Hydrological Risk Assessment of Old Dams: Case Study on Wilson Dam of Tennessee River Basin

Abebe S. Gebregiorgis[1] and Dr. Faisal Hossain[2]

Abstract: This case study presents a risk analysis reassessment for the oldest dam in the Tennessee River basin—the Wilson Dam—based on postdam flow data. The hydrologic risk of old Wilson Dam was computed from historical flow data (spanning pre and postdam periods) and reservoir volume at the dam site. Additional flow data not previously used in the design phase of the dam helped to update more robustly the probability of flood occurrence that exceeded a particular return period during the life of a dam. The generalized extreme value (GEV) distribution was fitted to historical peak flow (at the dam site) and annual maximum reservoir volume using the *L*-moment method. This reassessment approach has wide application in reservoir water and safety management for ageing dams. The study underscores the need for a review of risk analysis for ageing dams that have extensive postdam flow data, particularly in the United States. Furthermore, this case study also demonstrates the unique value of the *L*-moment method in incorporating postdam flow data for more robust risk analysis.

CE Database subject headings: Risk management; Dams; Tennessee; River basins; Case studies.

Author keywords: L-moment; Generalized extreme value; Hydrologic risk; Return period.

Introduction

Hydrologic risk is the probability of failure occurring on any hydraulic structure attributable to extremely low or high water flux. The failure may be grouped in two categories: i) structural failure and ii) performance failure. Structural failure may be caused by a dam break while performance failure can be caused by a flood (water excess) or drought (water shortage) (Nagy et al. 2002). Dams are always subjected to probability of failure in achieving the intended objectives during their life span. One of the main causes for dam failure is flooding (e.g., overtopping attributable to inadequate spillway design), which can be considered a performance failure (Baker et al. 1988).

The International Commission on Large Dams (ICOLD) states that a dam with height from the foundation of 15 m or more or between 5 and 15 m with storage capacity greater than three million cubic meters can be classified as a large dam. According to a report by the World Commission on Dams (WCD), the number of large dams has been increasing rapidly since the 1930s. At a global level, more than 45,000 large dams have been built to store river water for various purposes (WCD 2000). There are approximately 75,000 dams in the United States, representing a combined storage capacity of about 43 trillion cubic feet of water (Graf 1999). Hypothetically, the volume of water stored in all reservoirs can reach a depth of 0.42 ft (12.8 cm) if it inundated the entire United States. This enormous amount of water is stored to provide valuable services to the nation such as hydroelectric power generation, irrigation, and flood control. However, dams can cause catastrophic damage to both life and property if they experience either structural or performance failures.

Many dam failures have been recorded over the past several years (Terzaghi and LaCroix 1964; Vick and Bromwell 1989). Morena Dam in 1912, Goose Creek Dam in 1916, Horse Creek Dam in 1935, and Elk City Dam in 1936 are some of the well-known dam failures in the United States attributable to overtopping and inadequate spillway design (Singh 1996). The Tennessee River Basin (TRB) in the United States is a high rainfall and runoff producing basin. To counter the flood-prone nature of the basin, the Tennessee Valley Authority (TVA) built and maintained many dams in the 1930s and 1940s (TVA 1988). According to TVA (1988), flood-producing storms occur in the TRB area on average about once every two years.

Frequency analysis is typically used to estimate the design discharge of hydraulic structures for the corresponding selected return period based on available guidelines. Because most large dams in the United States were constructed between the 1930s and 1960s, a much larger amount of historical flow data for the basin likely exists today than what was available during dam design. These data can be used to revise extreme value distribution functions and return periods for various flow magnitudes. The design flood magnitude of an already constructed dam can be used to estimate the nonexceedance probability (cumulative frequency) of that particular design flood. If the annual maximum flood distribution is $F(x)$, the design flood quantile X_q corresponds to a specified value of the nonexceedance probability $F(X_q)$. This function ultimately leads to the estimation of hydrologic risk and provides a measure of safety for an existing dam against future hydrologic failure.

According to National Inventory of Dams (NID) produced by United States Army Corps of Engineers (USACE 2000), more than 85% of dams in the United States will be older than 50 years by 2020. Therefore, reevaluating the risk to the dams of overtopping by flooding during the remaining service life is important. Moreover, older dams have a sufficiently long record of data that was not incorporated during the design process. This additional data can potentially yield more robust estimates of the flow distribution tails.

[1]Dept. of Civil and Environmental Engineering, Tennessee Technological Univ., Cookeville, TN 38505-0001.

[2]Dept. of Civil and Environmental Engineering, Tennessee Technological Univ., 1020 Stadium Drive, Box 5015, Cookeville, TN 38505-0001 (corresponding author). E-mail: fhossain@tntech.edu

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For all of these reasons, the risk for which the dam was designed using data from the predam period has probably changed.

Another motivation for risk analysis can be found in the extensive presence of old dams in the United States (and in Russia and Eastern Europe) that demand repair and rehabilitation to ensure structural safety and continued usage into the long-term future. Simultaneous rebuilding and rehabilitation may not be attainable for all existing old dams from a financial point of view. However, an up-to-date risk assessment can have great value in prioritizing the maintenance sequence for these old dams. Dam safety agencies, lawmakers, and the public should be aware of the potential risk of dam failure by taking the necessary precautionary measures before overtopping occurs. Dam safety agencies are responsible for managing these risks for old dams and protecting the public against the devastation caused by such catastrophes.

Methods currently available to estimate such risk of failure by overtopping have become more sophisticated than the methods used during the period of dam design (Rao and Hamed 2000; Hosking and Wallis 1993). *L*-moments are such statistics used to summarize the shape of a probability distribution analogous to conventional statistical moments (mean, standard deviation, skewness, and kurtosis). The *L*-moment method is a convenient way of estimating statistical moments using a linear combination of sample data (Rao and Hamed 2000). Compared with the conventional moment method, the *L*-moment method is a better parameter estimation method because of its ability to yield a nearly unbiased estimate for all underlying distributions. Another very useful property of the *L*-moment method is that it is in sensitive to the presence of outliers in the data series (Rao and Hamed 2000). The parameters of the probability distribution (shape, location, and scale) can be estimated using method of moment (MOM), maximum likelihood (ML), and probability weighted moment (PWM).

MOM is the simplest method to equates sample moments to parameter estimates. However, this parameter estimation may not be available for all distribution types. ML involves selecting parameter estimates that gives the maximum probability of occurrence of the observation data. This method has desirable mathematical and optimality properties, because it results in minimum variance and unbiased estimates as the sample size increases. Therefore, with additional data spanning the postdam period, ML-based estimates are likely to be more accurate than other methods. However, the likelihood functions involve partial differential equations, in which case the result may not sometimes converge to a particular solution and ML estimates may also be unavailable. Like MOM, PWM is also simple to use and efficient; it is also robust like the ML parameter estimation method even in the case of a small sample (Rao and Hamed 2000).

An important assumption in statistical analysis is the concept of stationarity. The time series flow data applied is assumed to be stationary if its statistical parameter remains the same irrespective of time. In other words, the data series should be random in nature during the statistical analysis period. It is appropriate to mention herein this recently debated issue of stationarity (Milly et al. 2008). In our particular case study, the assumption of stationarity is justified using a simple temporal trend analysis and the change point detection test (Villarini et al. 2009a; Xiong and Guo 2004; Salas 1993), the Wald-Wolfowitz (W-W) test, and the lag-one serial correlation coefficient test (Rao and Hamed 2000). A detailed discussion of the stationarity assumption is presented in section 3-1 of this paper.

The objective of this technical note is to review the hydrologic risk of an aging dam to demonstrate the combined ramifications of the *L*-moment method and additional flow data on risk assessment. A risk analysis was carried out for the aging dam in TRB for different scenarios of extreme discharges (e.g., return periods of 100, 200, 500, 1,000, and 10,000 years). The implications of this study extend to all aging dams in the United States and around the world that are at risk of overtopping and cannot be structurally upgraded in the immediate future.

This study is organized as follows. Section 2 provides a description of the study area and data analysis, å followed by a description of the *L*-moment method and a procedure for fitting distributions (section 3). Sections 4 and 5 present the hydrologic risk computation and discussion of the results of the study, respectively. The last section (6) presents a summary and the major findings of the study.

Study Area and Data Analysis

Study Area

The study area is the Tennessee River Basin (TRB), which is located in the southeastern part of the United States [see Figs. 1(a) and 1(b)]. It has a drainage area of 40,900 square miles (105,930 sq. km.), and is one of the wettest regions in the country. The region receives mean annual precipitation of 51 inches (1,290 mm). Because of the high rainfall and runoff, the basin experiences high flood risk (TVA 1988).

According to the Association of State Dam Safety Officials (ASDO, 2002), the TRB has 656 dams and reservoirs. Because of business sensitivity, the design discharges for old dams in the TRB were not available for analysis. Hence, to circumvent this issue, we chose to perform hydrologic risk assessment for different design discharge scenarios that were considered realistic. The technique was applied to one of the oldest dam in TRB called the Wilson Dam [constructed in 1927; Fig. 1(b)]. The additional historic flow data pertained to the period from 1936 to 2007 from the stream flow gauging station managed by the United States Geological Survey (USGS) at Florence, Alabama (USGS station #03589500). Essentially, these 71 years of additional flow data after the construction of the dam, coupled with a more robust flood frequency assessment method, motivated us to reevaluate the risk for this aging dam.

Wilson Dam is located in Lauderdale County of Alabama (34° 48′ 03″ N and 87° 37′ 33″ W) and was constructed for the purpose of hydroelectric power generation. The Wilson Dam impounds the Wilson Lake, which has a flood-storage capacity of 53,600 acre-feet (TVA 1998). The construction of the Wilson Dam started and completed in 1918 and 1927, respectively, and the dam is 137 feet (42 m) high and 4,541 feet (1,384 m) wide across the Tennessee River. During the construction period, the initial investment at 1918 prices was almost $47 million. The dam has a power generating capacity of 675 megawatts (MW) of electricity.

Peak Flow and Reservoir Data Analysis

The hydrological risk of the hydropower Wilson Dam was systematically analyzed by considering annual peak flow and maximum reservoir volume. The annual maximum flow was considered just below the dam site. Hydrologic risk is defined as the probability of the dam structure being overtopped by excess inflow into the reservoir. Therefore, in hydrologic risk analysis of dams, volume of reservoir is a crucial factor for consideration relative to storage capacity and dam elevation. For this application, the inflow volume was converted to elevation using area elevation-area-storage curves. The elevation-area-storage curve for the Wilson Dam was obtained from the USGS's Reservoir Sedimentation Database (RESSED) (Source: www.ida.water.usgs.gov/ressed/) based on reservoir sedimentation surveys done in 1928 and 1936.

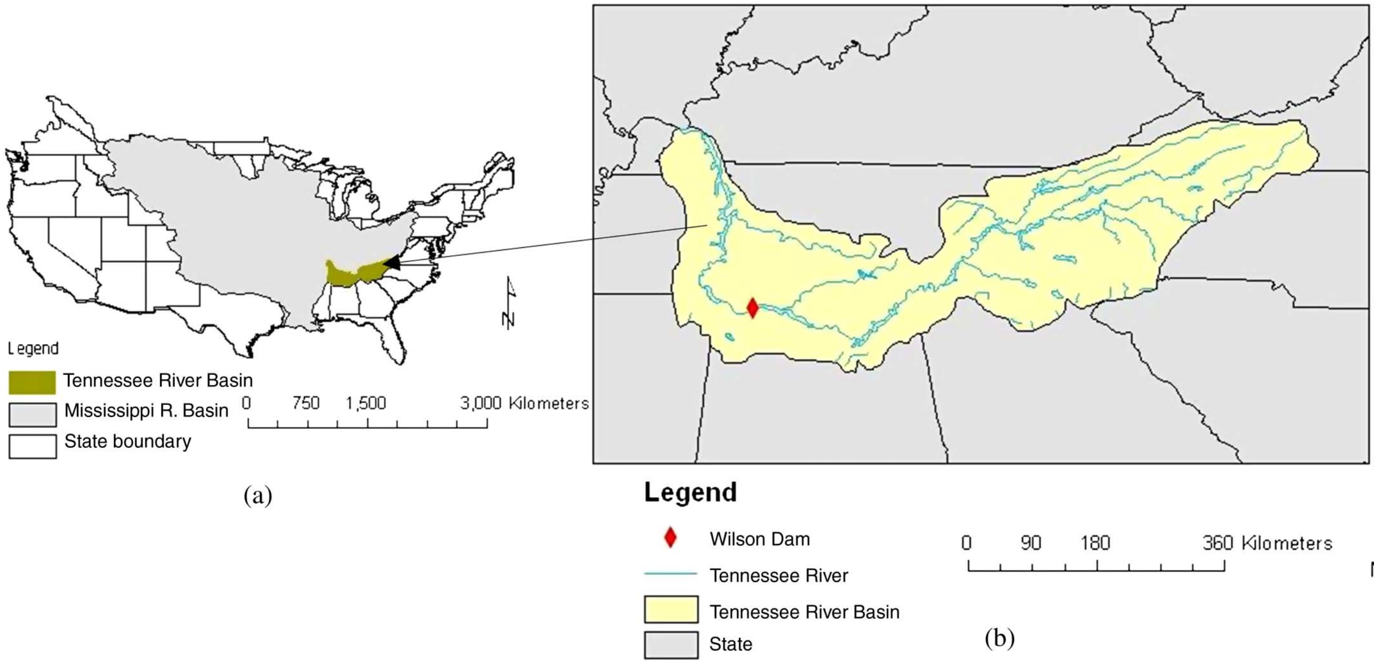

Fig. 1. Map of Mississippi and Tennessee River basin: (a) location of TRB; (b) location of Wilson Dam in the TRB

Area-elevation-storage curves change from time to time as they depend on the dynamic morphology of the reservoir bed (sediment deposition). Based on these actual surveys archived in the RESSED database, the elevation-area-storage curves are modified for the analysis period assuming that the same rate of sediment enters into the reservoir annually, as shown in Fig. 2. Generally, the sedimentation rate (or trap efficiency) is a function of the live storage of the reservoir. Therefore, this dynamically changing rate has an influence on hydrologic risk, especially in a basin in which land use and topological changes have been significant. Hence, our assumption of a constant annual sedimentation rate can be a limit to this study, which we explicitly recognize. However, the land use of the upper Tennessee River Basin is characterized by mostly forest cover (more than 64%), agricultural land of 27%, and urban area of about

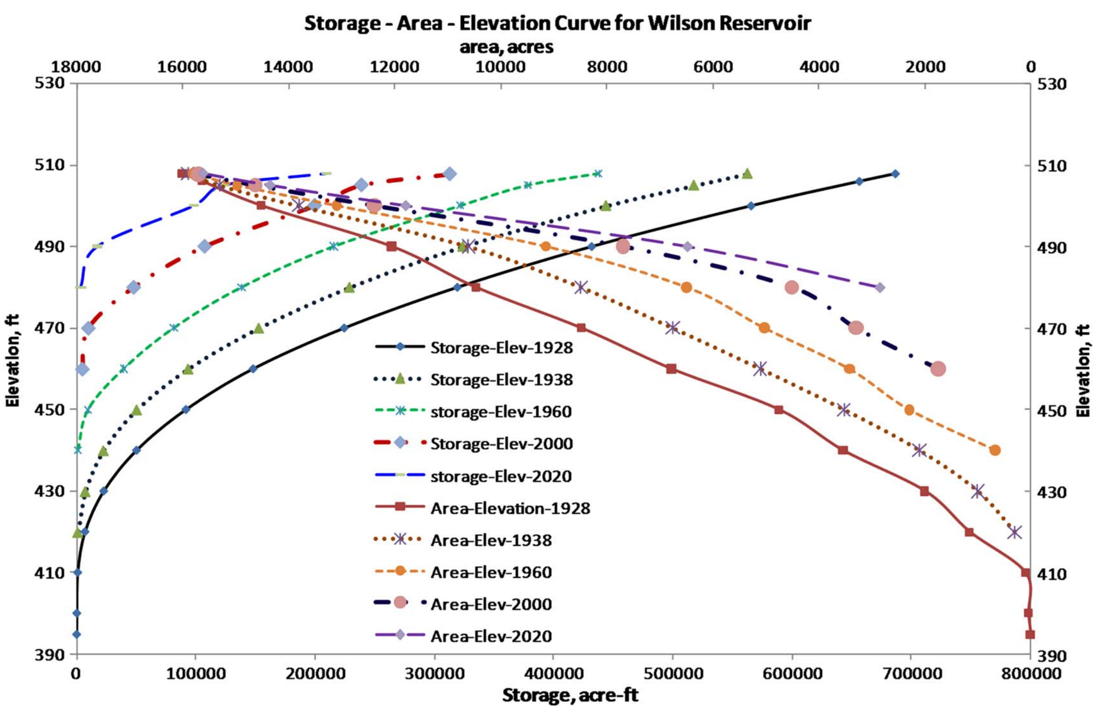

Fig. 2. Elevation-area-storage curves for the Wilson reservoir according to USGS surveys made in 1928 and 1936 (data taken from www.ida.water.usgs.gov/ressed/). The curves for the other years were modified based on the assumption of constant annual sediment rate inflow into the reservoir. These curves were used to get daily reservoir elevation data from the daily inflow volume. (Note: primary *x*-axis is storage in acre-ft and secondary *x*-axis is submergence area in acre)

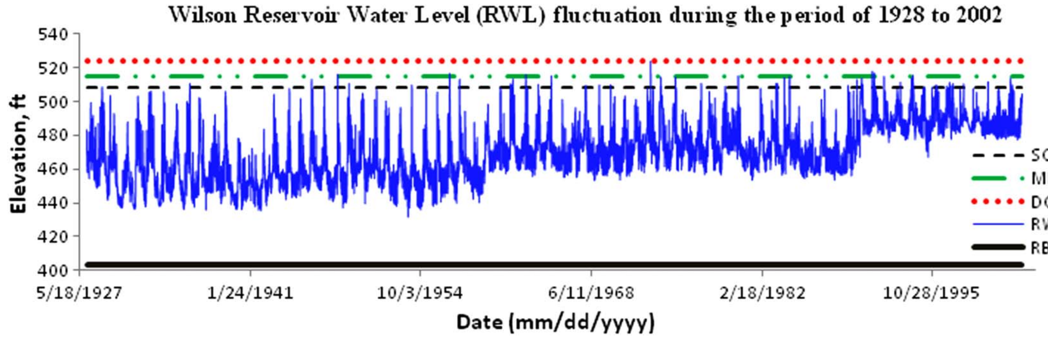

Fig. 3. Wilson reservoir water level for the study period (1927–2002) according to Fig. 2. NOTE: SCL, Spillway Crest Level; MRL, Maximum Reservoir Level; DCL, Dam Crest Level; RWL, Reservoir Water Level; RBL, River Bed Level

6%. The other 3% is described by open water and barren land (Johnson 2002). As the major portion of the basin is covered by forests, its variation of annual sediment yield may be expected to be minimal.

Based on the elevation-area-storage curve, the reservoir water level was determined for the study period as shown in Fig. 3. The reservoir water level repeatedly exceeded the maximum reservoir level, which shows the occurrence of flood beyond the design discharge that this study is addressing (hydrologic risk).

L-Moment Method for Risk Analysis

Stochastic and Trend Analysis for Annual Peak Flow and Maximum Reservoir Volume

Frequency models are not designed for analyzing regulated flows (Bradley and Potter 1992; Stedinger and Griffis 2008). Most of the rivers in the United States have regulated flow, which makes the implementation of that frequency model difficult. One reason is that the annual peak flow of the river is affected by reservoir (Villarini et al. 2009a; Buchberger 1981; Bradley and Potter 1992; NRC 1999; Williams and Wolman 1984; Graf 2006). In addition, the hydrologic trend of stream flow and rainfall is significantly affected by land-use changes (Villarini et al. 2009b; Graf 1999; Potter 1991) and climate change (Groisman et al. 2001; Garbrecht and Piechota 2006; Kiely 1999; Sivapalan and Samuel 2009).

In the case of regulated flow, one cannot directly fit the annual peak flow data in the appropriate distribution model to obtain flood quantile estimates from the data series (Buchberger 1981). Under such circumstances, the regulated peak flow is treated as a combination of two components: the deterministic component and the stochastic component. Hence, prior to frequency analysis, splitting the two components is crucial. The stochastic component can then be treated like nonregulated flow, independent and stationary for the purpose of fitting the frequency distribution model. Before fitting the distribution model to the annual maximum flow series, the validity of the stationarity assumption was checked using various approaches, as discussed next.

In this research, the minimum flow released from the reservoir (12840 cubic feet per second) was considered as the deterministic part of the flow, and it was removed from the annual flood peak series. This minimum flow is a combination of flow released through the reservoir bottom outlet as environmental flow and flow released from the powerhouse after rotating the turbine's blade during the low flow season. Flow released from the reservoir beyond this threshold discharge (overflow spillway) occurs because of flooding and is considered a stochastic component. The stochastic component of the flow series was checked for independence and randomness using the Wald-Wolfowitz (W-W) test and the lag-one serial correlation coefficient test (Rao and Hamed 2000).

The W-W test can compute the randomness of data set with respect to both the mean and the median. In this test, for the time series data to be possibly independent, the actual test statistic value should be less than the critical test statistic value, which is 1.96 at the 5% significance level. For the Wilson Dam, the test statistic value is found to be 1.01 and 1.48 with respect to the mean and the median, respectively, showing that the hypothesis of the correlation of the stochastic component of the annual peak flow can be rejected at the given significance level. The lag-one correlation coefficient of the stochastic component of the peak flow is 0.09, which is between the upper and lower limit of the correlation coefficients (0.22 and −0.25, respectively). According to the test results, the independent assumption can be justified reasonably.

Also, the assumption of the validity of stationarity was checked by simple temporal trend and change point analysis. The temporal trend shows how the time series data varies over a long period and the change point analysis helps detect changes in the mean of the time series data (Villarini et al. 2009a; Kiely 1999). The temporal analysis detected no significant noise, indicating the presence of a clear long-term trend in the time series for both discharge and reservoir volume [Figs. 4(a) and 4(b)]. Analysis of statistical order moment for streamflow data also shows a consistent trend during the study period, indicating that the *L*-moment ratios are preserved during this time [Figs. 4(c), 4(d), and 4(f)].

For the change point analysis, a sequential detection of the multiple change points algorithm called STARS was applied (Radionov and Overland 2005). This test helped automatically detect the presence of abrupt change in time series data of a certain time scale and magnitude. The time scale to be detected was controlled by cutoff length, and the maximum significance level at which the regime shift can be detected is given as the probability level. The Huber's weight parameter, which controls the weights assigned to the outliers, was considered as unity. The change point detection analysis was done for two different probability scenarios (0.05 and 0.1) and cutoff values (10 and 20 years), but the result remained the same as presented in Fig. 5.

The measure of the regime shift index (RSI) was calculated to indicate the significance of an abrupt change in the data series. A positive RSI value means the change point for that particular year is significant at the given probability. A negative value indicates that the regime shift at the given year failed and is assigned zero for the next data range (Randionov 2004). One and two change points were detected in the discharge and volume of reservoir data,

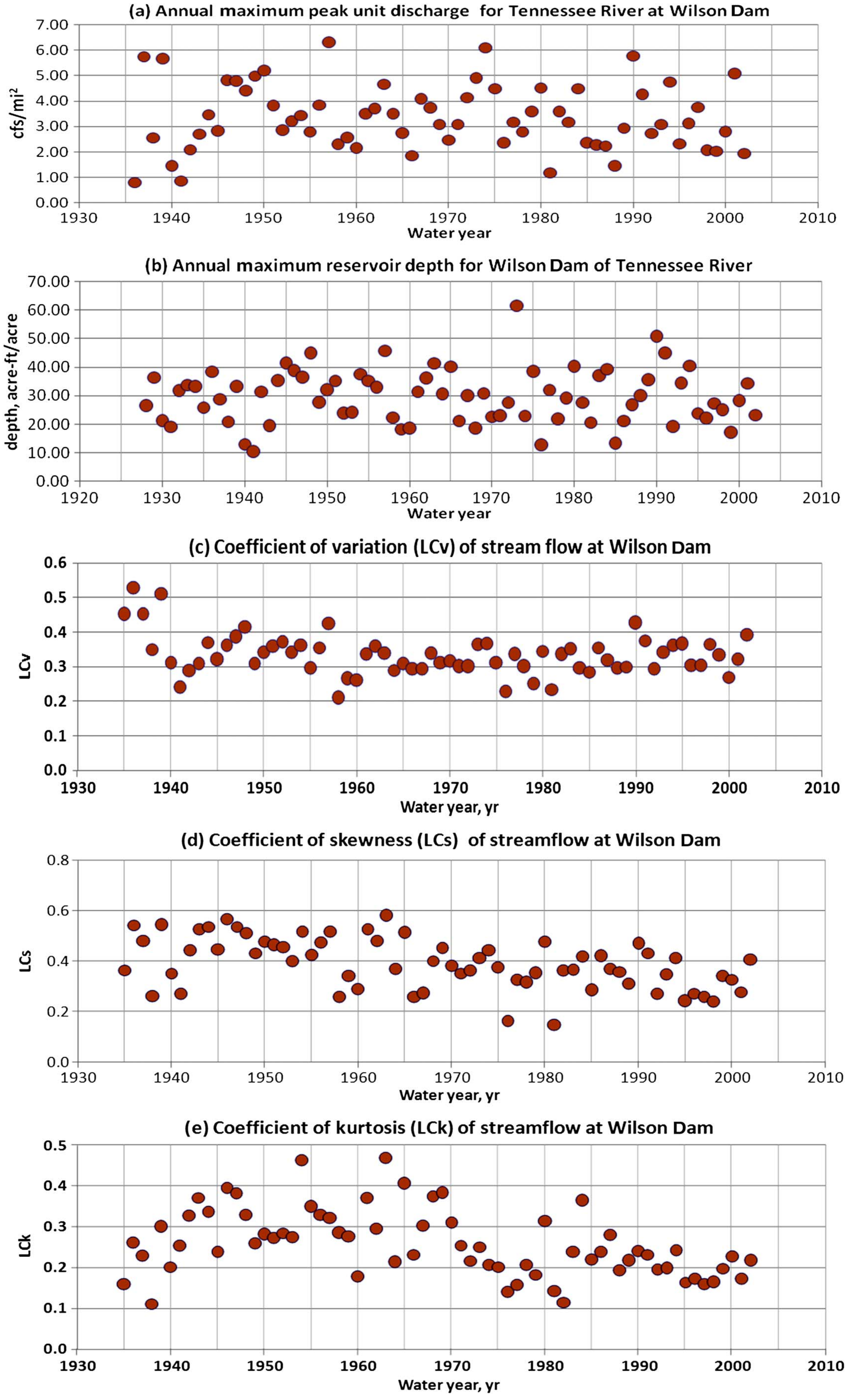

Fig. 4. a) Annual maximum unit discharge; b) Wilson reservoir depth; c) *L*-moment coefficient of variation; d) coefficient of skewness; e) coefficient of kurtosis of streamflow at Wilson Dam during analysis period to detect whether there is any significance noise (outlier) in the data series

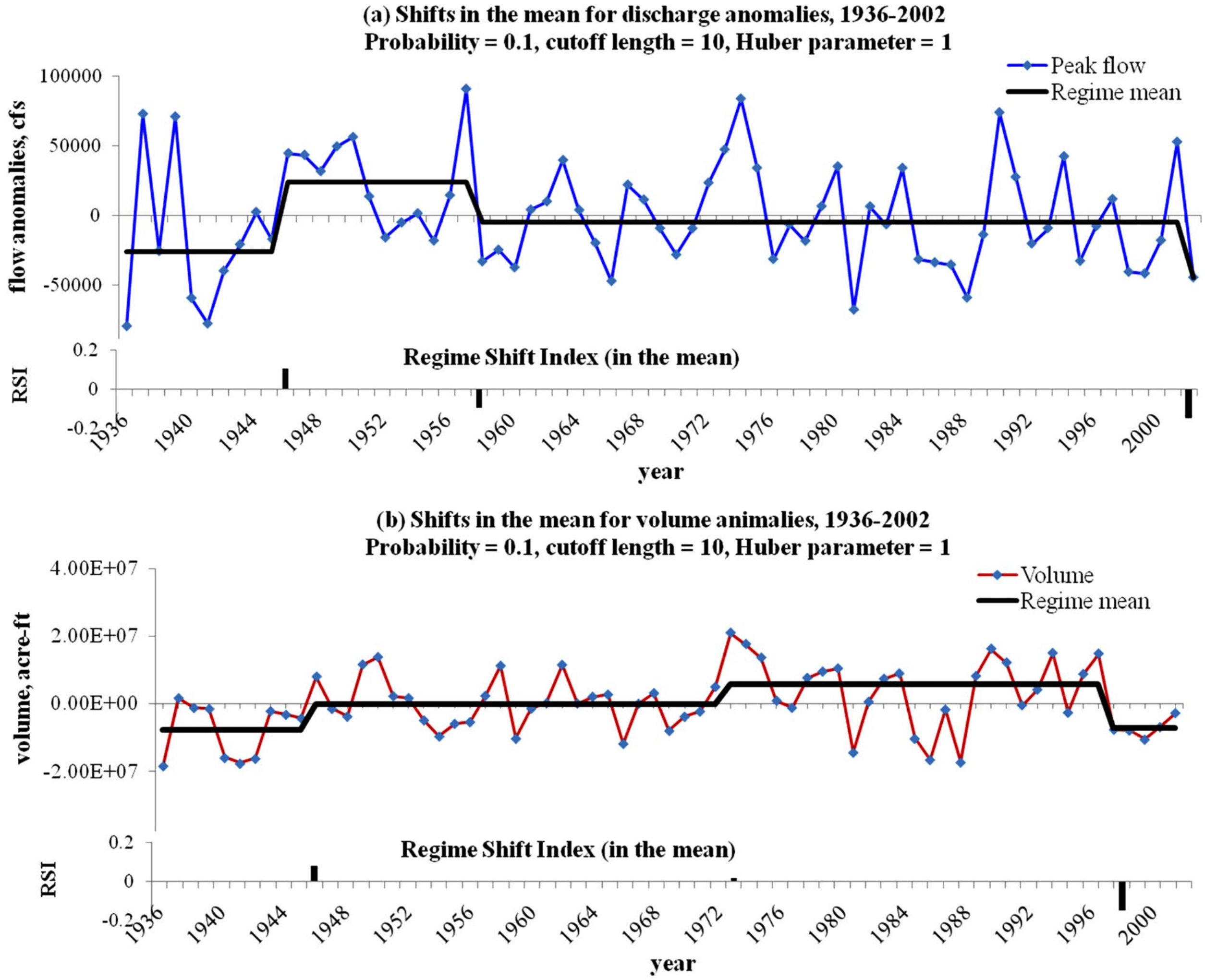

Fig. 5. Regime shift point and RSI during the study period a) for maximum annual flow; b) for the inflow volume. Probability of 0.1 and cutoff length 10 years were used in the analysis to locate occurrence of change point in the data series

respectively. The corresponding RSI values for these points are below 0.15.

In this study, in addition to the STARS test, a monotonic trend test was conducted on the annual maximum flow data to demonstrate whether or not the trend in the observed flow data is significant. The monotonic test was advocated as a new approach to identify stream flow trend patterns (Zhang et al. 2010; Kalra et al. 2008). The test involved repeated implementation of Mann-Kendall trend tests with different beginning and ending times. For further detail of the method, the readers are referred to Zhang et al. (2010). The Mann-Kendall statistics (p-values) for repeated N trend tests were plotted on the x-axis and y-axis (beginning time versus ending time, respectively) to visualize the occurrence of a long-term or short-term trend pattern. Fig. 6 shows no significant long-term trend in the data series. A trend is observed for the period beginning around 1945, which is also detected by the STARS test. However, this trend does not last to the beginning of the next period, and is not pronounced when other periods begin, except for the existence of some scattered trends as shown in Fig. 6. Around 1930, the beginning of the study period, no trend is observed for various ending periods. As a result of the above justifications, the assumption of stationarity is believed to be reasonable for this study.

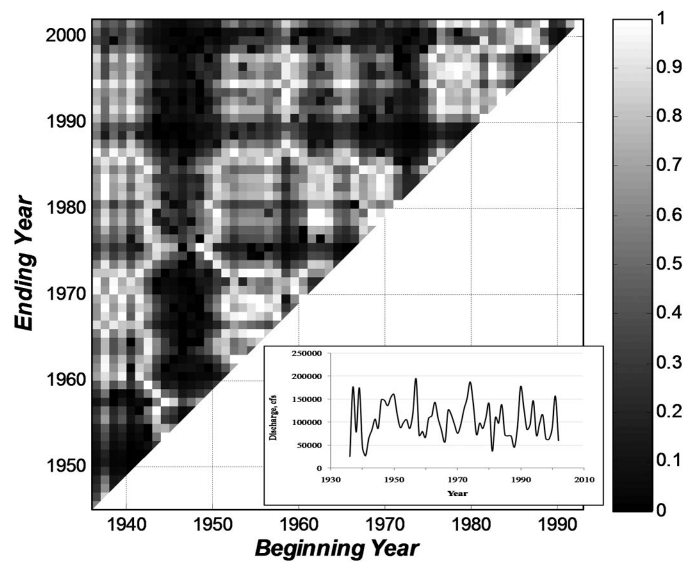

Fig. 6. Result of monotonic trend pattern analysis of annual maximum streamflows at Wilson Dam. The black color indicates the presence of significant trends and the gray shade indicates no trend in the data series at a significance level of 0.05

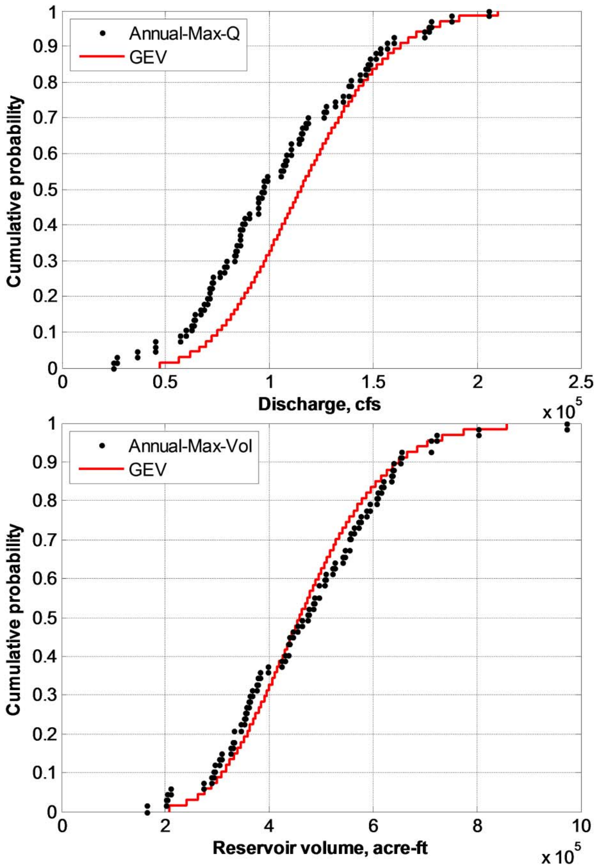

Fig. 7. *L*-moment ratio diagram of annual peak flow and inflow volume for Wilson Dam, which contributes to the selection of the best fit candidate distributions for fitting the historical flow series from the given distribution models in the graph. NOTE: GParto, generalized parto; Glg, generalized logistic; GEV, generalized extreme value; P-III, Pearson 3; LN, lognormal; Exp, exponential; EV1, extreme value 1; LLg, log logistic

Fitting Distribution for Annual Peak Flow and Maximum Reservoir Volume

Flood frequency analysis using the *L*-moment method estimated flood quantiles for different return periods. Identifying the type of distribution for a dam site is an important component for computing the nonexceedance probability function that was an input into determining hydrologic risk. The *L*-moment ratio diagram (LMRD) was calculated to identify and select the best fit distribution for the stochastic component of the annual peak flow and reservoir volume, as shown in Fig. 7. The *L*-moment skewness and kurtosis of the peak flow and maximum reservoir volume are plotted together to identify the closest distribution type, as shown in Fig. 8. Rao and Hamed (2000) provide further details on the selection procedure.

Generalized extreme value (GEV), Gamma, and Pearson III distributions were considered potential candidates for fitting the annual peak flow, and GEV for fitting reservoir volume. The goodness-o-fit measure (Z) helped select the best fit from the candidate distributions and tested whether a given distribution acceptably fit the data. According to Hosking and Wallis (1993), if the goodness-of-fit measure $|Z|$ is less than or equal to 1.64, the distribution is acceptable for the given data, and low values of $|Z|$ indicate a better fit to flow data. Accordingly, $|Z|$ is found to be 0.0024, 0.0156, and 0.0084 for GEV, gamma, and log Pearson distributions, respectively. Thus, GEV is selected as the best distribution for both the stochastic component of peak flow and reservoir volume at Wilson Dam, although the other two are also reasonable for fitting the flow data at the dam site. Furthermore, the Kolmogorov-Smirnov test is used to check whether both flow and reservoir volume data come from GEV distribution. The test depends on the greatest discrepancy between the observed and hypothesized cumulative frequencies, commonly called the KS-statistics. The null hypothesis, which states that the sample comes from the specified distribution, is rejected at a particular significance level if the computed KS-statistic is greater than the critical value for the given sample size. At the 5% significant level, the computed KS-statistics are 0.093 and 0.059 for the peak flow and reservoir volume, respectively. This result shows that the KS-statistics are less than the critical value (0.210), and the null hypothesis, which states that the observed data follow the specified GEV distribution, is accepted at the 5% significant level. Fig. 8 shows the cumulative frequency graphs for the observed data and the GEV distribution.

The method for distribution parameter estimation was selected as follows. First, the simulated and observed flood quantiles and inflow volume at the dam site were compared for different return periods (Fig. 9). A closer match to the actual value indicates the better method of parameter estimation. Hence, MOM was chosen as the preferred estimation method. Second, the confidence interval

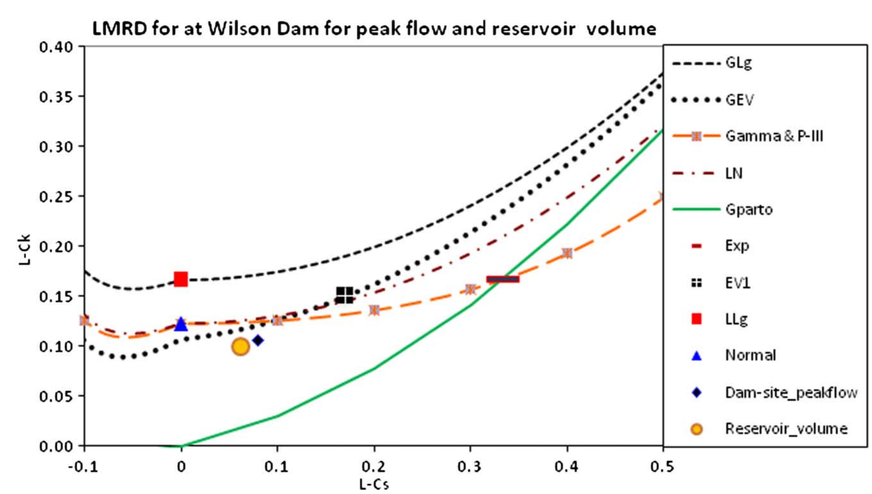

Fig. 8. Result of Kolmogorov-Smirnov goodness-of-fit test. The cumulative probability of GEV distribution and the annual maximum stream flow (upper panel); cumulative probability of GEV distribution and the annual reservoir maximum volume at Wilson Dam (lower panel)

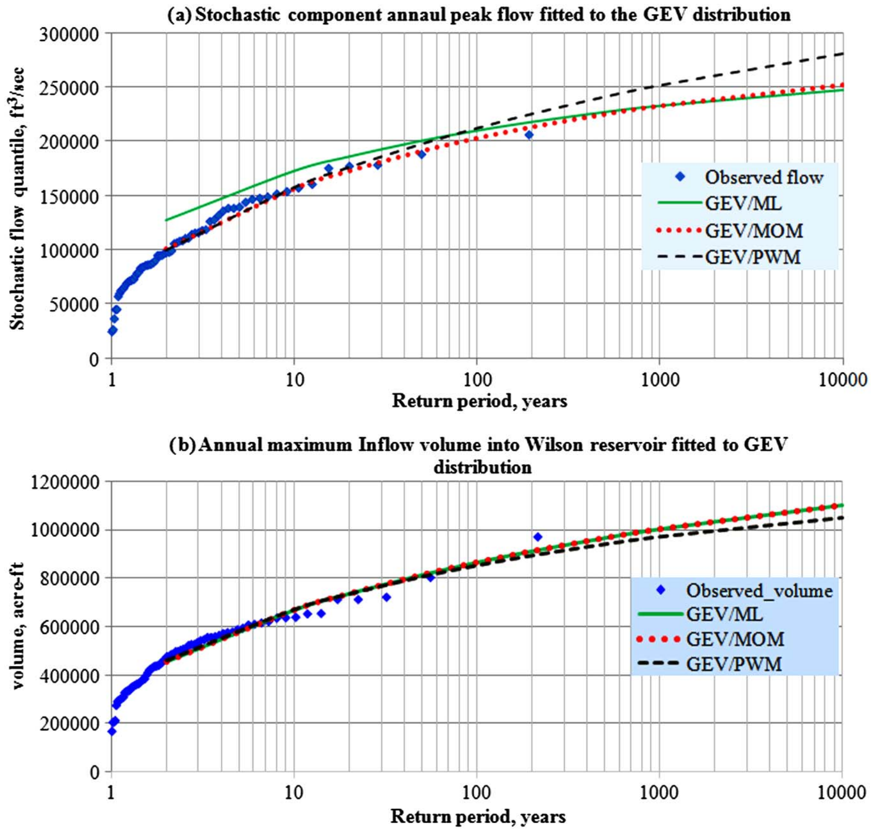

Fig. 9. Comparison of actual and simulated peak flow quantiles and inflow volume at Wilson Dam using general extreme value distribution (GEV) and three parameter estimation methods (method of moment, MOM; maximum likelihood, ML, probability weighted moment, PWM). The figure helps to examine how the three distribution-parameter estimation procedures (D/E) close to the observed peak flow and reservoir inflow volume

and standard error associated with the parameter estimation methods are used as selection criteria (Cunnane 1989; Rao and Hamed 2000). For the same confidence level (95%), MOM yielded a narrow confidence limit both for peak flow and inflow volume (Fig. 10). In other words, MOM generated a lower standard error of estimate (SEE) than PWM (Fig. 11). Therefore, MOM further justified its choice as the preferred parameter estimation method for the analysis of hydrologic risk.

Hydrologic Risk Analysis

Risk is the probability of occurrence of an extreme, dangerous, hazardous, or (more generally) undesirable event (Kite 1988). There are different risks related to dams, beginning from the first day of construction to the operation and maintenance periods. Such risks may be related to structural design, hydrologic processes, and economic or financial factors. This study focused only on hydrologic risk, which is instigated from the randomness of hydrologic processes and the occurrence of extreme events that disrupt the normal functioning of the dam. In the case of dam safety, risk can be explained as the chance of downstream flooding attributable to uncontrolled water release from a reservoir, resulting in the loss of life and property. The fundamental requirements in the design of a dam may be stated as follows: there should be no loss of life anticipated; there should be minimum economic loss; and there should be no adverse environmental impacts (Nagy et al. 2002; Chow et al. 1988; IAC 1982; Stedinger et al. 1993).

In engineering design practice, dams are expected to have a lifetime of 100 years or longer; consequently, the flood probability is also selected on that basis (Nagy et al. 2002). Hence, the 1 in 100 annual probability (equivalently, the probability that the maximum flood could occur during the lifetime of the structure) is an important parameter for risk analysis. It is very important to be clear that the maximum flood that could possibly occur during the lifetime of the structure (say, 100 years) does not mean that it is a flood with a return period of 100 years. This clarification can be defined by the relationship between hydrologic risk, the return period of the flood, and the lifetime of the structure.

Yen (1970) derived an expression for the risk of failure associated with a return period and the expected life of a project. The risk of failure R is directly related to the return period T. For exceedance probability p and nonexceedance probability q, the hydrologic risk R for the occurrence of design discharge X_T, can be given by

$$R = 1 - (1 - p)^n = 1 - q^n = 1 - (1 - 1/T)^n \tag{1}$$

where n = design life of the hydraulic structure. Therefore, the reliability, R_L, is

$$R_L = 1 - R \tag{2}$$

The nonexceedance probability of a flood estimated by a particular distribution model can be given by cumulative distribution function $F(x)$. The cumulative distribution function of X is the area under the probability density function $f(x)$, and is given by

$$F(x) = \int_{-\infty}^{\infty} f(t)dt \quad \text{for } -\infty < x < \infty \tag{3}$$

The cumulative distribution functions for the generalized extreme distribution is given by Rao and Hamed 2000

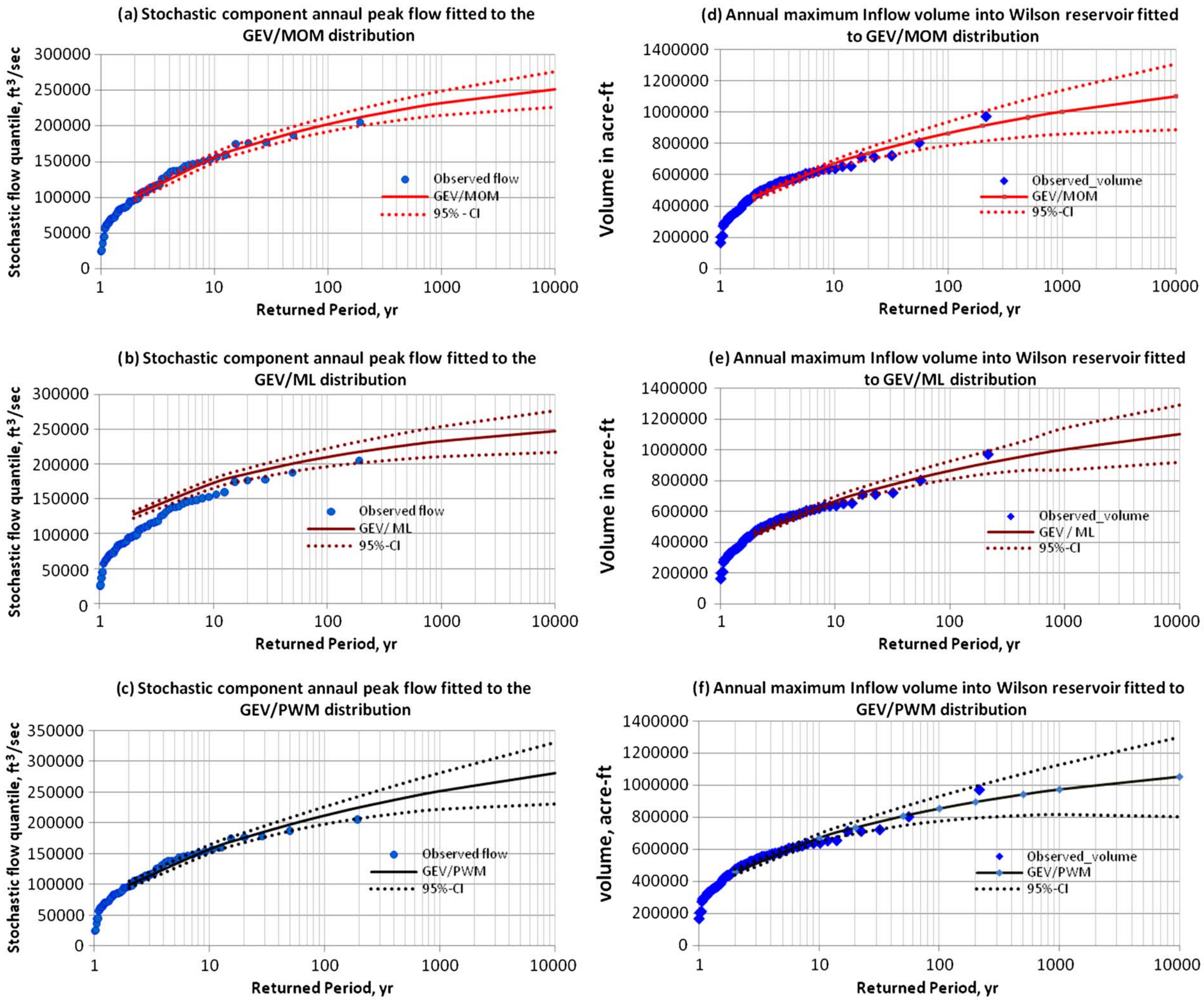

Fig. 10. Comparison of actual and simulated peak flood quantiles (a, b, and c) and inflow volume (d, e, and f) at Wilson Dam with the confidence interval associated with the general extreme value distribution. The figure helps understand how the observed flow quantiles fall within the confidence intervals for different return periods, which ultimately helps in the selection of the appropriate distribution-parameter estimation (D/E) procedure. NOTE: MOM, method of moment; ML, maximum likelihood; PWM, probability weighted moment; CI, confidence interval

$$F(x) = \exp\left\{-\left[1 - k\left(\frac{x-u}{\alpha}\right)\right]^{1/k}\right\} \tag{4}$$

where u, α and k are distribution parameters

The distribution parameters were estimated from the stochastic component of the historical data at the dam site.

The nonexceedance probability is the same as the cumulative density function of the given distribution, so one can write as

$$q = F(x) \tag{5}$$

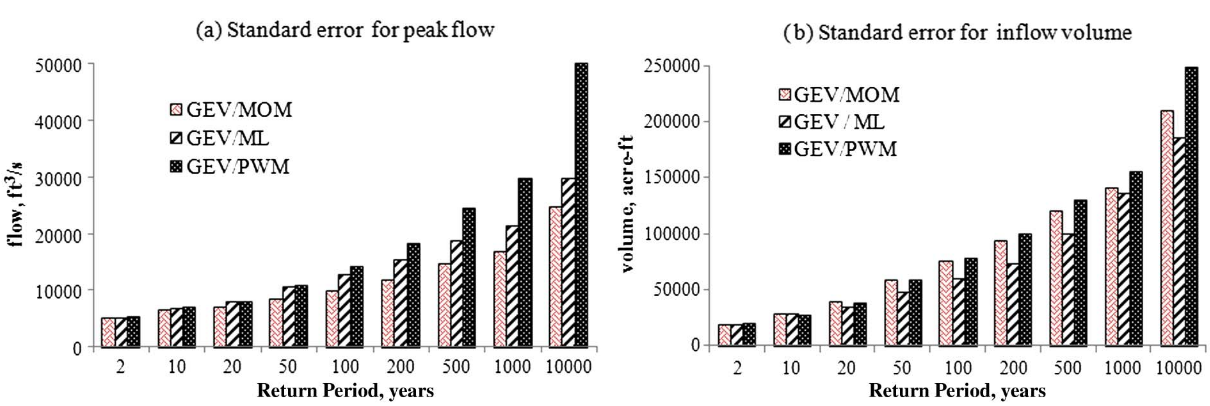

Fig. 11. Comparison of standard error of estimate (SEE) for MOM and PWM parameter estimation methods. In the case of peak flow, SEE is smaller for MOM whereas for inflow volume SEE is smaller for ML

Computing the parameters from the sample data at the dam site and substituting the design discharge X_T for x, the estimator is rewritten as:

$$\tilde{q} = \tilde{F}(x_T) \tag{6}$$

The estimator of the corresponding risk $\hat{R}$ for the n-year period is defined by

$$\tilde{R} = 1 - (1 - \tilde{p})^n = 1 - \tilde{q}^n \tag{7}$$

Results and Discussion

From the historical peak flow and reservoir inflow volume at Wilson Dam, the distribution parameter estimates were determined using MOM. Thus, the nonexceedance probability was given by Eqs. (8) and (9) for the peak flow and inflow volume, respectively.

$$F(x_T) = \exp\left\{-\left[1 - 0.186\left(\frac{x_T - 87992}{37031}\right)\right]^{\frac{1}{0.186}}\right\} \tag{8}$$

$$F(x_T) = \exp\left\{-\left[1 - 0.145\left(\frac{x_T - 409904}{135823}\right)\right]^{\frac{1}{0.145}}\right\} \tag{9}$$

where x_T = peak flood quantiles and inflow volume estimated for return periods of 100 to 10,000 years

The design life of dams depends on the time required to fill the reservoir with sediment, the durability of appurtenances structures, and the time required to perform the specific function for which the dam was designed. Considering 100 years as a design life of a dam, and for a dam to serve effectively for 100 years or longer, is the norm (Morris and Fan 1998). Therefore, the hydrologic risk analysis was performed for four life time scenarios: 1) for the current (as of 2010) age of the dam at 83 years; 2) for a design life of 100 years; and 3) for the lifetime of the structure at 150 and 200 years (Fig. 12).

Tables 1 and 2 present the calculated hydrologic risk for different scenarios. For instance, for the existing age of the Wilson Dam (as of 2010), the hydrologic risk was found to be 56.5% for a flood having a return period of 100 years. Practically, this result means that the probability of a flood with a 100-year return period occurring in 83 years of service life is 56.5%. Therefore, if a dam is designed for a 100-year return period, the hydrologic risk is 0.565. In general, the calculated hydrologic risk presented in Tables 1 and 2 for different scenarios needs to be compared with the permissible hydrologic risk used during the design of the structure. If the calculated hydrologic risk is larger than the permissible risk, precaution and safety measures should be taken to ensure the future
2 service life of the structure.

The issue of permissible risk is difficult to address by defining a certain threshold value beyond which the risk is not acceptable. The Australian National Committee on Large Dams (ANCOLD) (2003) Guidelines on Risk Assessment recommends that risk of reservoir failure should be as low as possible to ensure safety and economic feasible (Peter et al. 2003; Salas et al. 2003). This is because the determination of risk depends on the extent of damage (both life and economic) attributable to failure of the structure (hydrologic risk), runoff response of the catchment (flood generating characteristics), and location of the dam (downstream condition). However, different guidelines are in place for selecting the return period or
3 design flood of hydraulic structures by different agencies.

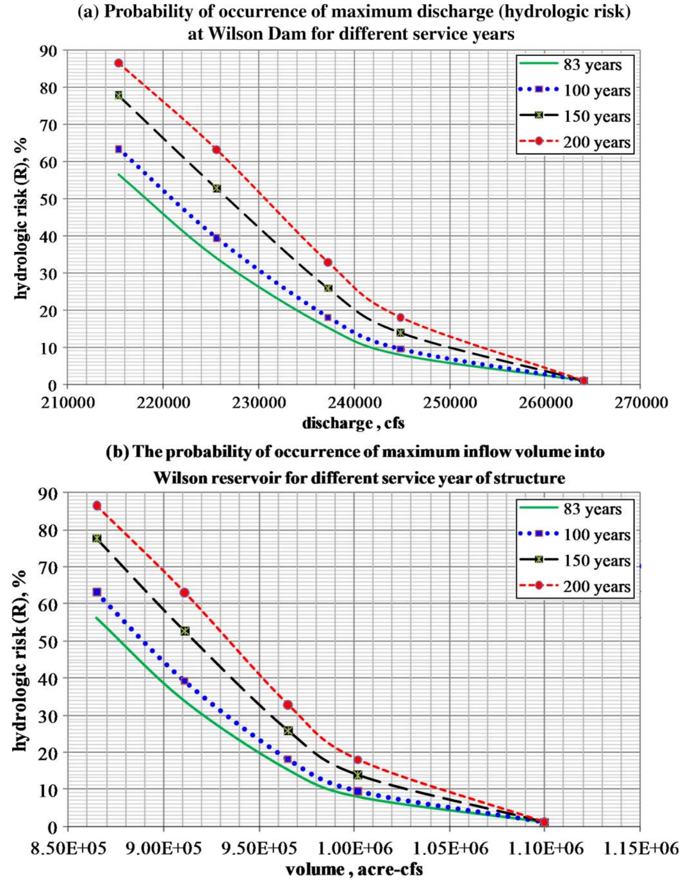

Fig. 12. Relationship between return period and service life of dam for various hydrologic risks (R) for occurrence of a) extreme discharge at Wilson Dam b) extreme inflow volume into Wilson reservoir

Fig. 12 indicates the probability of occurrence of extreme discharge and inflow volume (synonymously called hydrologic risk) for different dam lifetimes. The figure was developed to show the relationship between the magnitude of the extreme events and their probability of occurrence within the given lifetime of the dam.

The hydrologic risk for different extreme events can be determined from the graph based on service life of the dam. As the service life increases, the hydrologic risk of a particular event occurring also rises. One can determine the probability of occurrence of, for instance, designed discharge for a given service life by knowing the spillway maximum discharge capacity. In this study, the magnitude of the official design flood was not known. However, agencies that operate the dam and know the spillway design discharge can use this information as a decision-making tool. In fact, design flood is not only a physical term; it also has public policy, political, legal, economic, and technical dimensions to it (Nagy et al. 2002). Decisions made are directed at determining the extent to which responsible policymakers wish to, or are able to, protect downstream populations, the environment, and the wealth of society against flood hazards.

Various possibilities and considerations are available for estimating a design flood for a given level of acceptable hydrologic risk. The basic motivation of this paper was to initiate a fundamental shift in how we reevaluate the hydrologic risk of aging dams for the purpose of safety and economic viability by using extensive postdam flood data and the LMRD method. Our understanding is that the extensive postdam flow data currently available for

Table 1. Hydrologic Risk and Reliability Analysis using GEV/MOM Distribution/Parameter Estimation Method for Peak Flow at Wilson Dam

	Q_{TS}, cfs	$q = F(x)$	R	R in %	R_L in %
		83 years service life (in 2010)			
100 years of return period	202482	0.9900	0.5654	56.5	43.5
200 years of return period	212756	0.9950	0.3399	34.0	66.0
500 years of return period	224428	0.9980	0.1528	15.3	84.7
1,000 years of return period	232019	0.9990	0.0795	7.9	92.1
10,000 years of return period	251225	0.9999	0.0082	0.8	99.2
		100 years of design service life (up to 2027)			
100 years of return period	202482	0.9900	0.6336	63.4	36.6
200 years of return period	212756	0.9950	0.3938	39.4	60.6
500 years of return period	224428	0.9980	0.1811	18.1	81.9
1,000 years of return period	232019	0.9990	0.0949	9.5	90.5
10,000 years of return period	251225	0.9999	0.0099	0.99	99.01

NOTE: The analysis was performed for existing and assumed designed service life of the dam; Q_{TS}, Stochastic component quantiles; q, Nonexceedance probability; R, Hydrologic risk; R_L, Reliability.

Table 2. Same as Table 1, except for Inflow Volume into Wilson Reservoir

	Vol, acre-ft	$q = F(x)$	R	R in %	R_L in %
		83 years service life (in 2010)			
100 years of return period	864896	0.9899	0.5708	57.1	42.9
200 years of return period	911103	0.9949	0.3442	34.4	65.6
500 years of return period	965367	0.9980	0.1551	15.5	84.5
1,000 years of return period	1001855	0.9990	0.0808	8.1	91.9
10,000 years of return period	1099797	0.9999	0.0084	0.8	99.2
		100 years service life (up to 2027)			
100 years of return period	864896	0.9899	0.6391	63.9	36.1
200 years of return period	911103	0.9949	0.3985	39.9	60.1
500 years of return period	965367	0.9980	0.1838	18.4	81.6
1,000 years of return period	1001855	0.9990	0.0965	9.6	90.4
10,000 years of return period	1099797	0.9999	0.0101	1.0	99.0

NOTE: Q_{TS}, Stochastic component quantiles; q, Nonexceedance probability; R, Hydrologic risk; R_L, Reliability.

the vast network of aging dams in the United States are not leveraged to their fullest extent to determine more robust risk management protocols.

Conclusion

This study shows that the generalized extreme value is the best fit distribution for historical flow at the Wilson Dam site in the Tennessee River Basin using the L-moment method. The study suggests that use of long years of historical flow data to analyze future hydrologic risk of old dams helps for operational and planning purposes. Tables 1 and 2 present the hydrologic risk scenarios for 83 and 100 years of dam service life. The hydrologic risk was found to be higher for the designed floods having a return period of 1,000 years and shorter. The higher the hydrologic risk, the higher the probability of failure (risk) because of a hydrologic event like flooding and overtopping during the remaining service period. The corresponding hydrologic risk can be determined from knowing the return period of design flood of an old dam. This is important information for dam operation agencies. Based on the existing conditions of a dam, they can decide whether or not the computed hydrologic risk is acceptable. For instance, given the existing conditions of the dam, Table 1 show that if the acceptable hydrologic risk is 5%, the safest return period is 1,000 years. Therefore, if the return period of the designed discharge is shorter than 1,000 years, the dam is more likely subject to hydrologic failure.

Risk analysis also involves the process of identifying the likelihood and extent of the consequences associated with failure. Depending on the downstream conditions, there may be a situation in which no tolerable risk can be introduced during the design. From an economic point of view, there is always the possibility of accepting risks up to a certain limit in some cases. This case study provides important insights into the value of additional flow data and robust flood frequency analysis protocols for operating agencies of aging dam infrastructures (e.g., TVA or the United States Bureau of Reclamation).

In this changing environment, assumption of hydrologic stationarity can be considered a limitation of this research (Sivapalan and Samuel 2009). However, applying a robust method of analysis such as the L-moment method, which is not easily affected by changes in hydrologic trends, produced an acceptable result. We hope that the results obtained in this study will be cross-checked independently by dam agencies with the design criteria used during the design period to evaluate the risk associated with the remaining service life of the structure. We also hope that our methods, as they are generic enough for implementation, will be applied by the same agencies on a vast number of aging dams in the United States and around the world to undertake a policy revision based on reassessment of risks.

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