*

As mentioned earlier, reservoir release of the next TDP, i.e., $R(t+1)$, is determined at the end of the current TDP based on the available reservoir storage and management experiences. In general, reservoir release is reduced from its normal release volume of the corresponding TDP once the reservoir stage falls below the lower bound of the rule curves. Thus, it is reasonable to predict $R(t+2)$ and $R(t+3)$ based on a regression equation of reservoir stage $H(t)$ versus reservoir release $R(t+1)$. A set of TDP-specific regression relationships of $H(t)$ versus $R(t+1)$ is established for $H(t)$ which is below the lower bound. From Equation (3a), $\hat{S}(t+1)$ can be predicted, and then, $\hat{H}(t+1)$ can be calculated using the stage-storage relationship. $\hat{R}(t+2)$ is thus calculated using the regression equation of $H(t)$ versus $R(t+1)$ if $\hat{H}(t+1)$ is found below the lower bound of the rule curve. If $\hat{H}(t+1)$ exceeds the lower bound, then the normal release volume should apply. $\hat{R}(t+3)$ can also be calculated in a similar manner.

## CASE STUDY

The Shihmen Reservoir, located in northern Taiwan, with a drainage basin of 763 km$^2$, was selected as our study site. Thirty years (1964-1993) of the ten-day-period reservoir inflow data were used in this study. As Table 1 illustrates, inflow data reveal a strong seasonal variation. The dry season runs from November 1 (beginning of the 31$^{st}$ TDP) to May 20 (end of the 14$^{th}$ TDP) of the next year. Figure 1 displays the reservoir operation rule curves.

### *Kriging Approach to Reservoir Inflow Prediction*

For the kriging approach to reservoir inflow prediction, structural analysis was initially performed to yield a variogram that characterizes the temporal

TABLE 1. Average and Standard Deviation of Ten-Day-Period Reservoir Inflow (1964-1993).

| Month | TDP | Average Inflow (CMSD) | Standard Deviation (CMSD) |
|---|---|---|---|
| January | 1 | 158.14 | 101.98 |
| | 2 | 132.18 | 51.85 |
| | 3 | 155.86 | 83.58 |
| February | 4 | 299.86 | 240.67 |
| | 5 | 270.72 | 386.93 |
| | 6 | 200.88 | 202.64 |
| March | 7 | 253.22 | 184.27 |
| | 8 | 309.68 | 335.71 |
| | 9 | 383.43 | 459.60 |
| April | 10 | 289.52 | 184.16 |
| | 11 | 279.13 | 232.38 |
| | 12 | 283.44 | 323.68 |
| May | 13 | 257.92 | 160.03 |
| | 14 | 242.21 | 96.50 |
| | 15 | 514.70 | 340.39 |
| June | 16 | 728.13 | 537.67 |
| | 17 | 628.20 | 363.04 |
| | 18 | 628.78 | 493.89 |
| July | 19 | 423.54 | 224.65 |
| | 20 | 392.84 | 356.99 |
| | 21 | 625.02 | 644.72 |
| August | 22 | 679.71 | 576.07 |
| | 23 | 951.65 | 1274.26 |
| | 24 | 1049.6 | 1216.74 |
| September | 25 | 844.86 | 1102.38 |
| | 26 | 978.87 | 1095.54 |
| | 27 | 1109.81 | 1189.29 |
| October | 28 | 765.63 | 1001.60 |
| | 29 | 542.17 | 512.93 |
| | 30 | 501.86 | 535.69 |
| November | 31 | 260.13 | 155.21 |
| | 32 | 261.01 | 233.55 |
| | 33 | 218.16 | 111.42 |
| December | 34 | 159.58 | 53.66 |
| | 35 | 139.71 | 55.00 |
| | 36 | 149.48 | 56.40 |

variation of $I(t)$. In our study, the inflow variogram was estimated using dry season reservoir inflow data. From the 30 years of inflow data, we first calculated experimental variograms for each of the 29 dry seasons. Next, the following exponential model (Figure 2), which characterizes the temporal variation of dry season reservoir inflows, was fitted to the average of the 29 dry-season inflow variograms:

$$\gamma(h) = 62600\ [1\text{-}\exp(\text{-}h/2.35)] \tag{16}$$

Here $\gamma(h)$ denotes the variogram in (cms-day)$^2$ and $h$ represents the time interval in TDP.

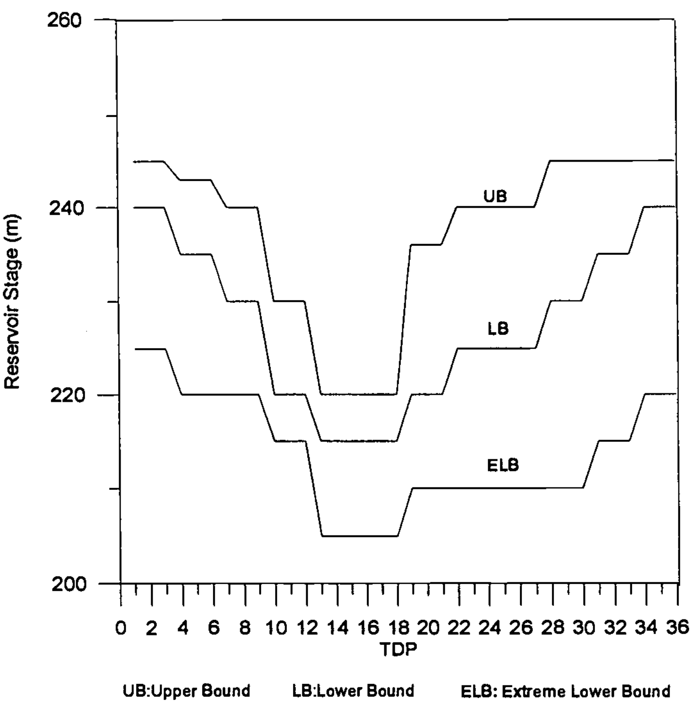


Figure 1. Operation Rule Curves of Shihmen Reservoir.

In Equation (12), previous observations $I(t_i)$, $i$ = 1, 2, . . . $n$, are needed to predict $I(t_k)$. Herein, we use three consecutive observations ($n$ = 3) to predict the next three inflows. Thus, the first predicted reservoir inflow was that of December 1 through December 10 (the fourth TDP of each dry season). Use of more previously observed data would lag our first prediction since the first prediction must be lagged $n$ TDPs from the beginning of the dry season. For instance, if five previous observations ($n$ = 5) were used, reservoir inflow of December 21 through December 31 would be the first predicted reservoir inflow.

The kriging weights $\lambda_{io}$ can be obtained from Equation (10) without knowing any real measurements since the variogram is only a function of distance. Therefore, reservoir inflow volumes of the immediate next three TDPs do not need to be predicted in their temporal order since $\gamma_{ij}$ in Equation (10a) depends only on points of observations used for prediction ($t_i$, $i$ =1,2, . . . ,n) and the time at which prediction is to be made ($t_k$). Except the first two TDPs of each dry season, there are three predictions of reservoir inflows for each TDP.

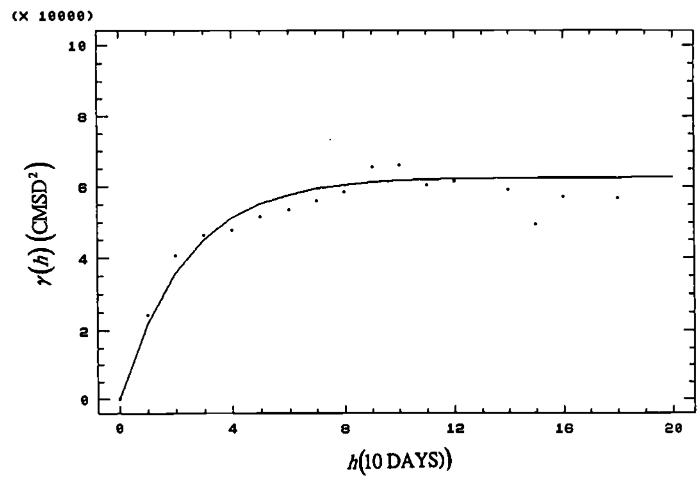


Figure 2. Variogram of the Dry Season Reservoir Inflow.

### *Time Series Approach to Reservoir Inflow Prediction*

In contrast with the kriging approach for which predictions of reservoir inflows are based on the dry-season variogram only, the time series approach requires consecutive all-season inflow data for ARMA model building. In this study, we analyzed ten-day-period reservoir inflows from 1964 to 1993. Fourier analysis of the reservoir inflow data revealed two significant frequencies, $\omega_1$ = 0.17453 and $\omega_2$ = 0.47124 (Figure 3). Corresponding periods of the two frequencies are 36 TDPs and 13 TDPs, strongly reflecting the annual cycle and seasonal variations of reservoir inflows. The harmonic components embedded in reservoir inflow were identified as:

$$\begin{aligned} C(t) &= \alpha_0 + \alpha_{11} \cos \omega_1 t + \beta_{11} \sin \omega_1 t + \alpha_{12} \cos 2\, \omega_1 t \\ &+ \beta_{12} \sin 2\, \omega_1 t + \beta_{13} \sin 3\, \omega_1 t + \beta_{14} \sin 4\, \omega_1 t \\ &+ \beta_{16} \sin 6\, \omega_1 t + \beta_{21} \sin \omega_2 t \end{aligned} \tag{17}$$

where $\alpha_0$ = 444.43, $\alpha_{11}$ = -216.56, $\beta_{11}$ = -241.22, $\alpha_{12}$ = -130.54, $\beta_{12}$ = 83.77, $\beta_{13}$ = 88.88, $\beta_{14}$ = -75.98, $\beta_{16}$ = -55.47, and $\beta_{21}$ = 61.90.

The residual $\xi(t)$ is identified as an AR(1) process based on its partial autocorrelation function and Akaike's information criterion.

$$\xi(t) = 0.36175\ \xi(t\text{-}1) + \varepsilon(t) \tag{18}$$

where $\{\varepsilon(t)\}$ is a purely random process with zero mean, and variance $\sigma_\varepsilon^2 = 42{,}127$ (cms-day)$^2$. Similar to the kriging approach, three predictions can be made for each TDP. However, time series approach of reservoir inflow prediction for the next three consecutive TDPs must be carried out in their temporal order.

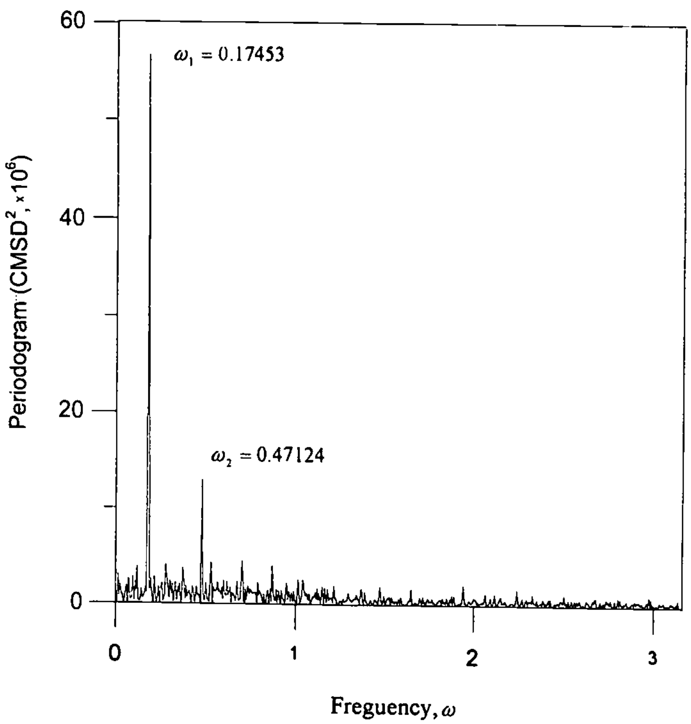


Figure 3. Periodogram of Ten-Day-Period Reservoir Inflow.

*Simulation of Reservoir Operation*

The stage-storage relationship of Shihmen reservoir is expressed by the following equation:

$$S = 0.0174\ (H - 158.3)^{2.71} \tag{19}$$

where $S$ denotes the reservoir storage volume in cms-day (CMSD), and $H$ represents the reservoir stage in meters above the mean sea level.

Two drought conditions are defined. Moderate drought occurs when reservoir stage falls between the lower bound and the extreme lower bound of the rule curves. Extreme drought occurs when the reservoir stage is below the extreme lower bound. The reservoir operation was simulated for each of the 29 dry seasons. As mentioned earlier, release volumes $R(t+2)$ and $R(t+3)$ must be predicted prior to predicting the reservoir storages $S(t+2)$ and $S(t+3)$. In general, reservoir release is reduced from its normal release volume of the corresponding TDP once the reservoir stage falls below the lower bound of the rule curves. If the reservoir stage exceeds the lower bound, downstream water demands are usually fully provided. Figure 4 provides examples of the $S(t)$-$R(t+1)$ relation for $S(t)$ lower than the lower bound. Since historic records were used for simulation, whenever the predicted drought/no-drought condition was consistent with the historic condition, the historic release volume of the next TDP, $R(t+1)$, was adopted. Two types of release volume predictions may apply if our simulations result in conflict drought/no-drought conditions against historic records. Initially, if a drought was predicted while no drought actually occurred, then release volume of the next TDP was predicted using regression equation of $S(t)$ versus $R(t+1)$ with $S(t)$ being lower than the lower bound. Second, if no drought was predicted while a drought did occur, then $R(t+1)$ was predicted using regression equation of $S(t)$ versus $R(t+1)$ with $S(t)$ being higher than the lower bound.

An indicator of an approaching drought, i.e., the drought lead time, was determined as DLT = $k$ if a drought was predicted to occur $k$ TDPs later. In our study, DLT $\leq$ 3 since only $S(t+1)$, $S(t+2)$, and $S(t+3)$ are predicted.

*Evaluating Probability of Success of Drought Prediction*

As mentioned earlier, three predictions of reservoir stage can be made for each TDP (except for the first two) in the dry period; each of these predictions corresponds to drought lead time of 1, 2, and 3 TDPs, respectively. According to results obtained from 29 dry-season simulations, the probability of success ($Ps$) of drought prediction, defined as the ratio of number of correct predictions to total number of predictions, for each TDP was tabulated in Tables 2 and 3. Drought prediction using kriging approach to reservoir inflow prediction clearly has a higher $Ps$ than using the time series approach for both moderate and severe drought conditions. For moderate drought conditions, at lead time of three TDPs, the kriging approach generally has a $Ps$ exceeding 0.8 (except for the 9$^{th}$, 10$^{th}$, and 12$^{th}$ TDPs) with an average of 0.86, while the average $Ps$ is 0.78 for the time series approach. Especially in the period between the 5$^{th}$ and the 8$^{th}$ TDPs, the kriging approach performs much better than the time series approach. The superiority of the kriging approach in this period is significant in that during this period an enormous amount

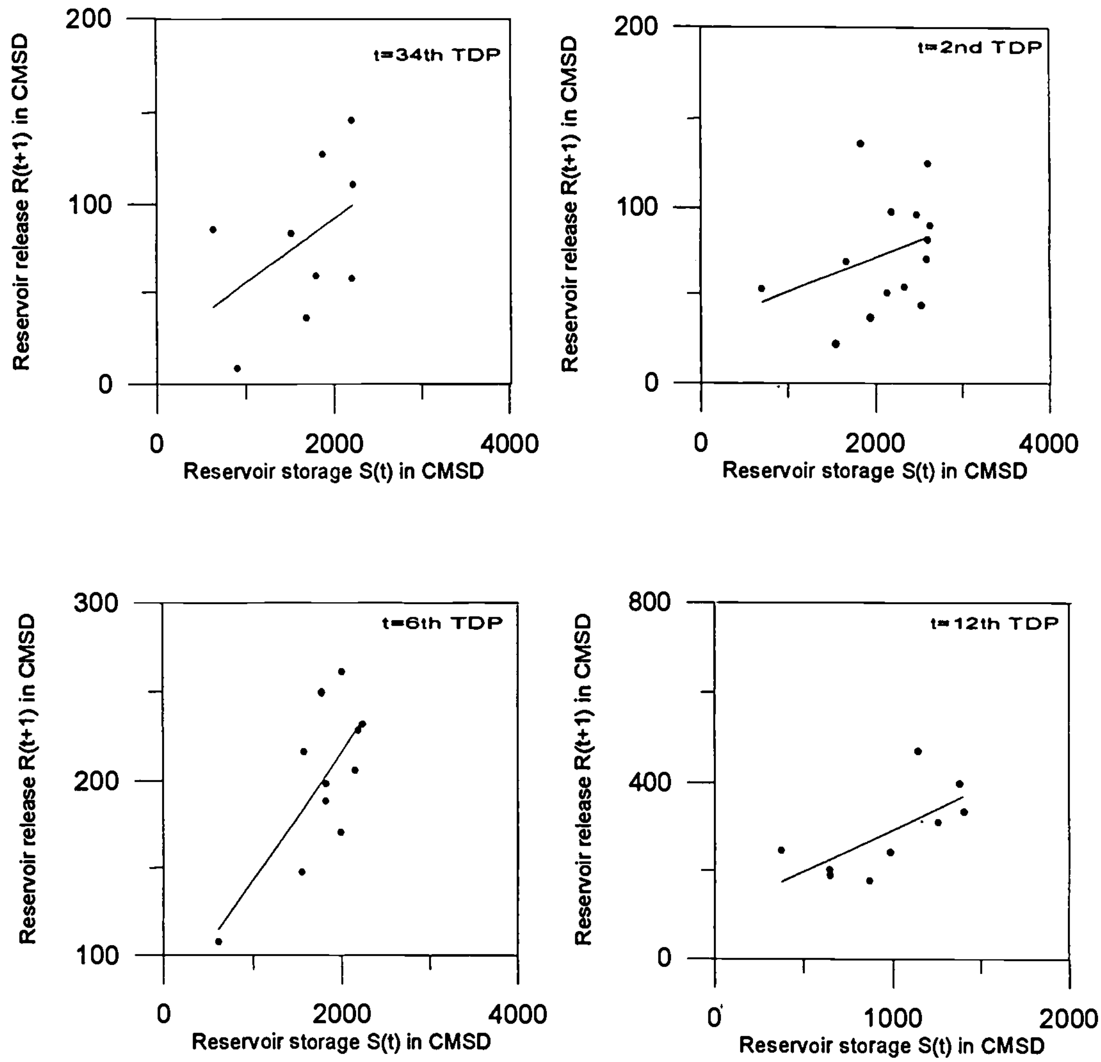


Figure 4. S(t)–R(t+1) Relationship for S(t) Lower Than the Storage of the Lower Bound of Reservoir Rule Curves.

of water is supplied to irrigate rice paddies. Accurately predicting the occurrence of the approaching drought in this period would facilitate water management authorities in reaching better decisions. For severe drought conditions, at a lead time of three TDPs, the kriging approach has an average Ps of 0.93 compared to 0.92 for the time series approach. The probability of success is critical in that it can be used by the reservoir agency to determine whether, at any TDP, remedial actions should be taken in response to a predicted future drought. For instance, a reservoir agency may decide to take remedial actions only if the *Ps* of that TDP exceeds 0.80. Thus, for a moderate drought, the kriging approach would require taking actions for most TDPs except the 9$^{th}$, 10$^{th}$, and 12$^{th}$ TDPs if drought is predicted one month in advance. However, the time series approach requires adopting actions for only the 34$^{th}$, 35$^{th}$, 3$^{rd}$, 4$^{th}$, 10$^{th}$, and 11$^{th}$ TDPs under the same circumstance.

An example of potential management practice using the information of DLT and *Ps* is described below.

If, at the end of March (end of the 9$^{th}$ TDP), as predicted, a moderate drought will occur at the end of April (DLT = 3), no remedial actions are taken since *Ps* of the 12$^{th}$ TDP, *Ps*(12), is 0.76 (lower than 0.80) for both approaches. However, if a severe drought is predicted to occur one month later, minor remedial actions are taken since *Ps*(12) is 0.97 and 0.90 for the kriging and time series approaches, respectively. As time passes, at the end of the 10$^{th}$ TDP, an approaching moderate drought is predicted to occur at the end of April, so moderate remedy actions are taken since *Ps*(12) = 0.86 > 0.80 and DLT = 2 only. Finally, at the end of the 11$^{th}$ TDP, a moderate drought is predicted to occur one TDP later (DLT=1) and *Ps*(12) = 0.97, so major remedy actions will be taken. The reservoir agency may take different levels of remedy actions:

TABLE 2. Probability of Success of Drought Prediction (*Ps*) (kriging approach of inflow prediction).

| t | DLT = 3 TDPs | | DLT = 2 TDPs | | DLT = 1 TDP | |
|---|---|---|---|---|---|---|
| | Moderate Drought | Severe Drought | Moderate Drought | Severe Drought | Moderate Drought | Severe Drought |
| 34 | 0.90 | 1.00 | | | | |
| 35 | 0.97 | 1.00 | 1.00 | 1.00 | | |
| 36 | 0.90 | 0.97 | 0.97 | 0.97 | 1.00 | 0.97 |
| 1 | 0.90 | 0.97 | 0.97 | 0.97 | 0.93 | 1.00 |
| 2 | 0.86 | 0.97 | 0.90 | 1.00 | 0.97 | 1.00 |
| 3 | 0.86 | 1.00 | 0.90 | 1.00 | 0.97 | 1.00 |
| 4 | 0.86 | 1.00 | 0.97 | 1.00 | 0.90 | 1.00 |
| 5 | 0.90 | 0.93 | 0.83 | 0.93 | 0.90 | 1.00 |
| 6 | 0.86 | 0.90 | 0.93 | 0.97 | 1.00 | 1.00 |
| 7 | 0.86 | 0.97 | 1.00 | 1.00 | 0.97 | 1.00 |
| 8 | 0.83 | 0.93 | 0.93 | 1.00 | 0.97 | 1.00 |
| 9 | 0.72 | 0.86 | 0.79 | 0.90 | 0.90 | 1.00 |
| 10 | 0.79 | 0.86 | 0.90 | 1.00 | 0.97 | 1.00 |
| 11 | 0.86 | 0.90 | 0.79 | 1.00 | 1.00 | 0.97 |
| 12 | 0.76 | 0.97 | 0.86 | 0.93 | 0.97 | 1.00 |
| 13 | 0.83 | 0.86 | 0.93 | 0.93 | 0.97 | 0.97 |
| 14 | 0.93 | 0.90 | 0.93 | 0.93 | 0.97 | 1.00 |
| Average | 0.86 | 0.94 | 0.91 | 0.97 | 0.96 | 0.99 |

TABLE 3. Probability of Success of Drought Prediction (*Ps*) (time series approach of inflow prediction).

| t | DLT = 3 TDPs | | DLT = 2 TDPs | | DLT = 1 TDP | |
|---|---|---|---|---|---|---|
| | Moderate Drought | Severe Drought | Moderate Drought | Severe Drought | Moderate Drought | Severe Drought |
| 34 | 0.90 | 0.97 | | | | |
| 35 | 0.90 | 0.97 | 1.00 | 1.00 | | |
| 36 | 0.79 | 1.00 | 0.97 | 0.97 | 1.00 | 0.97 |
| 1 | 0.76 | 0.97 | 0.83 | 0.97 | 0.86 | 1.00 |
| 2 | 0.72 | 0.97 | 0.86 | 0.97 | 0.97 | 1.00 |
| 3 | 0.83 | 1.00 | 0.90 | 1.00 | 0.93 | 1.00 |
| 4 | 0.90 | 1.00 | 0.90 | 1.00 | 0.90 | 1.00 |
| 5 | 0.66 | 0.97 | 0.72 | 0.93 | 0.79 | 1.00 |
| 6 | 0.66 | 0.90 | 0.76 | 1.00 | 1.00 | 1.00 |
| 7 | 0.69 | 0.90 | 0.86 | 1.00 | 0.97 | 1.00 |
| 8 | 0.76 | 0.90 | 0.79 | 0.90 | 0.90 | 1.00 |
| 9 | 0.76 | 0.83 | 0.83 | 0.90 | 0.90 | 0.97 |
| 10 | 0.83 | 0.86 | 0.83 | 0.93 | 0.97 | 1.00 |
| 11 | 0.86 | 0.83 | 0.90 | 0.97 | 1.00 | 0.97 |
| 12 | 0.76 | 0.90 | 0.83 | 0.93 | 0.93 | 0.97 |
| 13 | 0.76 | 0.83 | 0.90 | 0.90 | 0.93 | 0.93 |
| 14 | 0.76 | 0.90 | 0.83 | 0.90 | 0.90 | 0.93 |
| Average | 0.78 | 0.93 | 0.86 | 0.95 | 0.93 | 0.98 |

minor, moderate, or major actions according to the drought lead time. For a severe drought, similar management practice may apply but with higher *P*s, e.g., 0.90.

### *Estimated DLT of Historical Drought Events*

The above discussions have concentrated on predicting the drought occurrence for specific TDPs and the probability of success of drought prediction for each TDP. We now turn our attention to the DLT of each historical drought event, which normally lasts for several TDPs. During the drought run length, prediction of drought/no-drought occurrence can be made for each TDP, and thus, several predictions of drought occurrence can be made during a drought run. Herein, we focus merely on evaluating the lead time at which onset of historical droughts were correctly predicted.

From 1964 to 1993, there were 22 moderate drought events and nine severe drought events. The onset of these events was correctly predicted by the kriging and time series approaches with various DLTs, as shown in Figures 5 and 6. For the kriging approach, approximately 77 percent of total moderate drought events were correctly predicted at least two TDPs in advance (DLT $\geq$ 2) and only one event failed to be predicted. For the time series approach, only 64 percent of moderate drought events were correctly predicted at least two TDPs in advance and five events (23 percent) were not predicted at all. For severe drought events, approximately 78 percent were correctly predicted at least two TDPs in advance by the kriging approach with no failed event; however, only 11 percent of severe drought events were correctly predicted at least two TDPs in advance by the time series approach, and 22 percent of events failed to be predicted. The kriging approach clearly outperformed the time series approach in terms of the number of drought events being correctly predicted and their DLTs.

### *Duration and Water Deficit of Droughts*

The severity of a drought event is usually described by its duration and water deficit. The duration, or the run length, is defined as the time span of a drought event. In this study, we define the water deficit as the departure of reservoir storage from its normal volume. Other applications also use precipitation or stream flow to characterize the water deficit.

Since both the kriging and time series approaches make drought predictions with lead time less than or equal to three TDPs, they do not provide information about the drought duration for events lasting longer than three TDPs. As for the water deficit, both approaches predict reservoir storages for the next three TDPs, and thus, future water deficits can be estimated.

Let $D(t)$ and $\bar{S}(t)$ be the water deficit and normal reservoir storage of the $t^{th}$ TDP, respectively. Based on our definition for water deficit and Equation (1), the predicted water deficit is

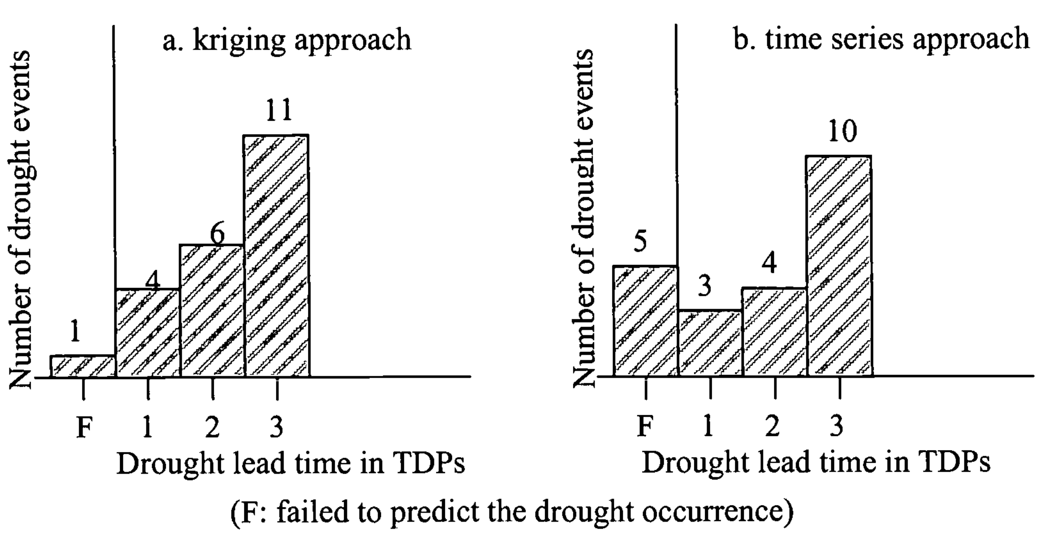


Figure 5. Successful Drought Prediction for Various DLTs for Moderate Drought Events: (a) Kriging Approach and (b) Time Series Approach.

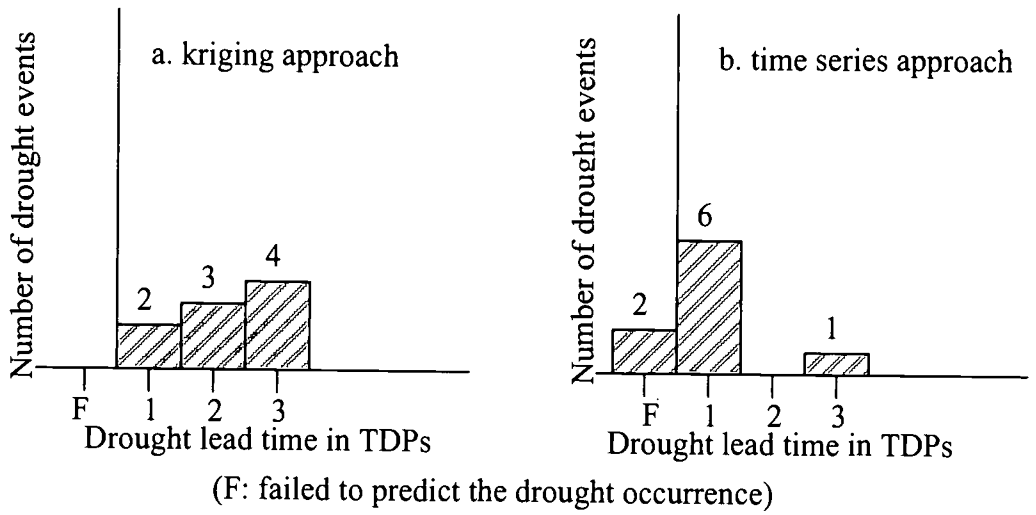


Figure 6. Successful Drought Prediction for Various DLTs for Severe Drought Events: (a) Kriging Approach and (b) Time Series Approach.

$$\hat{D}(t+1) = \hat{S}(t) - \overline{S}(t+1) \tag{20}$$

$$\hat{D}(t+1) = S(t) - \overline{S}(t+1) + \hat{I}(t+1) - \hat{R}(t+1) \tag{21}$$

where $\overline{S}(t) = \sum_{i=1}^{n} S_i(t)$, and $S_i(t)$ is the $t^{th}$ TDP reservoir storage of the $i^{th}$ year. Clearly, predicting the reservoir storage $S(t+1)$ is equivalent to predicting the water deficit $D(t+1)$.

Under current reservoir operations, reservoir release of the next TDP, i.e., $R(t+1)$, is determined based on the available reservoir storage $S(t)$ and the management experiences of the operation personnel. In this study, we established regression relations for reservoir storage $S(t)$ and reservoir release volume $R(t+1)$ to simulate the current practice of reservoir operations. This decision making process does not involve the potential water deficit. However, it is possible to use $R(t+1)$ estimated by the current practice as an initial estimate, and then iteratively fine-tune $R(t+1)$ by examining the predicted water deficit $D(t+1)$. In that case, regression equations for $S(t)$ and $R(t+1)$ only provide an initial estimate for $R(t+1)$, and the management experiences of the operation personnel will play a more important role in determining the final $R(t+1)$. However, equations for reservoir balance analysis (Equations 3a, 3b, and 3c) and reservoir inflow prediction (Equations 12 and 13) should still be used for drought forecasting. Improvement in reservoir operations is likely by considering potential water deficit in the decision-making process.

## CONCLUSIONS

An indicator of an approaching drought is particularly important for reservoir operations in Taiwan. The indicator signals the onset of approaching drought and can be used by reservoir management authorities to decide whether, when, and what remedial measures should be adopted. In this study the drought lead time was used as an indicator for drought management. Drought predictions were performed using approaches of the kriging and time series analysis and a subsequent reservoir operation simulation. According to simulation results, the kriging approach is clearly better than the time series approach in terms of the number of droughts being correctly predicted, the DLTs, and the probability of success of drought prediction. The superiority of the kriging approach may partially be attributed to the fact that reservoir inflow variogram is established using only dry-season reservoir inflows and more accurately represents the temporal variation of reservoir inflow of that particular season. In comparison, the time series approach must use all available and consecutive reservoir inflows to develop an ARMA model. Thus, the ARMA model considers the temporal variation of the entire process, dry- and wet-season both included. After removing the cyclic components, the temporal variation characteristics of reservoir inflow in dry-season and wet-season are assumed the same in the time series approach. The kriging approach is also advantageous in that it does not require using continuous and regularly sampled inflow data. This feature makes it more applicable when missing data are encountered in the time series.

Using the information of drought lead time and probability of success of drought prediction, reservoir operation in the dry season can be more efficient. However, reservoir management authorities must determine what probability of success is required to prompt taking remedial measures for moderate and severe droughts, e.g., 0.8 and 0.9, respectively. Also, different levels (minor, moderate, and major) of remedial measures should be planned and adopted according to the length of the predicted drought lead time.

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