Chapter 78

Risk, Reliability, and Return Periods and Hydrologic Design

BY

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ABSTRACT

The concepts of risk, reliability and return period are fundamental elements to the analysis of extreme hydrological events for the fields of water resource systems planning, and management as well as for flood and drought risk assessment and mitigation. This chapter reviews the main criteria for selecting the level of infrastructure protection and for defining hydrologic design variables within a risk-based framework, considering both univariate and multivariate design conditions. Approaches to hydrologic design under both stationary and nonstationary conditions are summarized.

78.1 INTRODUCTION

The concepts of risk, reliability, and return periods are widely used in the analysis of extreme events in the field of hydrology as well as for numerous other natural hazards including wind loads, sea levels, earthquakes, temperatures, and other phenomena. For example, the U.S. National Flood Insurance Program defines the floodplain in terms of the T=100-year flood, which is defined as the annual maximum river flood discharge (and associated flood elevation) that is exceeded with an annual exceedance probability (AEP) of 1% (q=0.01). If flood infrastructure were designed to protect against such an event, the structure would be 99% reliable, in any given year. If river conditions are expected to remain unchanged (stationary) in the future, we show later in this chapter that the reliability of that structure over a 50-year planning horizon would only be 60.5%, which is much lower than 99%. It is important to realize that the discharge with average return period T=100 years may arrive earlier (or later) than 100 years, because that is only the average return period, or the average arrival time of the next 100-year flood. Under stationary conditions, the return period is a random variable with an exponential distribution, so that it is much more likely that the 100-year flood will occur in the next 100 years, than in the subsequent 100 years, in fact there is a 63.4% chance that the 100-year flood will arrive before the first 100 years are over. Similar statements could be made for other natural hazards; however, the focus of this chapter is on statements of risk, reliability, and return periods relating to river discharge. The above statements concerning the likelihood of future flood events are the type of concepts which hydrologists need to be familiar with and which form the basis of this chapter.

78.1.1 Selecting the Level of Protection and Effective Risk Communication: Reliability versus Average Return Period

It is extremely important that hydrologists are able to communicate the probability of flood (and other natural) hazards in a manner which is clearly understood by those populations who will actually experience the impacts of such hazards. For example, the U.S. Geological Survey (Holmes and Dinicola, 2010) and other agencies, issue fact sheets, general information announcements, and videos which attempt to communicate and clarify the meaning of the T-year flood. One of the goals of this chapter is to describe our current understanding of the most effective approaches for communicating flood risks. We describe the various reasons why metrics, such as risk and reliability over a planning horizon, may be more effective for communicating flood risk than the traditional notion of an average return period (also see Read and Vogel, 2015; Serinaldi, 2015).

Traditional probabilistic approaches for defining risk, reliability, and return periods under stationary hydrologic conditions assume that extreme events arise from a serially independent time series with a probability distribution whose moments and parameters are fixed over the design life of a project. Most existing hydrology texts and handbooks provide a review of hydrologic design procedures under stationary conditions (see Stedinger et al., 1993; CEH, 1999). Normally, hydrologic design is based on a single random variable X, such as the annual maximum flood (AMF), or the annual minimum 7-day discharge. Normally X is assumed to arise from a process which is independent from 1 year to the next with a probability distribution function (PDF) denoted by $f_x(x)$ with cumulative distribution function (CDF) denoted by $F_x(x)$. A stationary PDF is one whose model parameters are assumed fixed over time. See Chapters 21 and 22 for definitions of commonly used PDFs and associated CDFs along with further information on how to fit a PDF and CDF to observations.

Consider a hydrologic design problem in which a structure is built to protect against an extreme event with an annual non-exceedance probability, $p=F_x(x)$. The design event for such a structure may be a river discharge for flood or low flow control. Such a design discharge is also called the pth quantile of X, denoted as x_p, which is the value of X with non-exceedance probability p. In flood frequency analysis, one often estimates the design event x_p from a series of annual maximum streamflows (see Chapter 21) in which case q=1−p is referred to as the AEP. Choice of an appropriate design discharge forms the basis of hydrologic design. In sections 78.2.1 and 78.2.2, we describe two general approaches to selection of a design discharge: (1) the traditional approach which assumes an AEP equal to q=1−p, and then computes the corresponding design discharge x_p and (2) a risk-based decision approach which computes the value of x_p as the discharge which maximizes the net benefits of the proposed water infrastructure.

78.1.2 Working Hypothesis: Stationarity versus Nonstationarity

Once a level of infrastructure is built to protect against a design event x_p, in any future year, a flood will either exceed that design event with probability q=1−p, or not, with probability p. If the flood series is independent in time and stationary, then the series of exceedances and non exceedances is said to follow a Bernoulli series. Some hydrologic processes are known to exhibit temporal persistence such as low flow series (Douglas et al., 2002) and water supply failures (Vogel, 1987) both of which can be more accurately modeled using a Markov model, instead of a Bernoulli model. Thus the values of AEP could change from 1 year to the next for a stationary Markov process. However, for a stationary Bernoulli process, the exceedance probability associated with the design discharge should remain constant over time.

Historically, the most common assumption in flood and drought frequency analysis has been that flood and drought series are temporally independent and stationary, in which case the non-excedance probability p, and its converse the exceedance probability q=1−p are both constant, over time.

There is now widespread acceptance in the field of hydrology that most hydrologic processes exhibit nonstationary behavior due to changes in land-use, climate, and water infrastructure. In spite of this nearly widespread acceptance combined with the popular quotation that "Stationarity is Dead" (Milly et al., 2008), there is still very good reason to employ traditional methods based on stationary hydrologic processes as emphasized by Matalas (2012), Montanari and Koutsoyiannis (2014), and Vogel et al. (2015). This chapter documents approaches to hydrologic design problem considering both stationary and nonstationary conditions as well as univariate and multivariate processes. We emphasize and present an integrated risk-based approach to hydrologic design, considering uncertainties arising from all relevant sources, which in turn enable hydrologists to consider both stationary and nonstationary conditions together.

78.1.3 Selecting the Hydrological Design Variable: Univariate versus Multivariate

Many hydrologic design problems involve several random variables, thus a focus on river discharge alone may not be sufficient. For example, in the design of stormwater, best management practices, such as detention basins, hydrologists are concerned with both hydrograph peaks and volumes. Similarly modern levee design considers the probability of levee failure and overtopping and often uses several design variables in addition to peak discharge (e.g., water levels and duration of the event, flow velocities, levee fragility, etc.). A multivariate context arises when the hydrological load for the structure of interest is a function of two or more hydrological variables that are correlated with each other (e.g., flood peak and volume).

Such multivariate concerns and nonstationarity introduce additional uncertainty into the process of decision-making. In reference to such multivariate hydrologic processes Yue and Rasmussen (2002) describe conditions in which a single-variable frequency analysis considering only flood peak or volume alone can lead to estimates of flood events, and associated costs, which are much greater than necessary. The chapter ends by examining how existing approaches may be adapted for use under nonstationary conditions and in a multivariate context.

78.2 PROBABILISTIC AND RISK BASED APPROACHES TO HYDROLOGIC DESIGN

This chapter focuses on the application of probabilistic and risk based approaches to hydrologic design, yet it is important to realize that other non-probabilistic approaches exist. For example, in the design of large dams, some hydrologists still resort to the use of a deterministic interpretation of envelope curves (see section 78.2.1). Castellarin et al. (2005) and Castellarin (2007) provide a probabilistic interpretation of envelope curves which Vogel et al. (2007) extended to enable probabilistic statements to be made regarding estimates of the probable maximum flood (PMF). Although deterministic and stochastic approaches are available for estimation of extraordinary flood magnitudes [National Research Council (NRC) 1988], much greater attention has been given to the development of deterministic methods, than stochastic methods, for estimating extraordinary flood magnitudes including the probable maximum flood and the probable maximum precipitation (PMP) (Cudworth, 1989).

Although previous hydrology research relating to hydrologic design assumes both a stationary past and future, there is now a nearly pervasive awareness of potential nonstationarity in hydrologic processes due to anthropogenic influences on climate, land use, and water infrastructure. The notion that "stationary is dead" is now pervasive as indicated by over 1,000 citations, to date, of Milly et al. (2008). We should not be so quick to dispense with the notion of stationarity given that to date, most of our water infrastructure was designed under the assumption of stationary conditions yet there have been "very few failures of the nation's water management infrastructure—that is, where the infrastructure failed before its design capacity was exceeded" (Stakhiv, 2011). Matalas (2012) provides ample reasons for questioning "the degree to which real or perceived nonstationarities in hydrologic processes (should) affect the underlying processes and methods of making water planning and management decisions." He argues that "the assumption of stationarity has not yet been pushed to the limit of its operational usefulness in the face of a changing climate." In the following section we outline methods of hydrologic planning under both stationary and nonstationary conditions. Our approach to nonstationarity involves adapting traditional risk-based approaches which have served us well under stationary conditions.

78.2.1 Existing Methods for Hydrologic Design Based on Stationarity

Return Periods of Design Events under Stationary Conditions

Without loss of generality, we focus on the design of flood-risk mitigation measures; analogous concepts hold for other water-related problems and hydrological design variables. Although we begin our discussions with a background on the use of return periods in hydrologic design, we emphasize here and in subsequent sections that risk-based decision making (RBDM) is now a well-established methodology which can be used in place of the traditional design-event approach which selects a particular average T-year event usually specified by regulation, and then designs the necessary infrastructure to protect against the hydrological event with that specified average return period. We further emphasize here that, in spite of the widespread usage of return period nomenclature in hydrology, there are good reasons to temper their use as a metric of communicating flood risk (Read and Vogel, 2015; and Serinaldi, 2015).

Assume a series of AMF discharges arise from a stationary process that is independent in time; then in each year, an AMF exceeding some design threshold event x_p will occur with probability q=1−p. Since in this case the AMF process is stationary, we expect the exceedance probability of the design event x_p to be constant over time. The waiting time (also known as the return period) to the occurrence of the next AMF which exceeds x_p is defined as τ, and follows a geometric probability mass function (PMF) so that:

$$P[\tau = t] = q(1-q)^{t-1} \quad t=1, 2, \ldots, n \tag{78.2.1}$$

where, τ and t are the theoretical and observed values of the waiting time respectively, n is the planning horizon and q is the exceedance probability. In Eq. (78.2.1), the return period is assumed to be a discrete random variable, resulting in a geometric PMF; if it were assumed to be a continuous variable the resulting PDF of the return period would be exponential. The expected waiting time (or average return period) to the next AMF which exceeds x_p is given by:

$$E[\tau] = \sum_{t=1}^{n} t \cdot P[\tau = t] = \frac{1}{q} = T \tag{78.2.1}$$

The average waiting or recurrence time T is often referred to, incorrectly, as the return period. In reality, $T = 1/q$ is the average return and τ is the return period. Furthermore, we note that most hydrology texts do not give a derivation of why $T = 1/q$ nor do they distinguish between the properties of τ and T. Given the widespread usage of the relation $T = 1/q$ in hydrology, it is surprisingly difficult to find examples of the derivation in Eqs. (78.2.1) and (78.2.2) (Douglas Fernandez and Salas, 1999; Douglas et al., 2001; Wigley, 2009), in spite of the fact that Fuller (1914) and Gumbel (1941) first introduced the idea of the average return period.

There are two interpretations of the average return period T under stationary conditions. As shown above, T is the average number of years one must wait until the occurrence of the next flood with exceedance probability q. Cooley (2013) also shows that under stationary conditions, the expected number of flood events (exceeding the AMF flood with exceedance probability q) is equal to unity over the next T years.

The variance of the return period is also easily derived from:

$$Var[\tau] = E\left[\tau^2\right] - E[\tau]^2 = \sum_{t=1}^{n} t^2 \cdot P[\tau = t] - \frac{1}{q^2} = \frac{p}{q^2} \tag{78.2.3}$$

For very rare floods, the non-exceedance probability p is roughly unity, which implies that $Var[\tau] \approx 1/q^2 = T^2$, so that the mean and standard deviation of the return period are roughly equal. Since the PMF of τ contains only a single parameter, q, the mean of its distribution $T = 1/q$ is said to be a "sufficient" statistic for summarizing the complete probabilistic behavior of the return period. This fact is predicated upon the assumption that the values of p and its complement q, do not change from 1 year to the next, which is only true under stationary conditions. Under nonstationary conditions, the average return period is an extremely complex function of properties of the PDF of the flood magnitudes and the degree of nonstationarity so that T is no longer "sufficient" for describing the behavior of τ (see Read and Vogel, 2015; Serinaldi, 2015).

Return Periods for Dependent or Persistent Hydrologic Events

The average return period can be defined in different ways depending on whether the hydrologic design depends on initial project conditions or not. Two definitions of return period are possible, the time between two hydrologic events of interest, and the unconditional time to the next event of

interest. We term these two return periods as the conditional and unconditional return periods. For example, if one's interest is in water supply failures, droughts, and low streamflow sequences, all of which exhibit temporal correlation, ones interest would focus on the conditional return period (see Lloyd, 1970). The definition of return period introduced in (78.2.1–78.2.3) is the unconditional return period which is much more widely adopted than the conditional return period introduced by Lloyd (1970) and others. In practice, the unconditional return period is more useful than the conditional return period, because it does not require an assumption regarding initial conditions; hence, it more closely corresponds to design conditions. In other words, one does not usually assume that a flood or drought has just occurred, when planning for the next flood or drought.

An advantage of the conditional return period is that it has been shown to be insensitive to streamflow persistence or correlation (Lloyd, 1970). The same cannot be said for the unconditional return period, $T=1/q$, defined above which is commonly used in hydrology, so that hydrologic persistence can have an important impact on the average return period associated with many hydrologic processes which exhibit persistence (see Douglas et al., 2001).

To account for persistence in hydrologic processes on the properties of the return period, numerous approaches have been adopted including the use of a two-state Markov model (Vogel, 1987; Fernandez and Salas, 1999; Sen, 1999). Vogel (1987) defined the average return period of a reservoir system failure as the expected number of years before the first occurrence of a system failure (i.e., flood or drought). Vogel (1987) showed that the average return period defined in this way is indeed affected by streamflow persistence. Fernandez and Salas (1999) and Sen (1999) developed more general formulations for estimating the average return period of design events in the presence of persistence.

It is not only return periods that are impacted by hydrologic persistence. Estimates of hydrologic design events, the subject of Chapters 21 and 22, can also be impacted by hydrologic persistence. For example, Potter (1992) describes a procedure for accounting for persistence in the determination of the probability distribution of annual maximum water levels. Tasker (1983) recognized the effect of persistence (temporal correlation) in streamflow records on the reliability of design flood estimates and developed a method for quantile estimation (see Chapter 21 for further information on quantile estimation) using the effective record length, n_e, which, in most cases, is less than the actual historical record length, n, when persistence is present in the streamflow record. Vogel and Kroll (1991) describe a method for accounting for both the temporal and spatial correlation of flood and low flow series, when ones interest is in extending short streamflow series.

Return Periods of the Flood of Record and Envelope Curves

A flood discharge which exceeds all previous flood discharges is said to be the flood of record (FOR). Envelope curves are regional plots describing the upper bound on the FOR for many watersheds in a region versus drainage area. Envelope curves representing the current bound on flood experience have limited use because of our inability to assign to them an exceedance probability. Castellarin et al. (2005) and Vogel et al. (2007) developed approaches to estimate the exceedance probability of the expected regional envelope curve as well as an individual regional envelope curve, respectively.

Since the FOR is of interest in hydrologic investigations which employ envelope curves, it is important to understand the theoretical properties of the return period associated with an FOR. Wilks (1959) and Gumbel (1960) derived various properties of $T_{r,n}$, defined as the return period associated with the rth order statistic, where r = 1 represents the largest observation in a sample of length n. Wilks (1959) and Gumbel (1961) show that the expectation of $T_{r,n}$ associated with the rth order statistic in a sample of size n is given by:

$$E\left[T_{r,n}\right]=\frac{n}{r-1} \text{ for } r\geq 2 \tag{78.2.4}$$

Interestingly, the average return period associated with the largest observation (the FOR) is infinite under stationary conditions. From Eq. (78.2.4), regardless of how large the FOR is, or how long ago it occurred, on average, one will need to wait until eternity, to experience a flood greater than that record. This result should raise some questions concerning the suitability of using the average return period in flood planning, even under stationary conditions (see Read and Vogel, 2015; and Serinaldi 2015; for further discussion). Similarly, from Eq. (78.2.4) all higher order moments of the return period associated with the FOR (r = 1) are infinite, though moments do exist for floods smaller than the FOR (i.e., $r\geq 2$).

In contrast to the expectations of the recurrence time of the next FOR which is infinite; other measures of central tendency do exist, such as the mode, median, and geometric mean of the recurrence time of the FOR... Since the moments of the recurrence time of the FOR do not exist, one could instead use the mode, median, or quantiles to describe its distribution in lieu of its moments for stationary processes. Gumbel (1961) gives the geometric mean T_G, median T_{median}, and mode T_{mode} of the waiting time to the next record flood as:

$$T_G=\exp\left[\sum_{j=1}^{n}\frac{1}{j}\right]\cong\gamma+\ln(n)=1.78n \tag{78.2.5a}$$

$$T_{median}=\frac{2^{1/n}}{\left(2^{1/n}-1\right)}\cong\frac{n}{\ln(2)}+\frac{1}{2}=1.44n+0.5 \tag{78.2.5b}$$

$$T_{mode}=\frac{n+1}{2} \tag{78.2.5c}$$

Note that in general, $T_{mode}<n<T_{median}<T_G$. Clearly these measures of central tendency of the waiting time to an observation which exceeds that of the largest value in a sample of size n vary over a significant range from roughly 0.5n to 1.8n.

Risk and Reliability under Stationary Conditions

The concept of reliability is one of the most widely used design criteria in water resources planning and management. For example, the concept of reliability is widely used in irrigation and water supply planning (Hirsch, 1979; Vogel, 1987; Harberg, 1997; Tung, 1999; Loucks, Loucks and van Beek, 2005) and many other fields (Kottegoda and Rosso, 1997; Modarres et al., 2009). Perhaps some of the earliest work which related the concept of annual reliability to the reliability over an N-year planning period associated with the design of flood control structures were introduced by Gumbel (1941), Thomas (1948), and Yen (1970). Hashimoto et al. (1982) suggest that reliability alone is not sufficient for understanding the performance of a water resource system because it does not reflect the consequences of a failure if it should occur. Instead, their now classic paper suggests that the three metrics of reliability, resilience, and vulnerability are needed to fully understand water resource system performance. Hashimoto et al. (1982) define reliability as the probability or likelihood that a system remains in a satisfactory state. Reliability is usually defined as the converse of the probability of failure, which in the case of AMF discharges, would be the exceedance probability q associated with the design event of interest. Thus if the annual probability of failure is defined as q, then the annual reliability R_a=1-q=p. Hashimoto et al. (1982) emphasize that neither the probability of failure nor reliability reflect the consequences of an extreme event. The notions of resilience and vulnerability (see Hashimoto et al., 1982 for definitions) are needed to reflect the consequences associated with an extreme event.

Historically, some hydrologists have referred to the probability of failure q, as the risk of an event. However, more recently, in the context of ecological, health, and other risk assessment studies, the term risk has been defined as the product of the probability of an event and its consequences. Since that definition of risk is now much more commonly used in most fields, we recommend no longer referring to the probability of failure as the risk of an event. Instead, we focus on the related concept of reliability of a project over its planning horizon n.

Most hydrology textbooks contain expressions which relate the reliability of a water project over an n-year planning horizon, R_n, to its annual reliability R_a. One can relate the annual reliability R_a, to the n-year reliability, R_n, as follows. The n-year reliability R_n is simply the probability of no flood event for the first n-years, which can be derived from the PDF of the return period τ in Eq. (78.2.1) as follows:

$$R_n=P[\tau\geq n]=1-P[\tau\leq n]=1-\sum_{t=1}^{n}P[\tau=t]=(1-q)^n=R_a^n \tag{78.2.6}$$

Note that Eq. (78.2.6) assumes that flood events in each year are independent; if the hydrologic process of interest exhibits serial correlation Eq. (78.2.1) no longer applies (see previous section on dependent or persistent processes). We recommend the use of the concept of n-year reliability R_n for future planning, because it reflects the likelihood of failure over the entire planning horizon of interest and is used in many other fields (see Table 1 in Read and Vogel, 2015).

When a hydrologist performs a design based on the T-year flood, its reliability over the next n-year planning period is obtained from Eq. (78.2.6) as:

$$R_n=\left(1-\frac{1}{T}\right)^n \tag{78.2.7}$$

The above relationships between the annual reliability and the reliability over an n-year planning period were first introduced by Thomas (1948) and

further analyzed by Gumbel (1941) and Yen (1970). Those relationships depend upon the fundamental assumption that flood flows are independent and identically distributed variables. These relations are in widespread use as evidenced by their inclusion in both hydrology handbooks (Chow, 1964; IACWD, 1982; Stedinger et al., 1993; Tung, 1999) as well as in many textbooks (Bras, 1990; Viessman and Lewis, 2003; Mays, 2005) and journal papers (Gumbel, 1941; Thomas, 1948; Yen, 1970; Wigley, 2009; Salas and Obeysekera, 2014; Read and Vogel, 2015).

One concern with using the average return period T to denote risk of flooding is that it does not capture the impact of the planning horizon on the project of interest, as does the concept of reliability over a planning horizon R_n. Note that according to Eq. (78.2.7) the reliability is only 60.5% when the design event is based on the 1% exceedance (q = 0.01) event (T = 100-year flood) for n = 50-year project life. Considering that the design life of much of our water infrastructure is greater than 50 years, and that reliability decreases as project life increases for a given design average return period T, careful attention should be given to how the reliability is impacted by the planning horizon for structures which have been designed on the basis of an average return period.

Other fields concerned with hazard planning ensure a much higher reliability over typical planning horizons than corresponding reliabilities associated with the 100-year flood so commonly used in hydrologic planning (see Table 1 in Read and Vogel, 2015). For example, earthquake design regulations suggest protection against a "less than 2% chance of failure (collapse) occur(ring) in a 50-year project life" (National Earthquake Hazard Reduction Program, 2010). This level of protection corresponds to a reliability over 50 years of 98% and a corresponding design earthquake magnitude with an average return period of T = 2,475 years. By comparison, traditional flood frequency analysis which often bases designs on an average return period of T = 100 years corresponds to reliabilities of 78%, 61%, and 37% over a range of n = 25, 50, and 100 year planning horizons, respectively.

When designing for protection against a flood with an average return period T, of interest is the reliability over a design life equal to its average return period n = T, in which case one obtains:

$$R_{n=T} = \left(1 - \frac{1}{T}\right)^T \tag{78.2.8}$$

Yen (1970) points out that in the limit, as $T \to \infty$, $R_{n=T} \to \frac{1}{e} = 0.368$ which is an extremely low reliability when compared with other fields of engineering.

Analogous to the conditional and unconditional return periods discussed earlier, the reliability over an n-year planning horizon, R_n, can be defined using either a conditional or unconditional approach. Douglas et al. (2002), and Fernandez and Salas (1999) use a two state Markov model to derive expressions for the unconditional n-year reliability R_n, for events which exhibit serial persistence. Similarly, Sen (1999) uses a two state Markov model to derive expressions for the conditional n-year reliability R_n, for events which exhibit serial persistence.

Risk-Based Decision Making under Stationary Conditions

Risk-Based Decision Making is a well-established methodology that determines appropriate levels of infrastructure based on the expected damages avoided versus the cost of the infrastructure required (National Research Council, 2000; Tung, 2005) and is now standard practice by U.S. Federal agencies (see Stakhiv 2011 for references). RBDM can be used in place of the traditional design-event approach which selects a particular average T-year event usually specified by regulation or experience, and then designs the necessary infrastructure to protect against the hydrological event with that specified average return period. Instead, the goal of RBDM is to choose a level of infrastructure protection that minimizes the total expected annual cost (including flood damage costs) of the infrastructure, which is labeled "Annual Installation Cost" in Fig. 78.1. Alternatively, RBDM may maximize the project net benefits.

Thus an RBDM process may lead to flood-risk mitigation measure against a flood event either larger or smaller than, say, the 100-year flood, which is a common design event considered in the traditional analyses.

One of the most common approaches to performing RBDM for sequential decision problems is to use a decision tree. A decision tree is the graphical equivalent of a stochastic dynamic program which is a well developed mathematical programming method used in the areas of operations research, industrial engineering, and management science. A decision tree describes the sequence of possible decisions for numerous alternatives along with their probabilistic and economic outcomes. It is a very powerful approach because it combines a graphical representation of the overall set of alternatives and decisions, with a framework for making risk-based decisions. Decision trees

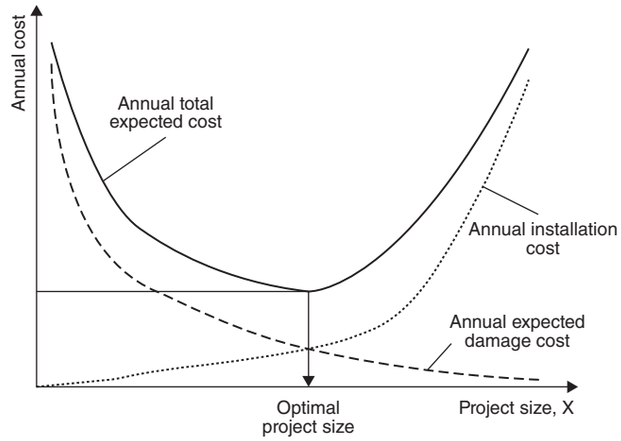

Figure 78.1 The Risk-Based design method for flood management. [*Source: Tung, 2005.*]

are described in most introductory textbooks in statistical decision theory and decision sciences as well as in most textbooks on water resource systems analysis (Loucks and Van Beek, 2005).

78.2.2 Probabilistic and Risk-Based Hydrologic Design under Nonstationary Conditions

Olsen et al. (1998) first described the theoretical properties of the various hydrologic design indices described in the previous section, under nonstationary conditions. Several investigators have sought to extend the results of Olsen et al. (1998) including the concepts of return period and reliability to nonstationary conditions. Interestingly, probably due to the tremendous attention and need to understand how to adapt to climate change, most of the key developments extending hydrologic design indices to nonstationary conditions have appeared primarily in the statistical and climate change literature (Wigley, 1988; 2009; Katz, 1993; Olsen et al., 1998; Parey et al., 2007; Cooley, 2009; Katz, 2010; Parey et al., 2010; Cooley, 2013). Salas and Obeysekara (2014) and Read and Vogel (2015) provide further extensions to the work of Cooley (2013) and Olsen et al. (1998), focusing on water resource applications of the various measures of return period and reliability which we summarize as follows.

Return Periods of Design Events under Nonstationary Conditions

Recall from the previous section on stationary methods that we defined the annual non-exceedance probability associated with a particular flood event as $p=F_x(x)$ along with its associated AEP q=1–p. If flood magnitudes are nonstationary and either increase or decrease systematically through time the exceedance probabilities q, will correspondingly increase or decrease over time to form a series $q_1, q_2, q_3, \ldots, q_t$. Under nonstationary conditions, the time to the occurrence of the next flood t, follows the distribution:

$$P[\tau = t] = f_\tau(t) = (1-q_1)(1-q_2)(1-q_3)\ldots(1-q_{t-1})q_t \tag{78.2.9}$$

Equation (78.2.9) is the PMF of the unconditional waiting time, recurrence time, or return interval until the occurrence of the first flood to exceed the design flood. Equation (78.2.9) describes a nonhomogeneous geometric random variable (see Mandelbaum et al., 2007), which is completely analogous to the homogeneous geometric variable described in Eq. (78.2.1). When the non-exceedance probabilities in Eq. (78.2.9) are all equal, as is the case for stationary series, then Eq. (78.2.9) reduces to the homogeneous geometric result for stationary series in Eq. (78.2.1). Salas and Obeysekara (2014) describe two separate cases that must be treated independently, one in which magnitudes of floods are increasing and one in which they are decreasing. Since increasing floods are the primary concern in hydrologic engineering design and for brevity, we only summarize the case of increasing floods here (see Salas and Obeysekara, 2014; for the case of decreasing floods).

For the case of increasing floods, there will eventually be a year t_{max}, in which the AEP of the flood q_t, is unity so that Eq. (78.2.9) becomes:

$$P[\tau = t] = f_\tau(t) = q_t \prod_{y=1}^{t-1}(1-q_y) \quad t=1,2,\ldots,t_{max} \tag{78.2.10}$$

Similarly, the CDF of the return period τ for the nonstationary case becomes:

$$P[\tau \le t] = F_\tau(t) = \sum_{y=1}^{t} f_\tau(y) = \sum_{y=1}^{t} q_y \prod_{t=1}^{y-1}(1-q_t) = 1 - \prod_{y=1}^{t}\left(1-q_y\right) \text{ t=1, 2,…, } t_{max} \quad (78.2.11)$$

where, $F_\tau(1) = p_1$ and $F_\tau(t_{max}) = 1$. Salas and Obeysekera (2014) describe several possible forms of nonstationarity which have different implications concerning the use of the above expressions and the behavior of t_{max}. If nonstationarity continues and the exceedance probabilities q_t continue to increase, they will eventually reach the upper limit of unity at t_{max}. However, if the exceedance probabilities asymptotically approach unity, or if for some reason the nonstationarity ends, then there will be no upper limit to the distribution of τ in which case $t_{max} \to \infty$.

Analogous to the above expressions, Mandelbaum et al. (2007) introduced the nonhomogeneous geometric probability distribution within the context of birth and death processes. They provide a convenient recursive expression for computing $f_t(t)$ from $F_t(t-1)$:

$$q_t = \frac{f_\tau(t)}{1-F_\tau(t-1)} \quad (78.2.12)$$

where $F_\tau(0) = 0$. Mandelbaum et al. (2007) also show how Eq. (78.2.12) can be used to define the structure of future sequences of exceedance probabilities which arise from various forms of the PDFs $f_t(t)$ and CDF $F_t(t)$.

Analogous to the expressions for the moments of the return period for stationary conditions in Eqs. (78.2.2) and (78.2.3), the PDF of the return period τ in Eq. (78.2.10) can be used to derive the moments of the return period under nonstationary conditions so that:

$$T = E[\tau] = \sum_{t=1}^{t_{max}} t \cdot f_\tau(t) = \sum_{t=1}^{t_{max}} t \cdot q_t \prod_{y=1}^{t-1}(1-q_y) \quad (78.2.13)$$

Cooley (2013) provides a useful computational simplification of Eq. (78.2.13) as

$$T = E[\tau] = 1 + \sum_{t=1}^{t_{max}} \prod_{y=1}^{t}(1-q_y) \quad (78.2.14)$$

Similarly, Salas and Obeysekera (2014) suggest computing the variance of the return period τ using the fact that $Var[\tau] = E\left[\tau^2\right] - E[\tau]^2$ so that

$$Var[\tau] = \sigma_\tau^2 = \sum_{t=1}^{t_{max}} t^2 \cdot q_t \prod_{y=1}^{t-1}(1-q_y) - \left[1 + \sum_{t=1}^{t_{max}} \prod_{y=1}^{t}(1-q_y)\right]^2 \quad (78.2.15)$$

Recall, that under stationary conditions the coefficient of variation of the return period τ is roughly equal to unity for rare floods, so that the mean return period provides an excellent summary measure of the distribution of future return periods.

Parey et al. (2007; 2010) and Cooley (2013) discuss another interpretation of the return period as the number of years one must wait until the expected number of events is unity. Cooley (2013) shows that both definitions are equivalent under stationary conditions. Let N be the number of exceedances that occur in the T years beginning with year y=1 and ending with year y=T. Under stationary conditions, N follows a binomial distribution, but that is no longer the case under nonstationary conditions. Cooley (2013) shows that under nonstationary conditions, when the expected number of flood events to exceed the T year event is equal to 1, T can be computed as the upper limit in the following sum:

$$E[N] = 1 = \sum_{y=1}^{T}\left(1 - F(x,y)\right) \quad (78.2.16)$$

where, $F(x,y)$ is the nonstationary CDF of the AMF series, x, where y represents the year. Read and Vogel (2015) found that for a nonstationary lognormal model, the definition of T in Eq. (78.2.16) led to nearly identical results as the traditional definition of T given in Eqs. (78.2.13) and (78.2.14), for a broad range of hydrologic conditions, thus we do not discuss the definition in Eq. (78.2.16) further.

Risk and Reliability under Nonstationary Conditions

Under stationary conditions, the relationships between the n-year reliability R_n, annual reliability R_a, and planning horizon n are given in Eq. (78.2.6) and between *n-year reliability Rn*, average return period T, and planning horizon n are given in Eq. (78.2.7). Such relations are in widespread usage, thus one expects that analogous relationships could be useful under nonstationary conditions. Salas and Obeysekera (2014) suggest that under nonstationary conditions, the n-year reliability R_n is given by:

$$R_n = \prod_{t=1}^{n}(1-q_t) \quad (78.2.17)$$

As was shown in Section 78.2.1, under stationary conditions, when the AEP is constant, the n-year and annual reliabilities are related via $R_n = R_a^n$.

Use of the Traditional Decision-Making Process under Nonstationary Conditions

Given the tremendous interest in the subjects of climate change, urbanization and their subsequent impact on hydrologic processes, a risk-based decision framework under nonstationary conditions is of vital importance. Perhaps the most common example of nonstationarity in hydrologic design involves impacts of urbanization. See Chapter 132 "Storm Water Management, Best Management Practices, and Low-impact Development" and Chapter 149 "Human Impacts on Hydrology" for further background on deterministic approaches for handling urbanization and other forms of nonstationarity.

Using a traditional decision-making process under nonstationary conditions, a trend is first evaluated for statistical significance separately from the economic project evaluation. First, a hypothesis test is performed and the statistical significance α of the trend is estimated. If α is below some prespecified critical value, usually $\alpha_{critical}$=0.05, the economic analysis is performed to evaluate the economic viability of a proposed flood management plan. If α exceeds the critical value the trend may be dismissed and the economic analysis is often not performed.

Normally, under either stationary, or nonstationary conditions, two possible economic analyses are considered, one which is based solely on an arbitrary design event, such as the 100-year flood, and an RBDM approach which would choose a level of infrastructure to protect against that design event which maximizes the net benefits of adaptation (the estimated damages avoided less the cost of the proposed adaptation). In either case, whether an RBDM approach or a fixed design event is employed, an economic analysis of nonstationary conditions would normally be performed only if a trend was found to be statistically significant. If the analysis concluded that no trend is evident, the consequences of under-preparation would normally, neither be computed nor ever even considered in a traditional analyses. The reminder of this section describes the critical need to adapt existing RBDM approaches for use under nonstationary conditions, because the added uncertainty concerning the existence (or not) of a trend needs to be considered in the RBDM process.

There is a wide range of possible situations which exist relating to uncertainty in future flood projections as well as the myriad of consequences associated with either protecting or not protecting against projected flood damages. A full RBDM analysis is needed in order to integrate all relevant information (both costs and benefits) concerning future regrets which result from various sources of economic, social, natural, and other forms of uncertainty. For example, within a flood control context, "regret" would be defined as the difference between the flood damages corresponding to a particular project design and the minimum damages if one had perfect information about the future. See Rosner et al. (2013) for a nonstationary RBDM analysis which considers the concept of regret. Also see Stakhiv (2011) for a discussion and references to a "no regrets" approach to RBDM in water resources.

A Risk-Based Approach to Flood Management under Nonstationary Conditions

Flood (or drought, or other water resources) management decisions in a nonstationary world are inherently sequential decisions, which depend critically on the uncertainty inherent in future projections of flood scenarios and their corresponding consequences. Nevertheless, there are remarkably few examples of the application of RBDM to nonstationary water resource problems in the scientific literature. There are also very few examples of the use of decision trees under nonstationary conditions. This is particularly surprising because nonstationary decision processes are sequential decision processes which are subject to uncertain economic outcomes, and a decision tree or a stochastic dynamic program are the natural approaches to apply to such decision problems. Fiering and Matalas (1990) provide one of the earliest examples of a sequential statistical decision process for evaluating various alternatives in the context of nonstationarity (climate change). Chao and Hobbs (1997) give a brief history of decision analysis applications to climate change; and apply a mathematical version of a decision tree known as a stochastic dynamic program for evaluating breakwater adaptation under possible climate change impacts on Lake Erie. Hobbs et al. (1997) were the first to apply a decision tree approach to water resources management under climate change, and recently the method has been resurrected (see Gersonius et al., 2013).

A critical challenge in the application of decision trees to the problem of RBDM under nonstationary conditions involves estimation of the necessary probabilities associated with various outcomes (branches of decision tree). Hobbs et al. (1997) demonstrate use of a Bayesian approach to analyzing the necessary probabilities in the decision tree for evaluating alternative adaptation strategies for climate change for the Great Lakes. Similarly, Manning et al. (2009) describe a Bayesian analysis consisting of aggregating predictions from suites of model predictions, such as Global Circulation Models (GCMs) or Regional Climate Models (RCMs).

Another approach for applying an RBDM using a decision tree under nonstationary conditions would be to integrate the uncertainty inherent in projections of future trends. Such an analysis must incorporate the uncertainty associated with our ability to detect changes in flood series. Rosner et al. (2013) introduced an RBDM approach for use under nonstationary conditions, using a decision tree, with the outcome probabilities based on Type I and Type II error probabilities associated with statistical trend hypothesis test outcomes. Their approach integrates numerous considerations including: a nonstationary GEV model of flood frequency, the uncertainty inherent in the trend detection process, natural hydroclimatic uncertainty and a detailed economic analysis associated with the various infrastructure alternatives under consideration. The resulting process enables the decision maker to ask the question when enough information is available to warrant making a particular flood management adaptation decision under nonstationary conditions.

Integration of Trend Detection and Decision-Making

Adaptation planning in the context of flood management under nonstationary conditions depends critically on trend detection and a subsequent trend model; hence, it is important to understand the limitations and concerns surrounding tests of statistical significance of trends. Studies which seek to identify trends in flood series are now widespread. All of the many previous flood studies we have reviewed which have sought to determine whether a trend exists in flood series, have employed a null hypothesis, H_o, of no trend and most have chosen an associated significance level of α=0.05. A significance level of 0.05 implies that if there really is no trend (that is assumption of H_o), we will only (mistakenly) report trends 5% of the time. The societal consequences of making such a mistake is that we will prepare for a trend, when it does not exist, which we term over-preparedness. Shouldn't society also be interested in the likelihood of under-preparedness? Surely there are situations in which society will regret having been under-prepared for consequences of events which could have been avoided. See Vogel et al. (2013) for a complete discussion of this issue.

Null hypothesis analysis, termed Null-Hypothesis Significance Testing (NHST), focuses only on our understanding of conditions of no trend, because all such hypothesis tests were derived under conditions of no trend. Thus the alternative hypothesis, H_A, when trends do exist, is usually ignored along with its probability of occurrence known as the probability of a Type II error which is termed β. The decision matrix for the general trend detection decision problem is depicted in Fig. 78.2. Statisticians would define the term "power" of this hypothesis test as the likelihood of detecting a trend, when it exists. Of particular concern to us are the likelihood of Type II errors, which is both out of our control, and involves significant associated societal consequences because they imply no societal response is necessary when one is warranted (see Vogel et al., 2013).

A true RBDM approach would avoid the need to define a critical value for either the Type I or Type II error probabilities. Numerous fields, including psychology, economics, social sciences, meteorology, and medical research, have called into question the value of NHST tests due to its focus on its dependence upon a single, often arbitrary, significance level (Cohen, 1994; Nicholls, 2000; Ziliak and McCloskey, 2008). Such concerns over the use of NHST are now widespread, though remarkably, none of those studies we have reviewed well on the most important criticism of all, that of ignoring the probability of Type II errors, a concern of paramount interest when one considers societal regret associated with under-preparation against future flood risks.

	No trend (H_o)	Trend (H_A)
No societal response	$1-\alpha$	β **Type II error** (under-preparedness)
Societal response	α **Type I error** (over-preparedness)	$1-\beta$ **Power**

Figure 78.2 Decision matrix for the General Trend Detection Decision Problem, with Null Hypothesis, H_o, and Alternate Hypothesis, H_A, shown.

Concerns about NHST are crucial to the fields of geophysics, climate science, and water resources engineering, where the trend analysis could have an impact on major infrastructure decisions. Remarkably, it is only very recently and rarely that researchers have raised concern over the importance and impacts of Type II errors in the climate and hydrologic sciences (Ziegler et al., 2003, 2005; Cohn and Lins, 2005; Trenberth, 2008; Morin, 2011; Vogel et al., 2013). Some journals have even banned the use of NHST (Trafimow and Marks, 2015). Though many studies have discussed the importance of considering Type II errors in the analysis of trends and other hypotheses, they did not consider the resulting impacts on infrastructure decisions and societal preparedness, as was considered by Rosner et al. (2014) and is discussed below. A Type II error in the context of an infrastructure decision implies under-preparedness, which is often an error which is much more costly to society than the Type I error (over-preparedness) which the NHST focuses on.

The physical implication of a Type I or over-preparedness error in adaptation decisions for flood management is wasted money on unneeded infrastructure. The physical repercussions of a Type II or under-preparedness error, on the other hand, are major flood damages due to inadequate protection. Decision makers are poorly served by statistical and/or decision methods that do not carefully consider both sources of error.

There is a continuing need to acknowledge the tremendous uncertainty associated with our ability to discern trends from other natural phenomenon such as persistence (see Cohn and Lins, 2005) as well as complications due to seasonality, censoring, and other issues (see Chapter 11 in Helsel and Hirsch, 2002). One of the main arguments against Null-Hypothesis Significance Testing (NHST) is its adherence to a single critical value $\alpha_{critical}$ (often chosen equal to 0.05). Use of NHST implicitly places disproportionate emphasis on the Type I error probability α, while the power 1-β is rarely reported, despite the importance of Type II underdesign error probabilities, for example, in flood management applications.

There is very little attention given to the power of trend tests in the water and climate literature. Lettenmaier (1976) first introduced to the water resources literature analytical expressions for the power of a hypothesis test based on ordinary least squares (OLS) linear regression in the context of trend detection in water quality management. Bowling et al (2000) performed a similar analysis to determine the minimum detectable difference or the smallest trend one could discern to be statistically significant. Interestingly, even though exact analytical expressions exist for computing the power of a trend test based on OLS regression we found it quite difficult to locate textbooks or primer papers which document such analyses. This is especially surprising given the widespread use of linear regression for performing trend analyses. Examples of primer papers on the power studies for trend detection based on linear regression are common in the medical sciences (Dupont and Plummer, 1990; 1998) though we could only find a few examples of analytical power studies in the water literature (Lettenmaier, 1976; Bowling et al., 2000; Ziegler et al., 2003; 2005; Vogel et al., 2013; Prosdocimi et al., 2014; Rosner et al., 2014).

Remarkably, of the hundreds and possibly thousands of studies which have examined trends in hydroclimatic variables, we could only find a few studies which computed either the probability of Type II errors or the power. For example, Ziegler et al. (2005) used GCMs to predict trends in annual precipitation on the Mississippi basin, and then performed Monte Carlo simulations to determine the minimum length of record which would be needed to detect trends of those magnitudes. They found that between 82 and 143 years would be required to detect a trend corresponding to Types I and II error probabilities of α=0.05 and β=0.10, respectively. Ziegler et al. (2003; 2005) employed the simple analytical approximation to the power of a *t*-test introduced earlier by Lettenmaier (1976). Morin (2011) performed a similar analysis using Monte Carlo simulations to estimate the minimum magnitude of change in annual precipitation at over 9,000 stations globally, that could be detected over a 50-year period. He reports minimum detectable trends given Types I and II error probabilities of α=0.05 and β=0.50.

Although Vogel et al. (2011) and Rosner et al. (2014) employ a simple nonlinear model (fit using linear regression) to characterize trends in flood levels as a function of time, they and others recommend use of physical covariates for explaining trends in hydrologic processes. More complex trend analyses are possible by incorporating other covariate predictors of the trend such as precipitation (Prosdocimi et al., 2014); climatic indices (Kwon et al., 2008; Steinschneider and Lall, 2015), large scale atmospheric or oceanic spatial fields (Renard and Lall, 2014) and/or trends in other moments (Villarini et al., 2009). Vogel et al. (2011, see appendix) found that an exponential model obtained by relating the logarithm of instantaneous annual

maximum streamflow to its year of occurrence provided an excellent approximation for thousands of river gages across the continental U.S. (See Prosdocimi et al. (2014) for a similar analysis in the United Kingdom.) Even for highly nonlinear trends, OLS regression can often provide a good approximation to trends by employing the ladder of powers to "linearize" the relationship (Helsel and Hirsch, 2002). Helsel and Hirsch (2002) provide a detailed background on trend tests and how to improve their power, given the tremendous challenges associated with distinguishing between trends, seasonality, and persistence. Regression is an attractive approach to modeling trends because it provides a graphical summary display of the results, prediction intervals for trend extrapolations are easily derived, analytical expressions for the Type II error probabilities are available and rigorous statistical tests are available for evaluating overall model integrity and residual behavior.

Yue et al. (2002), Yue and Pilon (2004), Onoz and Bayazit (2003), and Morin (2011) have examined the power of the Mann–Kendall test and other nonparametric trend tests, using Monte Carlo analysis. To our knowledge, no published study has provided analytical expressions for the power of the Mann–Kendall test; however, Kendall reports analytical expressions for the probability distribution of the Mann–Kendall statistic under both the null and alternative hypothesis, so it is surprising that none of the existing water literature exploits that fact. It is also interesting to note that Morin (2011) found that for his particular application, the power results of the linear regression and the Mann–Kendall were nearly identical, though results of only one technique was reported in the paper.

78.3 MULTIVARIATE PROBABILISTIC AND RISK-BASED APPROACHES TO HYDROLOGIC DESIGN

Above, our focus was on hydrologic design when a single hydrological variable could be used to describe the return period or reliability associated with system of interest. Such a univariate framework is useful for many practical hydrologic applications which depend solely on peak flood discharges (e.g., hydraulic design of bridge openings and culverts) or critical low flow discharges. Yet hydrological loads for structural design often depend on multiple hydrological variables that are significantly correlated to each other (see Grimaldi et al., 2011). Common examples include flood risk mitigation problems in which hydraulic routing processes are important, such as in the design of detention/retention basins, as well as dam sluice gates and spillways, where there is a need to characterize the entire flood hydrograph both in terms of flood peak discharges and volumes (see Requena et al., 2014). In reference to such multivariate hydrologic processes, Yue and Rasmussen (2002) concluded that "under a given return period, the flood peak/volume value given by the single frequency analysis is greater than those by the joint distribution. This implies that if one neglects the close correlation between flood peak and volume, and carries out single-variable frequency analysis on flood peak or volume only, the severity of a flood event may be overestimated. If a hydrologic engineering design is based on the results from the single-variable frequency analysis, then this overevaluation will lead to an increased cost. Hence, single-variable frequency analysis cannot provide a sufficient probabilistic assessment of a correlated multivariate event."

In traditional multivariate frequency analyses, correlated variables are modelled using standard bivariate or multivariate distributions (see Matalas and Langbein, 1962; Stedinger, 1983; Hosking and Wallis, 1988; Castellarin et al., 2005). However, this approach assumes (1) the same marginal probability distribution for all variables involved in the analysis and (2) a linear dependence between the PDFs; which have both been shown to be of limited practical applicability (e.g., Favre et al., 2004; Klein et al., 2010). These assumptions can be relaxed by resorting to the use of copula-based distributions (see Chapter 30) which are now widely used in hydrology as evidenced by the expanding literature on floods, precipitation, and droughts (see Genest and Favre, 2007; Zhang and Singh, 2007; Chen et al., 2013; Li et al., 2013; Sadri and Burn, 2014). With no loss of generality we focus on the bivariate case, when the theory of copulas is based on Sklar's theorem (Sklar, 1959):

$$F_{X,Y}(x,y)=\Pr\left[(X\le x)\wedge(Y\le y)\right]=C\left[F_X(x),F_Y(y)\right] \tag{78.3.1}$$

where, $F_{X,Y}(x,y)$ is the joint cumulative distribution function of random variables X and Y, with marginal PDFs $F_X(x)$ and $F_Y(y)$, respectively, and $C:[0,1]^2\rightarrow[0,1]$ is the copula function. Equation (78.3.1) does not require any assumptions concerning the marginal PDFs. The copula function enables the user to represent nonlinear dependencies between variables X and Y, for example, higher extremes more correlated than lower extremes (for details on copulas see Favre et al., 2004; Genest and Favre, 2007; Salvadori et al., 2007).

78.3.1 Return Periods of Multivariate Design Events

The theory of copulas offers a convenient and useful approach for mathematically representing the dependence structure of correlated hydrological design variables without making assumptions about their multivariate structure. The nonparametric nature of copulas is in part why they are now so widely used in hydrology and the geosciences, for the bivariate and multivariate frequency analysis of extreme events (see Li et al., 2012 for wind events, and Corbella et al., 2012 for ocean events and Chapter 30). Still, there is no unique or widely accepted definition of multivariate return periods in the scientific community. While the expected return period is univocally defined in a univariate environment and can be expressed as in Eqs. (78.2.2) and (78.2.13), for stationary and nonstationary processes, respectively, there are several different definitions of expected joint return periods (JRPs) for the multivariate context (see Salvadori et al., 2011; Gräler et al., 2013; Requena et al., 2013; Serinaldi, 2015).

Here we describe the expected JRPs for the bivariate case. The primary return period $T^{\cup}_{X,Y}(x^*,y^*)$ associated with the probability associated with the exceedance of either one of the two variables, that is, the bivariate event $E^{\cup}(x^*,y^*)=[x>x^*\cup y>y^*]$ (OR case), and the return period $T^{\cap}_{X,Y}(x^*,y^*)$ related to the probability of exceedance for both variables, that is the bivariate event $E^{\cap}(x^*,y^*)=[x>x^*\cap y>y^*]$ (AND case). $T^{\cup}_{X,Y}(x^*,y^*)$ and $T^{\cap}_{X,Y}(x^*,y^*)$ can be expressed as follows for annual series of X and Y:

$$T^{\cup}_{X,Y}(x^*,y^*)=\frac{1}{\Pr\left[(X>x^*)\cup(Y>y^*)\right]}=\frac{1}{1-F_{X,Y}(x^*,y^*)}=\frac{1}{1-C\left(F_X(x^*),F_Y(y^*)\right)} \tag{78.3.2a}$$

$$T^{\cap}_{X,Y}(x^*,y^*)=\frac{1}{\Pr\left[(X>x^*)\cap(Y>y^*)\right]}=\frac{1}{1-F_X(x^*)-F_Y(y^*)+C\left(F_X(x^*),F_Y(y^*)\right)} \tag{78.3.2b}$$

For these expected JRP's the following inequalities relative to marginal expected return periods $T_X(x^*)$ and $T_Y(y^*)$ hold:

$$T^{\cup}_{X,Y}(x^*,y^*)\le\min\left[T_X(x^*),T_Y(y^*)\right]\le\max\left[T_X(x^*),T_Y(y^*)\right]\le T^{\cap}_{X,Y}(x^*,y^*) \tag{78.3.2c}$$

Salvadori and De Michele (2004) introduced a secondary return period, or Kendall's return period, in order to identify in a multivariate context a univariate critical threshold (see also Volpi and Fiori, 2014):

$$T_K(t)=\frac{1}{1-K(t)},\ \text{with}\ K(t)=\Pr\left[F_{X,Y}(x,y)\le t\right] \tag{78.3.3}$$

where, $K(t)$ is the Kendall's distribution function associated with $F_{X,Y}$. $T_K(t)$ corresponds to the mean interarrival time of any event $E^t=\left[F_{X,Y}(x,y)>t\right]$, and therefore does not depend on a particular pair (x^*,y^*) and is defined for any value of t.

For a given pair (x,y), the following general inequality holds (see also Gräler et al., 2013):

$$T^{\cup}_{X,Y}\le T_K\le T^{\cap}_{X,Y} \tag{78.3.4}$$

The application of a traditional design event-based approach to hydrological design in a bivariate (or multivariate) context would require the selection of a particular design return period (e.g. 100 years) and definition (i.e., $T^{\vee}_{X,Y}$ $T^{\wedge}_{X,Y}$ or T_K) of the JRP, which results in the identification of an infinite set of events (x,y) in the xy space, that is, the curves illustrated in the examples of Fig. 78.3 (adapted from Requena et al., 2014). The hydrological design would then refer to a single bivariate (or multivariate) event, or a set of events associated with the selected JRP, and, following this rationale, the return level of structural failure would then be assumed to be equal to that of the selected hydrological design events. The literature provides guidelines for selecting multivariate design events (see Salvadori et al., 2011; Corbella and Stretch, 2012; Volpi and Fiori, 2012; Gräler et al., 2013).

However, this approach involves several degrees of subjectivity (e.g., ambiguities in the JRP definitions, infinite events associated with the same JRP, different probabilities of occurrence for these events) and, more importantly, the assumption of equivalence between the selected JRP and the expected return period for the failure of the structure, which may not hold leading to under or overdesigning (see Salvadori and de Michele, 2004; Gräler et al., 2013). The most recent studies for hydrological design in a multivariate context apply a radically different perspective, switching from a design event-based approach to a structure-based approach (see Volpi and Fiori, 2014).

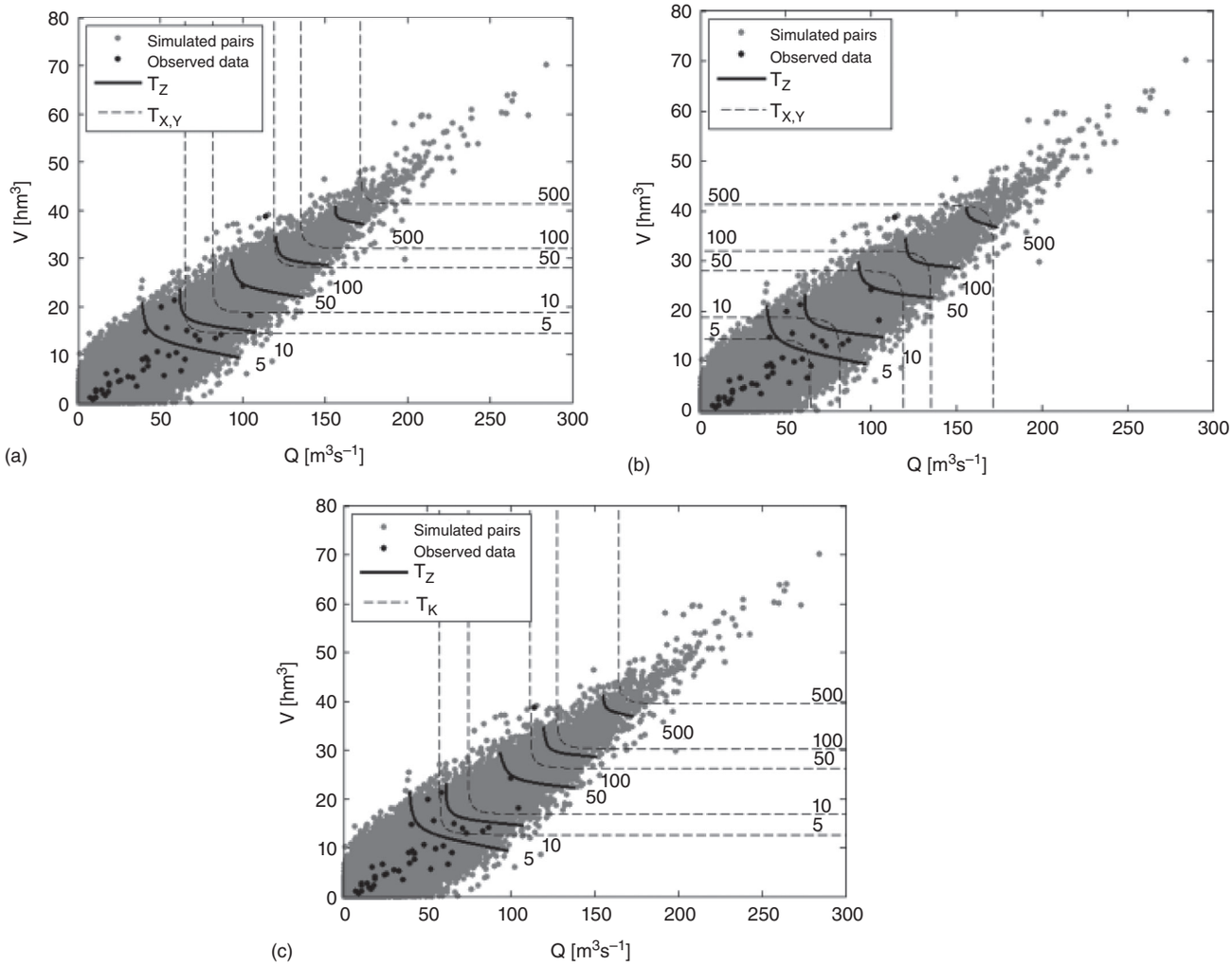

Figure 78.3 Example of multivariate design of a dam spillway as a function of design hydrograph volume, V, and discharge peak, Q: regions in the QV space associated with expected return period of 5, 10, 50, 100, and 500 years according to the definition of the structure-based return period T_Z (Eq. 78.3.6, bold line) and $T^{\vee}_{X,Y}$ (OR case, Eq. 78.3.2a dashed line panel a), $T^{\wedge}_{X,Y}$ (AND case, Eq. 78.3.2b, dashed line panel b) and T_K (Kemdall, Eq. 78.3.3, dashed line panel c) JRPs. [*Source: Adapted from Fig. 10 in Requena et al., 2013, p. 3034.*]

78.3.2 Hydrologic and Hydraulic Design Using Multivarate Events

Following Volpi and Fiori (2014), consider the design parameter Z (e.g., the size of a spillway, the elevation of a levee, etc.) or a quantity related to it, which measures the effects of the hydrological load on the structure; while X and Y are the pair of hydrological variables which identify the hydrological load on the structure (e.g., the peak discharge and the volume of a hydrograph). Let us suppose that Z depends on both hydrological variables X, Y through the structure function $g(.)$, i.e., $Z=g(X,Y)$, which mathematically expresses the interactions among the structure and the hydrological loads acting on it. The PDF of Z can be derived as:

$$F_Z(z)=\int_{D_Z} f_{X,Y}(x,y)\cdot dx\cdot dy, \text{ where} \tag{78.3.5a}$$

$$D_Z=\left[g(x,y)\le z\right] \text{ and } f_{X,Y}(x,y)=\frac{\partial^2 F_{X,Y}(x,y)}{\partial x\partial y}, \tag{78.3.5b}$$

provided that $f_{X,Y}(x,y)$ exists. From Eq. (78.3.5), if $Z>z^*$ determines a structure failure and X and Y are annual hydrological variables (i.e., annual maxima of flood peak and volume), the mean time elapsing between two successive structure failures can be expressed as:

$$T_Z(z^*)=\frac{1}{1-F_z(z^*)} \tag{78.3.6}$$

It can be easily shown that the structure-based and design event-based approaches coincide for the univariate case, i.e., when $z=g(x)$.

According to Eq. (78.3.5) and (78.3.6), calculating $T_Z(z^*)$ only requires identification of the region $D_Z(z^*)=\left[g(x,y)\le z^*\right]$ and evaluation of the above integral. For the sake of comparison, Fig. 78.3 (adapted from Requena et al., 2013) illustrates the infinite sets of bivariate events in the xy space associated with mean return periods of 5, 10, 50, 100, and 500 years, according to definitions Eqs. (78.3.2a), (78.3.2b), (78.3.3) and (78.3.6).

Unfortunately, in many cases of practical interest, the function $g(x,y)$ can be very complex and its evaluation needs to be based on simulated experiments. In those cases, the solution to the multivariate structure-based design can be obtained through Monte Carlo procedures structured as follows (see Requena et al., 2013; Volpi and Fiori, 2014): (1) generate a long series of synthetic pairs (x,y) with joint probability density function $f_{X,Y}(x,y)$; (2) compute the corresponding values of the design parameter $z=g(x,y)$; (3) evaluate the univariate PDF of the design parameter $F_Z(z)$ based on the computed series; and (4) select the design parameter z_T with return level equal to T.

78.3.3 Multivariate Risk-Based Design under Nonstationary Conditions

Multivariate risk-based design under nonstationary conditions is still an open research topic. To our knowledge, the hydrological scientific literature presents only one study addressing this very issue (see Bender et al., 2014). Bender et al. (2014) present a multivariate flood frequency analysis focusing on flood peaks and volumes, Q and V, for a streamgauge of the river Rhine and they show the impacts in terms of AND JRP [i.e., Eq. (78.3.2b)], and associated

design events (q, v), of different hypotheses on the stationarity/nonstationarity of the dependence structure between Q and V, as well as of the position, scale, and shape parameters of the Generalized Extreme Value distributions (see Chp. XXX in this volume) adopted for representing the Q and V marginals.

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