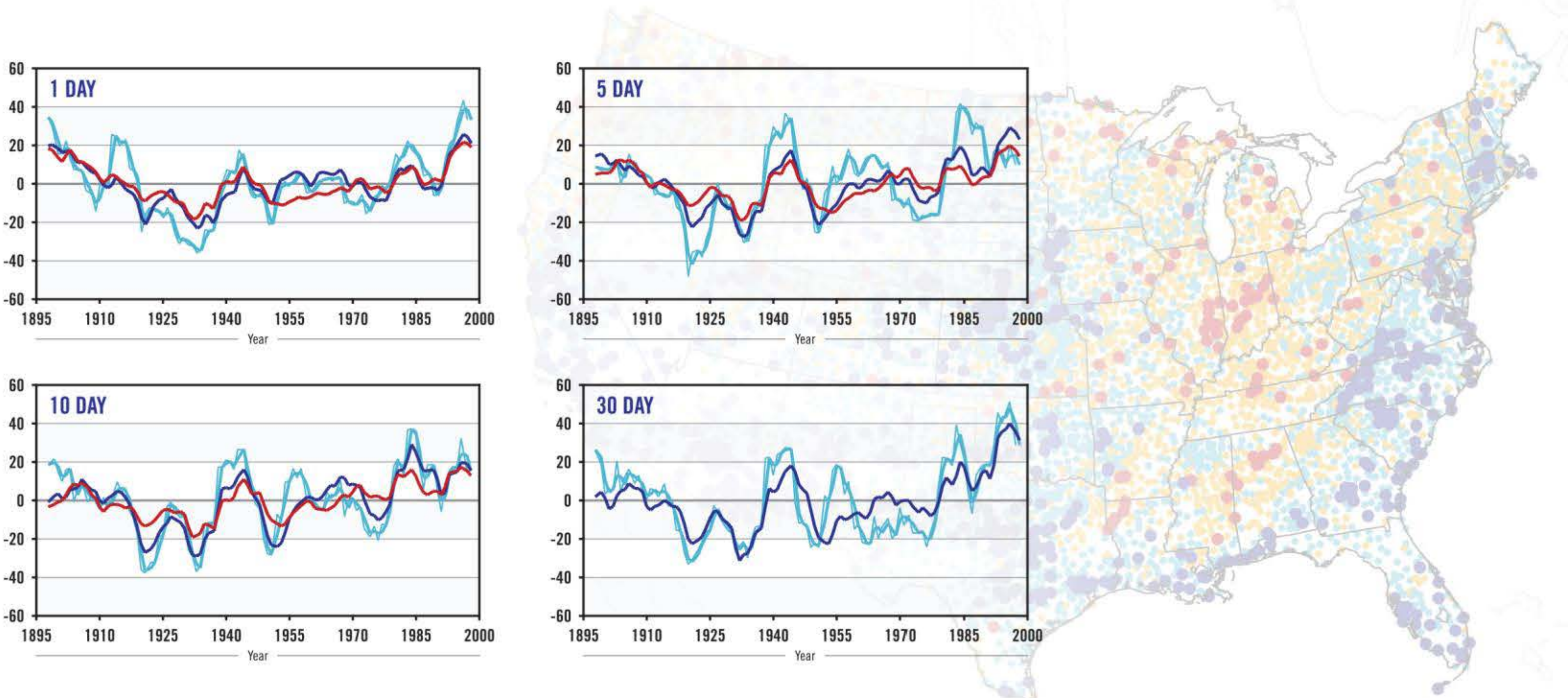
CWTS 2018-01, March 2018

FLOODS AND NONSTATIONARITY:
A Review



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14. ABSTRACT The stationarity assumption suggests that hydrologic processes are stationary through time. It has stood as a critical basis for traditional approaches in the field of hydrologic processes, but may lack fidelity since nonstationarities of various forms have been uncovered in historical, hydrological data.T his report provides a detailed analysis and literature review of work in the field. Specifically, the authors seek to better bound the definitions of stationarities and nonstationarities while exploring the relationships between weather patterns and flooding, simultaneously highlighting the mechanisms that drive nonstationarity variation over time.			
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Floods and Nonstationarity: A Review

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1. Executive Summary

The U.S. Army Corps of Engineers (USACE) manages critical hydrologic infrastructure across the United States, including reservoirs, locks, dams, and levees. To effectively plan, design, operate, and maintain this infrastructure, an accurate characterization of flood risk is essential. Recent research has suggested that the stationarity assumption, which has stood as a critical basis for traditional approaches in this field, may lack fidelity. Though the stationarity assumption suggests that hydrologic processes are stationary through time, nonstationarities of various forms have been uncovered in historical, hydrological data. This has forced researchers and planners to take nonstationarities into account as they move forward with critical activities.

As a whole, this report provides a detailed analysis and literature review of work in the field. Specifically, the authors seek to better bound the definitions of stationarities and nonstationarities while exploring the relationships between weather patterns and flooding, simultaneously highlighting the mechanisms that drive nonstationarity variation over time. This allows for a deeper discussion of trend and long-term persistence (LTP) detection techniques and how these techniques can be incorporated into flood frequency analysis, better accounting for nonstationarities in hydrological data. Through a multi-factored discussion on the impact of future changes on future floods, the authors extend basic concepts of frequency, risk, and reliability under nonstationarity conditions, summarizing how such approaches can be applied in a risk-based framework. For USACE, as well as planners and engineers more broadly, this allows for better informed engineering design to minimize flood risk in light of changing behaviors in hydrological processes and the mechanisms driving these changes.

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2. Introduction and Objectives

The U.S. Army Corps of Engineers (USACE) manages critical hydrologic infrastructure across the United States, including reservoirs, locks, dams, and levees. The planning, design, operation, and maintenance of this infrastructure require an accurate characterization of flood risk and the uncertainty and variability associated with that risk, which are founded on a quantitative estimate of the frequency and magnitude of the floods that could occur at a given location. The hydrologic methods that have traditionally been used for this type of flood risk analysis typically are built on assumptions that past and future floods arise from hydrologic processes largely stationary through time; therefore, the past informs future flood planning, management, and/or risk reduction strategies, as well as the quantitative estimates of frequency and magnitude these depend on. However, changes in land use and land cover, climate, water infrastructure, and other factors can lead to changes in the probability of flooding over time (meaning that hydrologic processes are nonstationary through time). Management of future flood risk therefore requires a general understanding of how nonstationarity in hydrologic processes could affect future flood risk and a set of tools to incorporate nonstationary hydrologic processes into engineering planning and design.

USACE works closely with the other major water resources manager in the U.S., the Department of Interior's Bureau of Reclamation (Reclamation), to understand how changes in hydrologic processes impact water management. USACE has more than 600 dams nationwide and Reclamation has approximately 500 dams west of the Mississippi River. The common missions of the two agencies are hydropower, dam safety and critical infrastructure, water supply, ecosystem restoration and protection, and recreation. USACE has additional federal authorities to act during floods, and both agencies are intensely interested in the issue of nonstationarity as it relates to flood frequency analyses and other aspects of water resources management (Brekke et al. 2009). In January 2010, both agencies, together with the federal interagency Climate Change and Water Working Group (CCAWWG), sponsored a forum for national and international experts to address issues and potential alternatives to the assumption of stationarity in hydrologic frequency analysis. The "Workshop on Nonstationarity, Hydrologic Frequency Analysis, and Water Management" addressed two primary issues: (1) how should water management agencies plan for and operate water resources in nonstationary conditions and (2) how should agencies develop and implement an effective collaborative approach to move forward (Olsen et al. 2010). This workshop led to a special collection of papers on the topic of nonstationarity in the Journal of the American Water Resources Association in June 2011 (Kiang et al. 2011).

This current nonstationarity document and the annotated bibliography accompanying it summarize the state of knowledge on the topic of nonstationarity, adding to the literature other agencies and water resources managers can use. The primary goal of this report is to provide a literature review of methods of hydrologic frequency analysis that can be applied under nonstationary conditions. A secondary goal is to support future technical guidance to be produced by USACE in the future, including:

- Guidance on how to evaluate stationarity versus nonstationarity in hydrologic processes at a particular location
- Guidance on how to account for nonstationary hydrologic processes in both flood frequency analysis and risk-based design of infrastructure
- General hydrologic guidance on how to deal with climate change in the context of flood frequency analysis.

This literature review and the annotated bibliography provide a vital resource for district and other USACE staff, to provide them with expert advice and direction that supplements guidance.

The remainder of this document is organized as follows: Section 2 provides historical context on the topic of nonstationarity for engineering design, as well as definitions of stationarity and nonstationarity. Section 3 describes the relationships between synoptic weather patterns and flooding, including recent advances relating to the impact of climate change and climate variability on extreme precipitation. Section 4 focuses on analytical methods for identifying trends and long-term persistence (LTP) in hydrologic processes due to both stationary and nonstationary processes. Section 5 reviews methods of flood frequency analysis that can incorporate nonstationary hydrologic processes. Section 6 reviews recent research on the impact of future changes in land use and/or climate change on future floods. Section 7 summarizes recent research, which extends basic concepts of frequency, risk, and reliability under nonstationary conditions and summarizes how such approaches could be applied in a risk-based framework.

3. Nonstationarity in Flood Frequency Analysis

A fundamental assumption in flood frequency analysis, and particularly in the *Guidelines for Determining Flood Flow Frequency* (Water Resources Council 1982), is that annual maximum flood discharges are independent and identically distributed (IID) random variables. This assumption implies that the statistical characteristics of the flood data are invariant with time, which enables the use of well-accepted statistical methods to estimate the annual probability of a flood with a specified magnitude or, conversely, the magnitude of a flood with a specified recurrence interval. These statistical representations of flow characteristics are central components of water resource planning and design.

Water resources engineers have always understood, however, that many rivers and streams exhibit temporal patterns that deviate from these assumptions, especially over long timescales and in situations where obvious changes in land use, climate, or infrastructure have caused changes in the distribution of flood discharges over time (e.g., Chow 1964). Some of the most widely invoked causative factors in nonstationarity in flow distributions include urbanization (Villarini et al. 2009a, Vogel et al. 2011, Prosdocimi et al. 2014, Slater et al. 2015 Hecht 2017) and changes in precipitation through time (USACE 2011). However, other potential drivers of nonstationarity have been cited, including changes in river channel capacity (Slater et al. 2015), and groundwater depletion (Hirsch 2011). Hirsch (2011) argued that hydrologists must not lose sight of these many sources of nonstationarity, recognizing that some of these may result in more significant changes than climate change. Using data from more than 400 basins, Slater et al. (2015) documented that changes in flood hazard driven by changes in channel capacity are smaller, but more numerous, than those driven by streamflow. This work demonstrated that accurately quantifying changes in flood hazard requires accounting separately for trends in both streamflow and channel capacity.

In watersheds where the imprint of anthropogenic activities appears in detectable changes in flood discharge records, traditional approaches for hydrologic design may need to be adapted to account for this nonstationarity in hydrologic processes. In particular, we must develop methods to use both historical flood information and current trends through time to estimate the frequency and magnitude of future hydrologic events. Such nonstationary flood frequency distributions will require new approaches to flood frequency analyses (Khaliq et al. 2006, Villarini et al. 2009a), including the integration of nonstationary distributions into a risk-based decision framework (Rosner et al. 2014). Vogel (2011) suggested that nearly every hydrologic method on which our profession is based will need to be adapted to account for the increased uncertainty driven by nonstationarity in hydrologic processes. The notion that "stationarity is dead" is now pervasive, as indicated by over 2,500 citations, to date, of Milly et al. (2008).

However, there are a number of reasons to be cautious in the application of new methods of hydrologic frequency analysis that account for nonstationarity. 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. Matalas (2012) provided 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 argued that "the assumption of stationarity has not yet been pushed to the limit of its operational usefulness in the face of a changing climate." Montanari and Koutsoyiannis (2014), Serinaldi and Kilsby (2015a), and Vogel et al. (2015) argued that there may still be very good reasons to employ traditional methods based on stationary hydrologic processes.

On the other hand, where hydrologic extremes are increasing and this trend is not detected, there is the risk of under-estimating future extremes and under-designing to prepare for them. To protect against this possibility, there is now compelling evidence for the need to consider methods of flood-frequency analysis based on both stationary and nonstationary hydrologic processes. The remainder of this report is devoted to this topic.

3.1 Stationarity Versus Nonstationarity

The terms stationarity and nonstationarity are not uniformly applied or defined in the water resources literature. Milly et al. (2008) described stationarity as "the idea that natural systems fluctuate within an unchanging envelope of variability." Similarly, Salas (1993) stated that "A hydrologic time series is stationary if it is free of trends, shifts or periodicity." Mathematically, given any time series of a hydrologic variable u_t ($t = \ldots, -1, 0, 1, \ldots$) and a cumulative distribution function of any set of n consecutive u's $F(u_{t+1}, u_{t+2}, \ldots, u_{t+n})$, if F is independent of t for all intervals $n > 0$, the time series is strictly stationary (Kendall et al. 1983). Put another way, for a stationary variable, the joint distribution of any set of n consecutive variables is the same, regardless of what subset of the time series is selected.

By extension, nonstationary hydrologic processes can be viewed as processes that do not conform to these definitions. Specifically, Westra et al. (2014) introduced the term ''hydrological model nonstationarity'' as the situation where hydrological model parameters vary in time, and thus depend on the period of record used for their estimation. Note, however, that while the presence of abrupt and slowly varying changes is generally interpreted as an indication of nonstationarity, these changes could also be related to short- or medium-term oscillations within a time series that is stationary overall (Klemes 1974, Potter 1976, Cohn and Lins 2005, Koutsoyiannis 2006) (Figure 3-1). Individual realizations from subsets of a stationary hydrologic time series can therefore exhibit excursions that persist for long time periods. If one considers a deterministic or a statistical-dynamical model for floods, then nonstationarity implies changes in the parameters of that model, not just in the short-term statistics, which could vary systematically, even with fixed parameters.

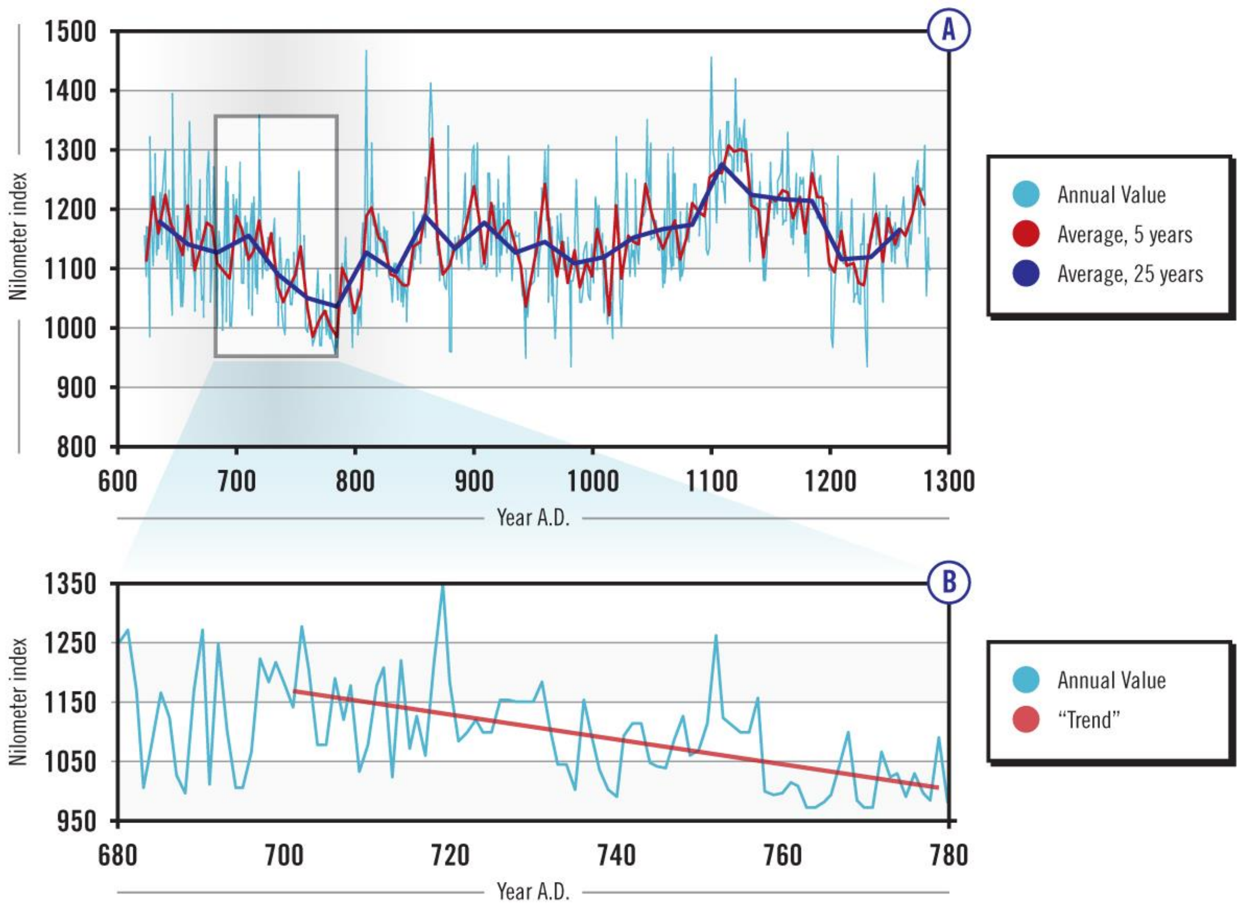


Figure 3-1: Time series that may be stationary overall (top) can contain an apparent nonstationary segment (Koutsoyiannis 2006).

3.1.1 Dynamical Systems Perspective on Nonstationarity

The dynamical systems literature provides another way to understand stationarity. Many nonlinear dynamical systems, including the climate system, admit multiple equilibrium regimes as solutions (Lorenz 1990). The transient response of such systems leads to persistence near one of these regimes, with infrequent transitions to another regime. The result can be long-term or interannual variability in each of these states, such that the statistics associated with the trajectories can vary markedly over time. Such variation in the statistics can occur even though the parameters of the underlying model do not change, and in that sense, the model is stationary. The statistical and the dynamical systems views of nonstationarity are consistent if one considers an infinite sampling horizon, and accounts for the joint distribution of the variables of interest at appropriate lags to capture the transition dynamics.

Under this dynamical systems perspective on nonstationarity, oscillatory or quasi-periodic climate dynamics that influence flood statistics can be considered stationary processes. However, the possibility exists for model parameters or external forcings to change the internal dynamics of a system, potentially changing over time to reach a different set of equilibria.

3.1.2 Functional Nonstationarity

From a purely statistical perspective, because persistent excursions can occur within a stationary process, distinguishing between stationary and nonstationary processes is difficult, and thus selecting a suitable modeling approach to adjust for nonstationarities is also difficult. This problem is compounded when relatively short-duration hydrologic records can make it extremely difficult to distinguish the decadal-scale oscillations resulting from climate variability in many locations from longer term trends (see Section 3). Moreover, the interacting impacts of climate change, urbanization, or other nonstationary factors on an observed hydrologic data set are commonly unknown (Villarini et al. 2009a).

The purpose of fitting a probability distribution to annual peak streamflows for hydrologic design, however, is not necessarily to fully describe their underlying probability distribution but rather to make probabilistic statements about flood characteristics for a future planning horizon or project lifetime in a functional engineering environment. Therefore, the issue is not whether observations arise from a long-term excursion from some underlying stationary process but rather whether the probability distribution of future floods will resemble the distribution that is obtained from fitting a probability distribution to observations over a historical record. Jain and Lall (2001) present an example of how complex, low-frequency variations in climate states can lead to interannual, interdecadal, and longer variations in flood magnitudes that may be predictable, contingent on the predictability of the underlying climate state. In doing so, they demonstrated the challenge of distinguishing stationary from nonstationary behavior, as well as the use of a simple nonstationary model of climate states to improve future predictions of flood frequency.

For the purpose of water resources engineering and management, we define stationary hydrologic time series as those that “fluctuate within an unchanging envelope of variability” (Milly et al., 2008). If a population of floods is stationary by the Kendall et al. (1983) definition (Section 2.1), but the time series is in the midst of a decades-long excursion due to internal climate dynamics, then traditional frequency analysis methods could be extended to other information, such as paleoflood information, to properly constrain and/or interpret the estimates. USACE (2014) describes appropriate methods for use of paleoflood information in USACE analyses. Similarly, if a population of floods is stationary by the Kendall et al. (1983) definition, but a watershed has undergone urbanization over several decades, followed by restoration efforts, traditional frequency analysis methods need to be extended to consider information regarding the impacts of such urbanization and restoration efforts, to properly model the future flood frequency relationships. Figure 3-2 discusses the effect of urbanization on analysis of streamflow.

Aberjona River—Massachusetts

The Aberjona River basin in the Boston metropolitan area has a 74-year record of annual peak flows (1940–2013) that enables a long-term analysis of the impacts of urbanization on floods. Using a data fusion approach that combines recent one-meter-resolution satellite imagery with building construction dates obtained from tax assessor files, Vogel (2017)[6] documented that 26%–34% of the total watershed area is currently impervious, while only 6%–13% of the total watershed area was impervious in 1940. This urbanization has coincided with a statistically significant upward trend in observations of the annual maximum instantaneous streamflow over that same period (see Figure 2 in Vogel et al. 2011). It was also discovered that impervious cover, along with population and housing density proxies of urbanization, have statistically significant correlations with this observed increase in annual maximum instantaneous flows.[1]

Similar to Villarini et al. (2009a), Hecht (2017) argued that in such situations when a watershed has undergone rapid and continuous urbanization over a historical period, estimates of design flood events should be revised to reflect current conditions, including incorporating observed changes in impervious cover (Prosdocimi et al. 2015). Hecht (2017) and Serago (2016) documented approaches for revising estimates of design events to reflect current conditions, when significant nonstationarities have been observed over the historical period. The practice of using indicators of urbanizations as covariates in nonstationary flood frequency analysis was further explored by comparing the impacts of different urbanization indicators (e.g., population density, housing density, impervious cover) on extreme design flood events.[1]

Trend in annual maximum for Aberjona River, Massachusetts. Note log scale on y-axis, and general upward trend in annual maximum streamflows throughout the record (after Vogel et al. 2011).

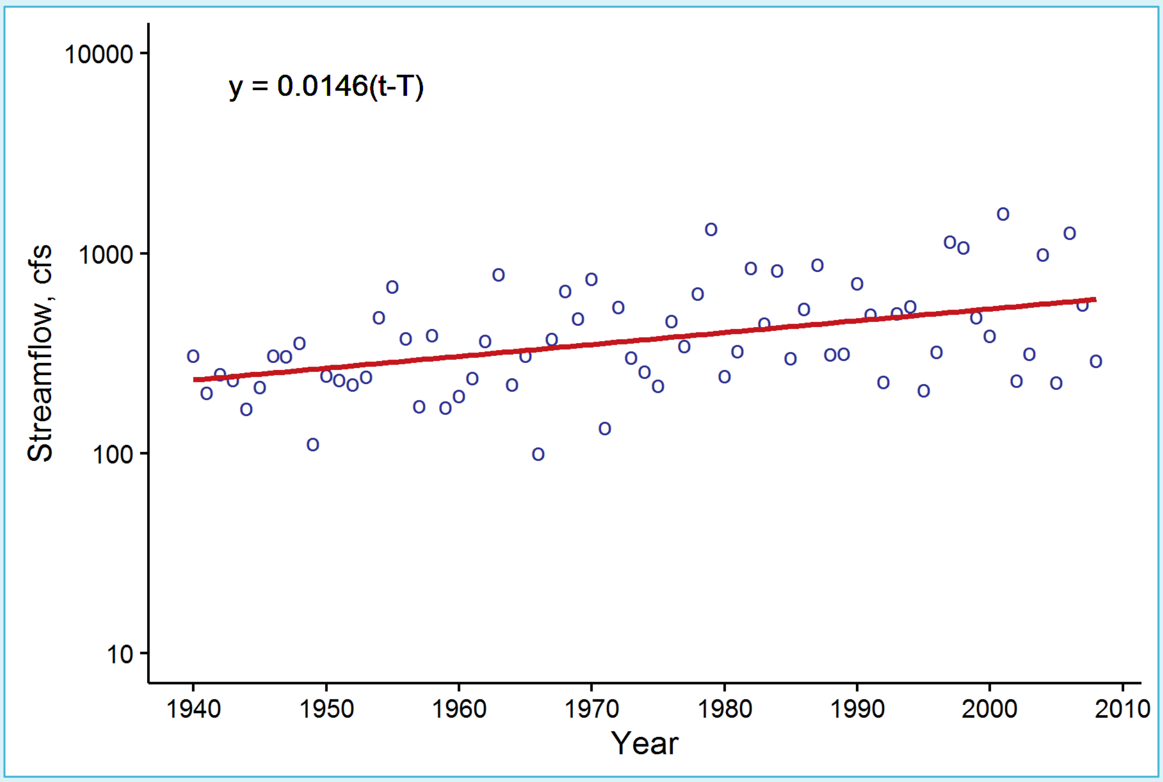


Figure 3-2: Aberjona River—Massachusetts.

6 Vogel, personal communication, 2017.

4. Climate and Floods

To incorporate consideration of nonstationarity into flood frequency analysis, it is important to understand the context in which floods occur and the ways in which apparently stationary climate drivers are changing as a result of anthropogenic climate change and variability. This section summarizes some of the extensive literature on large-scale atmospheric circulation patterns, decadal and multidecadal oscillations in ocean/climate state, and the correlations between these different climate states and flood frequency/magnitude. The key points from this section are as follows:

- Regional flood frequency analysis, even under assumed stationarity, can be improved with information on the scale and nature of atmospheric circulation mechanisms and the surface hydrologic mechanisms that govern floods for watersheds of different size.
- Climate variations over periods of years and decades influence the mechanisms of moisture delivery in a persistent way over relatively large geographical scales.
- Large-scale climate teleconnections that can persist for decades may modulate the mechanisms that lead to changes in flood incidence. Two caveats apply: teleconnections can be difficult to find and trace to effects and are strongly contingent on location.
- Many climatic factors important to global and local hydrologic processes have changed and are projected to change more as a result of anthropogenic carbon-related forcing, and there is significant evidence of changes in extreme precipitation and floods over the last century in many locations.
- In some regions a combination of annual maxima and peak over threshold modeling may be useful to describe flood frequencies, because there may not be a single dominant mechanism driving flooding. However, changes in the mechanisms and their persistence must be explored further to begin to evaluate future projections for regional flood frequency, including seasonal expression.

Hirschboeck (1988) defined *flood hydroclimatology* as the study of the climate context of floods (i.e., an understanding of the long-term variation in the frequency, magnitude, duration, location, and seasonality of floods, as determined by an interaction of evolving regional and global ocean and atmospheric circulation patterns). This definition is broad enough to cover precipitation and storm-surge-induced flooding. Hirschboeck (2003) suggested that *"unusually large floods in drainage basins of all sizes"* may be related to large-scale atmospheric circulation anomalies. Understanding how storm tracks shift may be key to understanding how the frequency, intensity, and location of hydrologic extremes may evolve as climate changes. Hirschboeck's (2003) observation is that meridional moisture transport from the Pacific and Atlantic oceans leads to most of the extreme floods in the continental United States. A number of studies have investigated these linkages (Jain and Lall 2001, Kwon et al. 2008, Lima et al. 2015, Dettinger et al. 2011, Barth et al. 2017).

Later, Hirschboeck (1991), following on a study by Bryson and Hare (1974), reproduced seasonal moisture pathways into different regions of the United States and connected them to the operative circulation systems associated with extreme rainfall and flooding in each season. The key insights from Hirschboeck (1987a, 1988) and Hirschboeck et al. (2000) frame some of the central topics surrounding the linkages between climate and flooding, and include:

1. **Because extreme floods are often associated with blocking ridges and cutoff lows, it is reasonable to expect that drought and flooding may occur in adjacent areas.**

   As an illustration, in the spring and summer of 2011, the Southwest experienced nearly the worst drought since the 1930s Dust Bowl, yet the Mississippi River basin had a significant flood with waves of precipitation hitting different sub-basins as the season progressed.

2. **Floods are fundamentally variable and climatic variations over decadal and longer periods lead to temporal variations in the mean, variance, and other statistics of regional floods (i.e., LTP).**

   Where regime-like behavior in climate exhibits LTP, one may need to account for a heavy-tailed flood distribution (Mandelbrot and Wallis 1968 and 1969, Klemes 1974, Vogel et al. 2011, Koutsoyiannis 2003, Cohn and Lins 2005, Lins and Cohn 2011). Where the regimes are quasi-periodic, because of forcing by El Niño Southern Oscillation (ENSO), the Atlantic Multidecadal Oscillation (AMO), the Pacific Decadal Oscillation (PDO), or other teleconnections, the incorporation of paleoflood information could average out such nonstationarities and be used as an approximation of a stationary flood frequency curve.

   Using both a long streamflow record and a 100,000-year integration of a physically based climate model for ENSO, Jain and Lall (2001) showed that there was structure in climate variability at multicentury scales. Thus, for each record length they considered, including those spanning the typical length of paleoflood records, the frequency with which rare climate extremes estimated from a given period were exceeded in a subsequent period of the same length was inconsistent with what one may expect by chance. The implication is that even without external forcing, the absence of stationarity creates a significant potential for under-design or over-design of flood infrastructure.

3. **Internal variability of the climate system can lead to multiple equilibrium solutions for the same forcing that may persist and lend a regime-like structure to atmospheric circulation, which may in turn lead to the persistence and nonstationarity of flood regimes.**

   A number of recent studies demonstrate the importance of climate regime-like structure in flood risk for the United States. Nakamura et al. (2013) demonstrated that the 21 most extreme historical floods in the Ohio River basin were associated with a persistent, large-scale atmospheric circulation pattern that funnels moisture from the Gulf of Mexico into the region. This circulation anomaly, rather than a moisture anomaly, was identified as the driving factor in these floods. Lavers and Villarini (2013a) examined the annual maximum flood peak records from 1979 to 2012 over the central United States and showed that the majority of the flood peaks over large areas of the study region, as well as the most intense ones, are associated with atmospheric rivers (narrow regions of strong water vapor transport). They also showed that these events are associated with characteristic pressure patterns, with high-pressure systems over the Gulf of Alaska and the U.S. East Coast, and a positive phase of the North Atlantic Oscillation (NAO). Knox (2000) pointed to abrupt changes in flood frequency in the Upper Mississippi and Colorado River basins over the Holocene epoch, associated them with key atmospheric circulation patterns, and noted that the increased incidence of floods in these regions corresponds to periods with relatively rapid climate change over the Holocene.

   Wilby and Quinn (2013) used the Lamb weather types for Great Britain, which classify synoptic weather patterns in the region, to explore the incidence of extreme floods for each Lamb weather type for 1871–2011. Similar work has been conducted for Germany by Petrow et al. (2009) and Prudhomme and Genevier (2011) for Europe. Wilby and Quinn (2013) found that flood recurrence in Britain exhibits decadal to multidecadal variability, with increased incidence of flooding between 1908 and 1934, 1977 and 1988, and from 1998 on. They found that five weather types account for 68% of flood occurrence, with three of these weather types associated with widespread winter floods. The mean frequency of occurrence of these flood-associated weather types does not show changes since the 1930s, but there is a trend toward declining persistence and increased precipitation associated with the anti-cyclonic weather types. A similar classification of weather types is currently not available for the United States, though it may useful for improving process-driven attribution of changes in flooding.

4. **In certain regions of the United States where multiple causal mechanisms are active, mixture distributions identified by Hirschboeck (1987a, 1987b, 1988) may be more appropriate for modeling floods and, as a result, climate change may be expressed in floods through shifting probability distributions of atmospheric regimes.**

   Hirschboeck (1987b) and Hirschboeck et al. (2000) discussed the spatial and temporal scales of meteorological phenomena and associated floods. Macroscale or synoptic scale circulation features develop over dozens of hours to many days and cover large regions. Specifically for catastrophic floods, Hirschboeck (1987b) provided a classification of circulation and precipitation mechanisms and scales for the United States that extends schemes originally proposed by Maddox et al. (1979, 1980). The associated features may be recurrent, covering a regional scale such that different parts of a large basin may experience heavy rain in waves, thus pre-conditioning the system for extreme flooding. Mesoscale processes may have relatively short durations and smaller areas of intense impact. The two scales may be linked through mesoscale convective complexes, such as those that form typically in the Midwest over the summer. As the larger scale circulation patterns increase in intensity, warm, moist, low-level jets, tropical storms, extratropical cyclones, and fronts become important. These have much larger scale, preferred travel directions that intersect with the orientation of drainage basin topography and duration.

   Finally, macroscale systems may be nearly hemispheric in scale and are associated with stationary fronts and blocking patterns that may persist for days. Particular phenomena of interest include (1) monsoonal circulations at subcontinental scales, and (2) pronounced wave patterns that interact with transient eddies or waves that lead to filamentary moisture transport from the tropics to the mid-latitudes. The latter were termed tropospheric rivers by Newell et al. (1992) and Newell and Zhu (1994) and have been replaced, more recently, by the terms “moisture conveyer belt” and “atmospheric rivers.” Figure 4-1 discusses atmospheric rivers.

Atmospheric Rivers, Tropical Cyclones and Flooding

Dettinger (2011) indicated that most historical floods in California are associated with atmospheric rivers (ARs). He analyzed the frequency and intensity of AR-related storms that occurred on the West Coast in historical data and in the seven Intergovernmental Panel on Climate Change (IPCC) general circulation model (GCM) simulations corresponding to the A2 Greenhouse Gas (GHG) Scenario that assumes increasing carbon dioxide (CO_2) emissions through the 21st century. He found that while average AR intensities do not change much in the projections, the models projected increased clustering of ARs in some years, increased total water vapor transport per AR, and notable increases in the transports of the very largest AR storms, all factors that portend an increase in severe flooding in California. ARs are thought to account for about 80% of historical floods in northern and central California (Dettinger and Ingram 2013) and significant peak floods in western Washington State (Neiman et al. 2011). Steinschneider and Lall (2015) developed an analysis of nonstationary precipitation extremes in California that included information on ARs for risk estimation. Related work is discussed in Dettinger et al. (2009, 2011). Lavers and Villarini (2013b) attributed much of the extreme winter/spring precipitation over Northern Europe to ARs. Lavers and Villarini (2013a) also found a strong relation between ARs and flooding over large areas of the central United States.

Villarini and Smith (2010) showed that there are large areas east of the Appalachian Mountains and Florida for which tropical cyclones (TC) are responsible for a significant fraction of the annual maximum flood peaks. Using the shape parameter of the generalized extreme value (GEV) distribution as a measure of tail thickness, they also showed that TCs control the upper tail of the flood peak distribution over these areas. These results are consistent with the findings by Waylen (1991) for Florida. Villarini and Smith (2013) extended their analyses to Texas and found that TCs are responsible for up to 20% of the annual maximum flood peaks along the coastal region. However, they are not associated with the largest flood events to the same degree found for the eastern United States. Kunkel et al. (2010) found that the contribution of North Atlantic TCs to heavy rainfall has been increasing over time. These results were then generalized by Villarini et al. (2014), who highlighted the regions of the United States that are more susceptible to large flooding from TCs.

Rainfall and flooding associated with tropical cyclones is not just a coastal issue, and it is not only of interest to the eastern United States. Galerneau et al. (2010) provided a climatology of predecessor rain events (PRE) over the 1995–2008 period (see also Moore et al., 2013). PREs are areas of heavy rainfall accumulations located about 1,000 km poleward of TCs. Rowe and Villarini (2013) examined the role of PREs as flood agents over the central United States. They showed that PREs can cause annual maximum flood peaks over large areas of the central United States, and flood peaks in excess of the 10-year flood peak. Moreover, PREs have been responsible for extensive flooding over some of the largest U.S. midwest metropolitan areas, including Chicago and Detroit.

Example of ARs in the Pacific Ocean, as simulated by reanalysis and GCM projections. These ARs are thought to be responsible for many of the extreme precipitation events in the western United States. Colors represent water vapor and vectors represent 925-mb wind field (Dettinger, personal communication, 2016).

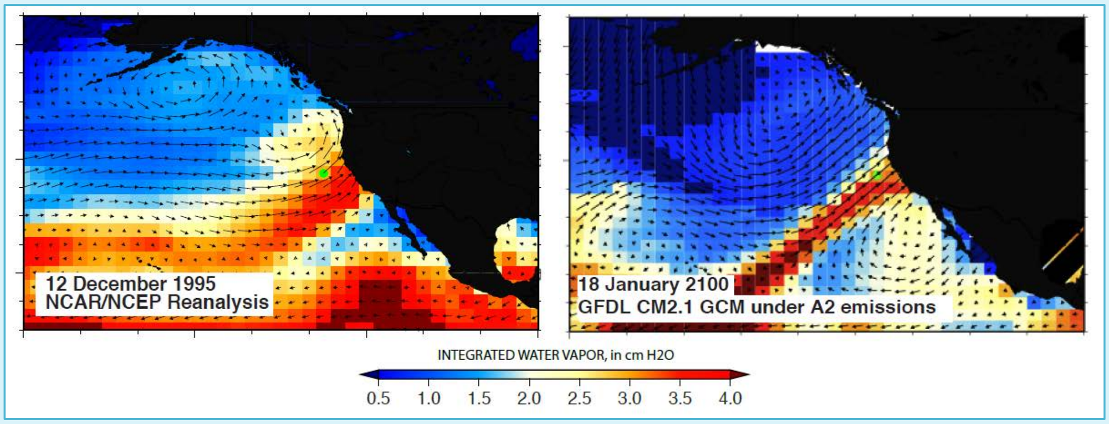


Figure 4-1: Atmospheric Rivers.

4.1 Role of ENSO and Other Teleconnections

The ENSO phase, as well as other large-scale teleconnections, modulate the occurrence of flooding in the United States, and as such, deserve some overview here. For example, Cayan et al. (1999) found a relationship between the ENSO phase and precipitation and flood/drought occurrence in the western United States. The response of streamflow to ENSO was clearer than that for rainfall, reflecting both the spatial averaging and integration of the signal in streamflow and the temporal persistence of the ENSO modulation relative to short-duration precipitation events. Pizarro and Lall (2002) used rank and raw correlations together to analyze the relationships between annual maximum floods and ENSO/PDO phases at 137 U.S. Geological Survey (USGS) Hydro-Climatic Data Network (HCDN) stations in the western United States. Their results indicated variable correlation of ENSO indices with regional hydrologic variables. Pizarro (2006) extended this work to nonlinear seasonal forecasts of flood potential at the same sites.

Andrews et al. (2004) analyzed the relationship between annual maximum floods in California and the Multivariate ENSO Index (MEI). Their results suggested that the general state of ENSO rather than the specific values of the MEI may influence changes in the underlying flood probability distribution. In Northern California (north of latitude 41ºN), the annual maximum flood was approximately 30% lower during an El Niño year than during non-El Niño years. They attribute the north-south variation in flood magnitude along the California coast during El Niño and non-El Niño conditions to the shift in the location of the polar jet relative to the coastline. The eastward extension, the southward displacement, and the rotation of the polar jet during the November–March period during El Niño conditions (Masutani and Leetmaa 1999) lead to tropical moisture being funneled to a more southern location associated with a more pronounced meridional flow.

Zhang et al. (2010) explored the effect of the ENSO, PDO, and NAO indices on 1-day and 3-day winter extreme precipitation over North America using composites of these indices and covariates in a GEV regression model. They found statistically significant relationships between the GEV parameters and the climate indices (Figure 4-2). They extended their analysis to consider how the probability of a 20-year return period precipitation event changes under La Niña and El Niño conditions, and show that over much of North America there is a strong relationship between the probability of a 20-year event and the ENSO index. They also found that the PDO broadly modulates extreme winter precipitation across the region, but that the areas with the strongest impacts are different from those for ENSO. This suggests that at least in certain areas, the joint influence of PDO and ENSO may be important for winter precipitation extremes. Bracken et al. (2015) evaluated relationships between large-scale climate regimes and streamflow in the upper Colorado River basin. Other authors have reported similar relationships between extreme flows and climate indices such as the PDO and ENSO at other locations worldwide (Antico et al. 2014, Vasiliades et al. 2015, Bennett et al. 2015, Li and Tan 2015, Lima et al. 2015).

Cool colors = positive values; hot colors = negative values. Data indicate that winter peak flows are related to ENSO cycles, which could lead to an appearance of nonstationarity in short climate records (after Zhang et al., 2010).

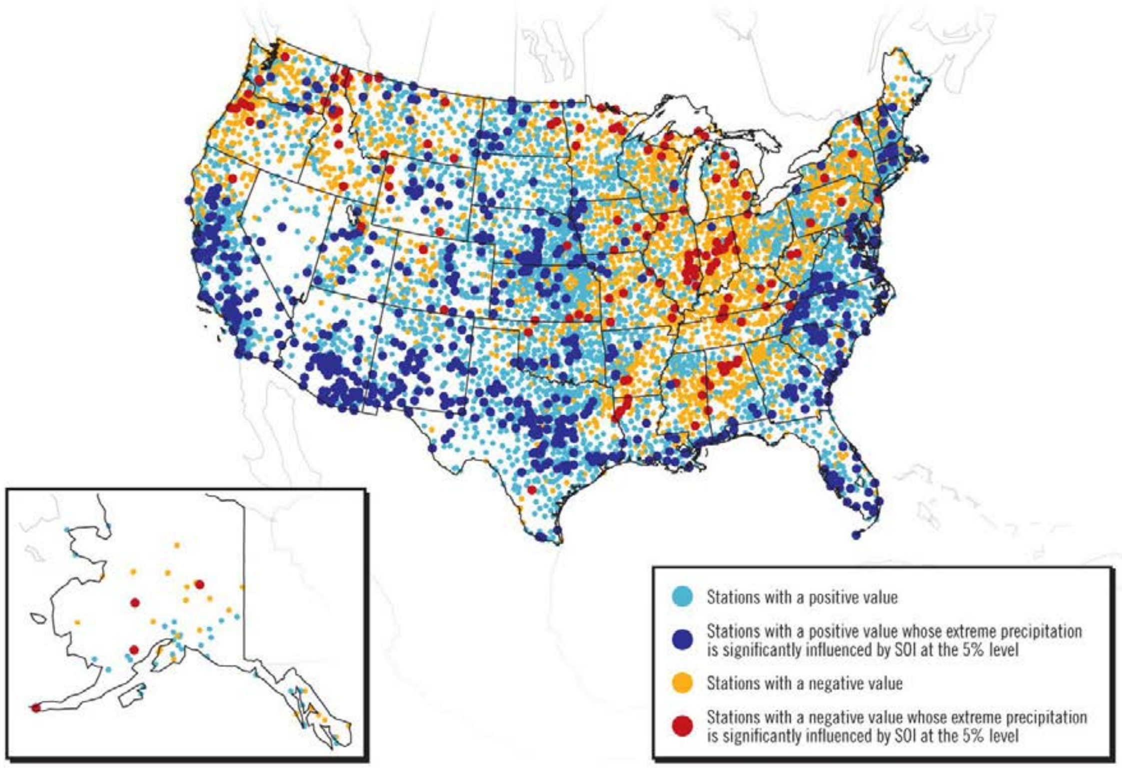


Figure 4-2: Difference in winter maximum daily precipitation between El Niño and La Niña years.

Kiem et al. (2003) and Micevski et al. (2006) investigated flood data from the east coast of Australia (94 stations from Queensland and New South Wales) for stationarity and concluded that floods are modulated by ENSO and the Inter-Decadal Pacific Oscillation (IPO). The IPO is derived in a manner similar to the PDO used in the Northern Hemisphere and has a similar multidecadal timescale. The effects of the IPO on flood magnitude for a given return period are magnified as one moves to higher latitudes, similar to the PDO impact in the United States. Corresponding shifts in the position of the Intertropical Convergence Zone (ITCZ) and the South Pacific Convergence Zone (SPCZ) are identified as supporting the basis for a climate-driven argument to explain the inter-decadal variations in the flood regime. Mondal and Mujumdar (2015) found that nonstationary distributions of extreme precipitation were modulated by large-scale processes such as ENSO.

4.2 Mixture Models

Although there is substantial evidence for broad correlations between flooding and large-scale teleconnections, flooding in many cases is driven by a much more complex mixture of atmospheric conditions. Smith et al. (2011) noted that floods in the eastern United States come from a mixture of landfall-based tropical cyclones and extratropical systems (see also Villarini and Smith 2010). They noted that the importance of tropical cyclones varies across the region, that clustering of tropical cyclone incidence is a factor, and that they can impact a large fraction of the sites when they occur. However, they also noted that extratropical cyclones in the winter/spring, coupled with orographic lifting and steering, can be significant factors in regional flood generation. Clustering of heavy rainfall events was analyzed using a nonhomogeneous Poisson process model with NAO, AMO, and ENSO climate indices as covariates. Modest evidence was found for the influence of these factors in modulating the incidence of extreme precipitation at a regional scale: the AMO, NAO, and ENSO were detected as significant in 11, 7, and 8 stations out of 38, respectively. They noted that spatial correlation in event precipitation is an important consideration, and needs to be modeled formally in stochastic models of flood generation. A similar analysis by Villarini et al. (2013a) using Cox regression showed that the Pacific/North American (PNA) pattern and NAO indices as surrogates for Pacific and Atlantic climate variability are significant modulators of the frequency of occurrence of floods over a threshold, and that antecedent rainfall is an important covariate as well. They also noted that it is possible that these climate indices are related to the rainfall process, and that their collinearity with rainfall should be examined more fully. In a later study, Mallakpour and Villarini (2016) found that PNA was a major factor in heavy precipitation in the Central US through its impact on moisture transport.

Grego and Yates (2010) considered finite mixtures of distributions for flood frequency estimation and used expectation maximization algorithms to estimate the mixing parameters. Shaw and Riha (2011) examined floods in the eastern United States in terms of the causative factors—annual maximum rainfall, annual maximum snowmelt, and occurrences of moderate rain on wet soils. They analyzed each factor separately and derived a compound distribution across these three types of events. This step is in the direction of connecting to climate mechanisms, but it is not pursued that far. Shaw and Riha (2011) found that even though there may be changes in the flood potential for an individual mechanism, often these may not be significant in the annual maximum flood frequency across the different types of events. They caution that it may not be fruitful to look at only GCM precipitation trends and extrapolate those results to conclude that humid, cold regions in high latitudes will see extensive changes in flooding due to increased rainfall intensities.

A range of mathematical techniques have been used to correlate flood probability to these mixtures of climate drivers. Waylen and Woo (1982) and Schuster and Yakowitz (1985) were among the first to propose modeling of probability density mixtures for flood frequency analysis. As an alternative to modeling mixtures that may arise from different climate or hydrologic mechanisms, Moon and Lall (1994) motivated the use of kernel quantile function estimators that could directly model heterogeneous quantile functions. Apipattanavis et al. (2010) presented an improved nonparametric flood frequency estimator using local polynomial regression applied to the empirical quantile function. They showed that the method is competitive with traditional parametric and mixture distribution methods for quantile function estimation with synthetic and actual streamflow data.

5. Change Detection, Attribution, and Hydrologic Design Under Nonstationarity

Changes in hydrologic processes may occur either abruptly or gradually, depending on the characteristics of the factors that influence those processes (McCuen 2003, Chandler and Scott 2012). For example, changes in water regulation caused by the construction of a dam would abruptly change downstream hydrographs; such changes are easily measured. Similarly, ongoing urban development within a watershed would gradually alter the shape of resulting flood hydrographs over time (Vogel et al. 2011). Statistical methods have been developed to detect a wide range of such hydrologic changes. However, as previously discussed, it is often very difficult to distinguish gradual trends from LTP in hydrologic records due in part to the limited length of those records. It is also difficult to distinguish systematic trends, whether they are abrupt or gradual, from either LTP or low-frequency variations because of internal climate dynamics. In the following section, we review recent advances in the detection of change.

5.1 Analysis and Detection of Change

Kundzewicz and Robson (2004) highlighted four main tasks when examining the presence of changes in hydrological records: data preparation, exploratory data analysis (EDA), application of adequate test statistics, and interpretation of the results. Data preparation is an often overlooked but fundamental part of any study dealing with the detection of possible changes in historical records. Key factors to consider are the quality of the data, changes in measurement techniques or instrumentation through time, presence of gaps and missing data, and the frequency with which data are collected. It is also important to focus on records with long, preferably continuous records, to place any observed recent changes in context with what has been experienced in the past (Blöschl and Montanari 2010, Hirsch 2011).

EDA uses exploratory graphical displays (Helsel and Hirsch 2002) to identify problems with the data, to identify slowly varying or gradual changes, and possibly spatial patterns in the data when analyzing multiple time series. EDA is particularly challenging when examining changes in flood frequency at hundreds of locations, though Helsel and Hirsch (2002) provided several alternatives, including the use of scatterplot smooths, polar smooths, Chernoff faces, stiff diagrams, piper diagrams, and rotated scatterplots. Other attractive approaches include the Multiple Taper Method with Singular Value Decomposition (MTM-SVD) (Rajagopalan et al. 1998), as well as multiwavelet analysis or principal component analysis (Helsel and Hirsch 2002).

After EDA, formal statistical analysis can begin. Typically, hypothesis tests for trend detection employ a null hypothesis that there is no trend in the time series, and an alternative hypothesis that there is a trend. The likelihood of rejecting the null hypothesis, when it is true, is known as the probability of a type I error, which is defined as α. Of critical importance for water resources planning is the probability of a type II error, ß, which corresponds to the likelihood that we will conclude there is no trend, when in fact a trend exists. Vogel et al. (2013) and Rosner et al. (2014) referred to the probability of type I and II errors as the probability of over- and under-design, respectively. For example, if an upward trend in flood magnitudes exists but is not identified (a type II error), flood control structures might be built too small to withstand a future extreme event (under-design). Although we seek the probabilities of both type I and type II errors to be as low as possible, the short records inherent in most hydrologic investigations often lead to a much higher occurrence of type II errors than expected. The causes and consequences of type I and type II errors are discussed in more detail in Section 4.4.

There are two general types of hypothesis tests to consider: parametric tests and non-parametric tests. When using parametric tests, we assume an underlying probability distribution for the hydrologic process of interest, which leads to a test statistic that also has a known probability distribution. Non-parametric tests, on the other hand, do not make assumptions regarding the statistical distribution of the hydrologic process of interest. The disadvantage of using non-parametric rather than parametric methods is that they are less powerful in detecting type II errors than the parametric alternatives, when the parametric model is plausible (see Helsel and Hirsch 2002, for examples). There are cases, however, where this loss of power is minimal, with the large advantage associated with the nonparametric methods of having less-restrictive assumptions (Helsel and Hirsch 2002, McCuen 2003, Kottegoda and Rosso 2008).

Here we focus on tests that allow for the detection of abrupt (Section 4.1.1) and slowly varying monotonic changes (Section 4.1.2). For those interested in the detection of cyclical changes, the Noether's test (Noether 1956, McCuen 2003) can be applied.

5.1.1 Detecting Abrupt Changes (Change Points)

Over the years, different hypothesis tests for change points have been proposed, as summarized by Reeves et al. (2007), and Beaulieu et al. (2008, 2012). Among the existing non-parametric change point tests, the Pettitt (1979) test is widely used in the literature. It is based on the Mann-Whitney test and enables testing whether two samples come from the same population or not. It is designed to detect a single abrupt change in the mean of the distribution of the variable of interest at an unknown point in time. It is also possible to compute the statistical significance of the change, as described in Pettitt (1979). Xie et al. (2014), Mallakpour and Villarini (2015a), and Serinaldi and Kilsby (2015b) reviewed the general performance of the Pettitt test for its ability to detect change points. A generalization of the Pettitt test is represented by the non-parametric Lombard test (Quessy et al. 2011). This test allows the detection of both abrupt and linear changes in the mean of the distribution of the variable of interest using the Wilcoxon score function. The Lombard test has been recently applied to flood and drought records (Assani et al. 2011, Mazouz et al. 2011, Villarini and Smith 2013).

The Bai-Perron test (Bai and Perron 2003) is a parametric test for change points that can be particularly useful because of its high degree of flexibility. This test assumes that the data are generated from a distribution belonging to the exponential family (e.g., gamma, exponential, Gaussian) and allows the detection of multiple change points at unknown points in time. The number of change points is selected using the Bayesian Information Criterion (BIC) (Schwarz 1978) as the penalty criterion. Other proposed alternatives to the Pettitt test include the use of variable fuzzy sets (Li et al. 2014), and a cumulative sum (CUMSUM) approach combined with a bootstrap test (Li et al. 2015). These methods have been applied to rainfall and runoff time series from northeast China, and the former method was shown to produce similar results to the Pettitt test.

The majority of the published studies examining the presence of abrupt changes in data series focus on changes in the mean of the distribution of the variable of interest. Much less attention has been given to whether abrupt changes occur in the variance of a variable of interest, even though changes in variance could have large impacts on water resource planning (e.g., if the tail of the distribution broadens; Katz and Brown 1992, Knox 1993, Meehl et al. 2000, Ferro et al. 2005). Note that for many distributions, any trend in the mean of the series will imply a trend in the variance of the same series. For example, for a lognormal variable x, one of the most common probability distributions in hydrology, a simple linear trend in the logarithm of y implies an exponential trend in both the mean and variance of x. An exponential trend has been found to provide a good fit to annual maximum series of both precipitation (Gilroy and McCuen 2012) and streamflow (Vogel et al. 2011, Prosdocimi et al. 2014).

Perreault et al. (2000) proposed a Bayesian change point test for the detection of abrupt changes in both the mean and the variance under the assumption that the data come from a Gaussian distribution. Villarini et al. (2009b, 2011a, 2011b, 2012; Figure 5-1) and Villarini and Smith (2010) applied the Pettitt test to the squared residuals with respect to a trend line to detect abrupt changes in the second moment of the flood peak distribution. The Lombard test can also be used to detect abrupt changes in the variance at an unknown point in time. USACE has developed a web tool for the detection of nonstationarities in annual maximum flow that uses a number of the statistical tests described above (Friedman et al. 2016, USACE 2017).

Underlying synthetic data have a change in mean from 10 to 12 at count = 50. Change points are most commonly detected using the Pettitt test (after Villarini et al. 2009b).

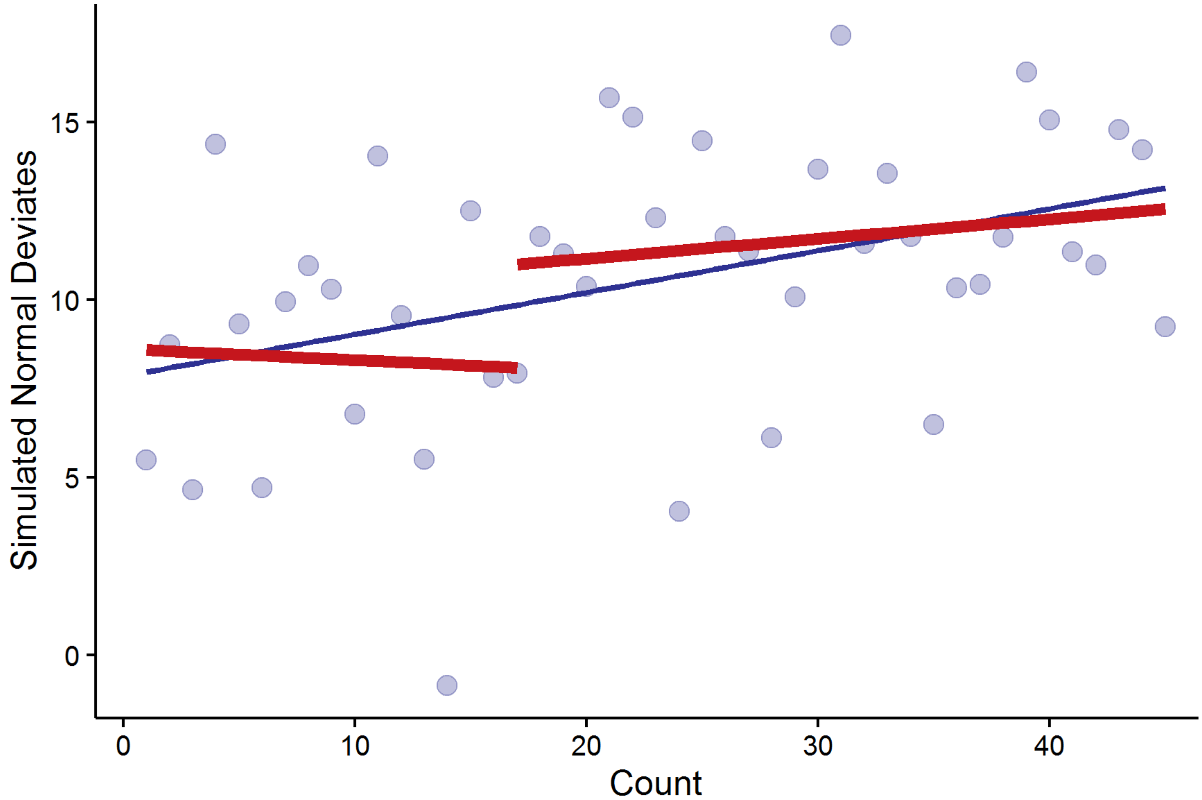


Figure 5-1: Impact of a change point on the trend analysis for a synthetic series of data.

Quessy et al. (2011) highlighted some of the difficulties in detecting abrupt changes in the second moment. Even though changes in higher moments may have even more dramatic effects on the extremes, their detection is complicated by the limited sample sizes normally encountered in practice. An alternative approach is to examine changes in the exceedance probability of a nominal quantile (Jain and Lall 2000, Sankarasubramanian and Lall 2003, Khalil et al. 2007), allowing a direct assessment of the changes in the tail of the distribution. Overall, the detection of abrupt changes in higher moments has received very little attention by the hydrologic community, despite the large impacts these shifts may have when dealing with extremes.

5.1.2 Detecting Monotonic Changes

The detection of monotonic patterns is generally performed using the Mann-Kendall and Spearman tests (Helsel and Hirsch 2002, McCuen 2003, Friedman et al. 2016). These are non-parametric tests to detect the presence of temporal patterns in the records and often exhibit similar power against common hydrologic alternative hypotheses (Yue et al. 2002). While the attention here is on monotonically increasing or decreasing patterns, we acknowledge that other more complex patterns may better describe the data (Hall and Tajvidi 2000, Ramesh and Davison 2002, Mudelsee et al. 2003, Villarini et al. 2009a, 2010).

The presence of linear trends is often tested using Pearson's correlation coefficient and/or linear regression. Two often-quoted limitations of linear regression are that it only allows the detection of linear trends, and that the significance of the results relies on the assumption that the residuals from the linear model follow a Gaussian distribution. Despite these limitations, there are several advantages of linear regression that make it an attractive choice for the detection of monotonic trends (Hecht 2017):

- If a linear model results in a plausible model of the trend, this model can potentially be useful for prediction purposes.
- Even for highly nonlinear trends, ordinary, weighted, and/or generalized least squares regression can often provide a good approximation by employing the "ladder of powers" to linearize the relationship. Helsel and Hirsch (2002) provided a guide to selecting appropriate (and possibly different) power transformations of the variables of interest to achieve linearity. Suitable transformations can usually be found to ensure linearity of the regression model and normality of the associated model residuals, an assumption needed for statistical inference on model coefficients and model predictions. In this case, retransformation biases need to be accounted for.
- Prediction intervals are easily computed for trend extrapolation and such intervals are of critical importance in water resource planning investigations (see Section 5.3 for a discussion of the limitations and issues associated with extending trends for predictions).
- Analytical expressions for the probability of a type I and II errors are available, which are of critical importance to risk-based decision making (Rosner et al. 2014).
- As shown recently by Hecht (2017), the use of heteroscedastic regression enables the development of a parsimonious model of both the mean and variance of the variable of interest, using only the regression model parameter estimates from the trend model of the mean.
- Matalas and Sankarasubramanian (2003) provided simple analytical formulas for correcting for the impact of persistence on the significance of trend tests based on regression.

As discussed in Section 7, an understanding of changes in the annual exceedance probability associated with future hydrologic events is of critical importance to hydrologic design and planning under nonstationary conditions. Given the importance of extremes in this context, an alternative to linear regression is to move away from examining trends in the quantity of interest (e.g., discharge) in favor of trends in the quantiles and exceedance probabilities associated with the random variable of interest. These changes should be examined both in time and space.

Katz (2013) argued that using nonparametric methods for trend identification and for fitting nonstationary extreme value distributions is inefficient because such methods are not appropriate for the heavy tails one expects from the theory for extremes. He argues that the nonstationary GEV distribution and Generalized Pareto Distribution (GPD) are attractive for nonstationary extreme value processes if the parameters are allowed to vary in time through an appropriate functional dependence on covariates (e.g., time or selected climate indices). In his examples, Katz considers both block maxima (e.g., annual maxima) and peak over threshold processes, the latter being considered through a generalized Poisson (GP) model. He argues that this is a more robust way of estimating trends in the full set of quantiles along with their uncertainty, than nonparametric alternatives. GP models were also used by Silva et al. (2014) to analyze flood data from northern Portugal. Similar conclusions were reached by Zhang et al. (2004), who performed Monte Carlo experiments comparing different methods for the detection of trends in extreme events. They documented greater power in detecting changes when considering the presence of trends in the parameters of the GEV distribution.

Within the modeling of extremes, some studies advocate a departure from the univariate at-site modeling of single records of extremes with a new focus on *spatial extremes*. The use of max-stable processes has received growing attention over the last few years, especially after recent work by Padoan et al. (2010). An appealing feature of these models is the development of a unified framework for simultaneously estimating the at-site parameters of the GEV distribution, which accounts for the dependence structure among flow series. In the hydrologic field, max-stable processes have been recently used by Padoan et al. (2010) and Westra and Sisson (2011) to describe the spatial and temporal variability in annual maximum precipitation over the Appalachian Mountains and Australia, respectively. Davison et al. (2013) provided an overview of the topic with a brief overview of potential Bayesian methods. A more in-depth discussion of Bayesian approaches to max-stable processes is provided by Shaby and Reich (2012). Section 5.2 provides a discussion on Bayesian alternatives to issues related to spatial and temporal extremes.

5.1.3 Spatial Correlation and Significance

A common problem in hydrology is to evaluate the statistical significance of trends in hydrologic variables at multiple sites in a region. Although these hydrologic variables are commonly correlated in space, statistical tests to detect the presence of either abrupt changes or monotonic patterns rely on an assumption of independence (i.e., one must assume that there is no correlation between individual observations). The violation of the independence assumption has an effect on the statistical significance of the test results because of an effective sample size that is smaller than the number of observations. Cox and Stuart (1955) stated, "… positive serial correlation among the observations would increase the chance of significant answer even in the absence of a trend.'' Different techniques have been proposed to accommodate for the potential presence of serial correlation, such as pre-whitening and trend-free pre-whitening (Kulkarni and von Stroch 1995, Yue et al. 2003), or corrections to account for the effective number of observations (Lettenmaier 1976). Linear regression is the only trend test for which analytical expressions exist to account for the inflation in the statistical significance of associated tests due to persistence (Matalas and Sankarasubramanian 2003). Khaliq et al. (2006, 2008) provide a discussion of different techniques to account for the presence of serial dependence in the data.

Both temporal and spatial correlation impact our ability to compute the true significance level associated with any set of multiple hypothesis tests, which is termed the field significance α_f. If the hydrologic variable of interest at each site in a group of m total sites is independent of all the other m-1 sites, then the significance level α of each of the individual hypothesis tests at the sites in the region are easily combined, as if one performed m separate independent experiments. Thus, with m sites and with m independent hypothesis tests, the field significance associated with all m tests, α_f, would be obtained from the expression $\alpha_f = (1-\alpha)^m$. In this case, the field significance represents the collective significance level associated with all m individual independent tests. Statisticians term such comparisons between individual tests as multiple comparison procedures (MCP), with the formula between α and α_f, termed the Bonferroni procedure (Simes 1986). For a recent review of a variety of different MCPs, see Vogel et al. (2009).

If the variable of interest exhibits spatial correlation, however, it is necessary to examine the impact of spatial correlation in the records of interest on the overall field significance associated with the group of tests (Livezy and Chen 1983, Douglas et al. 2000, Vogel et al. 2009, Hirsch and Ryberg 2012). It is intuitive that, if a statistically significant trend is detected at a particular location, it is more likely to be detected at close-by stations as well, because of the natural cross-correlation among hydrologic processes in nearby watersheds. Therefore, the inter-site correlation has an effect on the significance level of the trend tests by reducing the effective sample size. If unaccounted for, the spatial correlation would result in the rejection of the null hypothesis (no change) more frequently than if no spatial correlation were present. Different methods have been proposed to address this issue, such as the Walker's test and the false discovery rate (Wilks 2006) or bootstrap methods (Douglas et al. 2000, Hirsch and Ryberg 2012).

To increase the power of hypothesis tests and thus reduce the probability of type II errors, the most robust approach consists of multiple comparison procedures leading to an estimate of field significance, as discussed above. Future research is needed to address the power of alternative MCP procedures for their ability to detect departures from the null hypothesis, when streamflows exhibit both spatial and temporal correlations. Resorting to more than a single test will provide supporting evidence to the presence or absence of changes. If statistically significant changes are detected, it is then of paramount importance to understand their nature and causes, as discussed in the following section.

5.2 Attribution of Change

For hydrologic design, the ultimate goal of attribution is to improve our ability to project past and future changes in flood risk using both at-site and regional hydrologic information. Thus, once an abrupt or slowly varying change has been detected, it is important to understand what caused that change. For instance, is it possible to relate an abrupt change to human modifications of the catchment, such as the construction of a dam? Is it possible to explain the presence of a gradual change in terms of a slowly varying land-use change due to urbanization? Or is the most likely explanation related to variability in the climate system? Without this attribution, it is difficult to project changes into the future beyond simply extrapolating a recent trend forward in time.

At this time, several methods hold promise for attributing a change in flood frequency to human modifications of the catchment. Some researchers have investigated the use of climate models with different forcings in an effort to separate the relative contribution of each of them (e.g., Pall et al. 2011, Kay et al. 2011). However, others (e.g., Hirsh and Ryberg 2012) have found little evidence of changes in flood risk due to changes in atmospheric GHG. Cunderlik and Burn (2004) outline an approach in which trends in discharge are related to changes in hydroclimatic records using cross-correlation analyses on the residuals obtained from removing trend, seasonal, periodic, and autoregressive components. By relating the parameters of the selected flood peak distribution to predictors representative of climate variability (e.g., rainfall or large-scale climate indices) and changes in land use/land cover (e.g., total harvested area, percentage of impervious surface), it is possible to assess the relative contribution of each covariate in describing the changes in flood magnitude and variability over time (Villarini and Strong 2014).

Note that the development of statistical relations between flood peaks and predictors does not necessarily guarantee a causal link. It is therefore important to consider predictors that we would expect to be related to flooding, and interpret the results of the statistical modeling in light of the possible physical mechanisms.

5.3 Examples of Statistical Analysis of Change

Over the past two decades, a number of studies have examined the issue of nonstationarity in both precipitation and discharge records. In this section we summarize some of this literature as case studies, to illustrate many of the concepts described in Section 4.1.

5.3.1 Precipitation Records

A number of indices of extreme precipitation can be used as the basis of a trend evaluation, including maximum 1-day precipitation, maximum 5-day precipitation, 99th percentile wet days, and others (see Table 1 in Alexander et al. 2006). The particular metrics of interest vary among different studies, but there is a substantial body of literature describing trends in extreme precipitation over the latter half of the 20th century and the beginning of the 21st century, from different regions of the world.

Kunkel et al. (2013) provided a recent overview of the state of knowledge of extreme precipitation over the continental United States. They indicated that extreme rainfall events over the continental United States have generally increased since 1991 (see e.g., Figure 5-2). As described in Section 3, some of these regional differences in rainfall trends are likely to be related to large-scale circulation patterns, many of which have decadal-scale variability and many of which may be externally forced by anthropogenic climate changes. Other studies describing trends in total and extreme rainfall over the continental United States include Groisman et al. (2004, 2012), Groisman and Knight (2008), Peterson et al. (2008), Douglas and Fairbank (2011), and Villarini et al. (2011c, 2013b). Similar studies have been conducted in other regions of the world as well (Madsen et al. 2014, Yilmaz and Perera 2014).

Much of the literature examines this question from the point of view of climatology, using definitions of ‘‘heavy,’’ ‘‘very heavy,’’ or ‘‘extreme’’ rainfall, which are different from those definitions commonly used by civil engineers. Bonnin et al. (2011) identified the differences in meaning used by the climate and civil engineering communities and examined trends in the observed record in the frequency of exceedances (not trends in magnitudes). Using concepts recognized as the basis for design of the nation’s civil infrastructure, they examined trends in the number of exceedances of thresholds for a variety of precipitation frequencies and event durations used by civil engineers. They found that the estimated trends in exceedances at 1-day and multiday durations were statistically significant and increasing for the Ohio River basin and surrounding states, but that the reverse was true for the semiarid Southwest (i.e., not significant and decreasing trends).

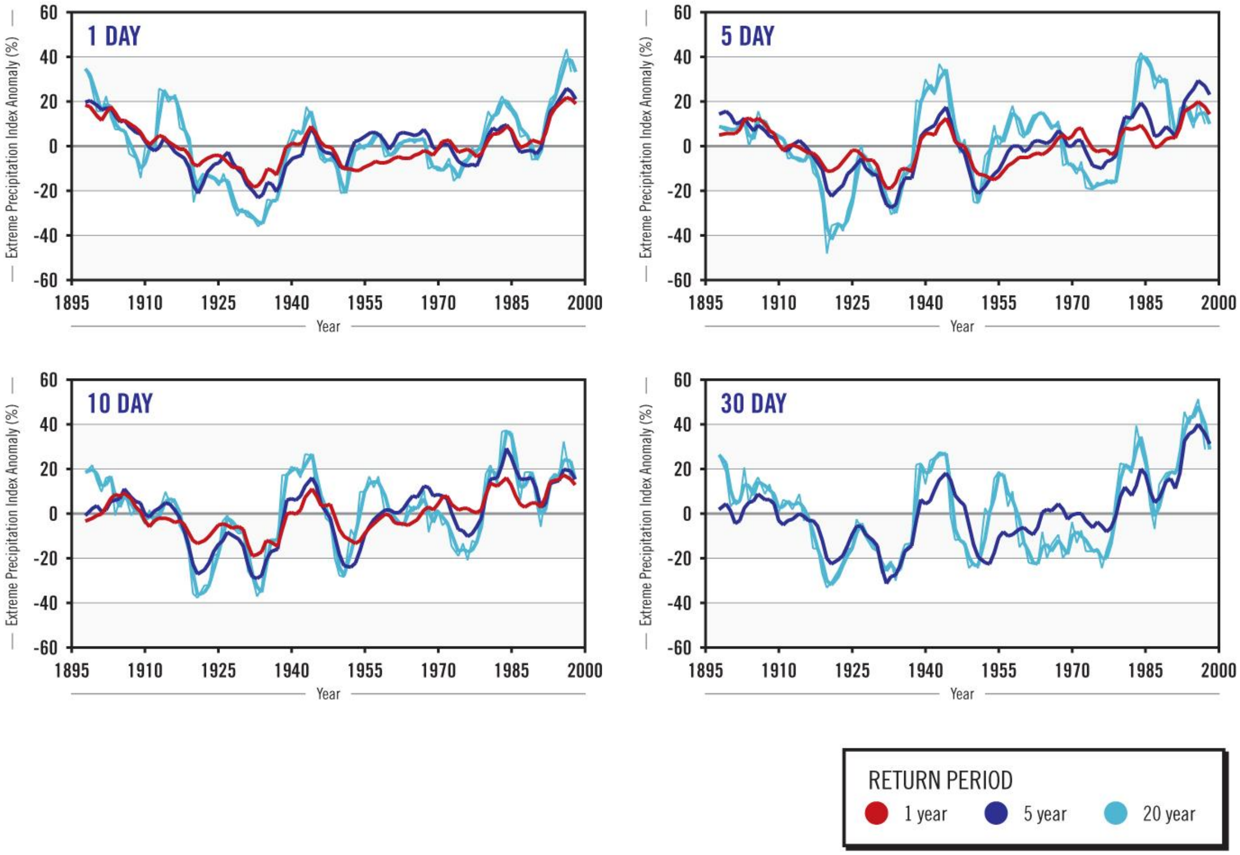


Figure 5-2: Trends in 1-day through 30-day extreme precipitation over the 20th century (after Kunkel et al. 2003).

5.3.2 Discharge Records

As summarized above, a large number of studies have documented increasing trends in heavy rainfall over large areas of the continental United States; similar studies have documented increases in heavy precipitation in other parts of the world, including Europe (Madsen et al., 2014). This, however, does not always translate into significant trends in peak flood discharge (Madsen et al., 2014). As discussed in Peterson et al. (2013), a possible explanation for these differences is that medium to larger catchments (i.e., larger than 1,000 km^2) tend to respond to rainfall events that last more than 1 day, whereas daily rainfall is the temporal scale generally used in rainfall studies. Another possible reason for the disconnect between rainfall and flooding is that many of the regions where increases in heavy rainfall have been documented have seen these increases primarily during seasons that do not produce flooding (Small et al., 2006).

As documented by Hossain (2014), one of the problems associated with the detection and attribution of a climate change signal in the flood peak record is related to the extensive modification that most of the watersheds in the United States have undergone between the 19th and 21st centuries. These modifications are related to changes in land use/land cover and stormwater systems, and construction of dams and systems of upstream reservoirs, all of which are superimposed on a climate change signal. For instance, changes in agricultural practice over the central United States and the related impacts on the hydrologic cycle have been the topic of a number of studies (Schilling and Libra 2003, Zhang and Schilling 2006, Schilling et al. 2008). Changnon and Demissie (1996) analyzed two rural catchments in Illinois and Indiana and found that changes in land use/land cover masked the effects that increasing precipitation would have on mean and peak discharge. Gebert and Krug (1996) discussed how changes in rainfall alone could not explain the changes in flood peaks over southwestern Wisconsin.

The strongest signal of streamflow change in the United States has been found in urban catchments (Vogel et al. 2011, Barros et al. 2014). Hejazi and Markus (2009) focused on 12 small urbanizing watersheds in northeastern Illinois and found that urbanization caused a 34% larger increase in flood peaks than climate variability. Villarini et al. (2009a) developed a nonstationary statistical model to describe the changes in magnitude and variability in the flood peak record of two highly urbanized basins in Charlotte, North Carolina. They used population (a proxy for urbanization) and rainfall as covariates to explain the changes in mean and variance in these flood peak records. Villarini et al. (2013c) also examined two urban catchments in the Chicago metropolitan area and found that increasing urbanization resulted in an increasing number of large flood events. Vogel et al. (2011) found large increases in flood magnitudes corresponding to some of the most populated areas of the country. Barros et al. (2014) found similar results for the southeastern region of the United States. Using data from a single urbanized watershed, Ogden et al. (2011) found that runoff in urbanized watersheds with a considerable impervious area show a marked sensitivity to rainfall rate, whereas for extreme rainfall events with a recurrence interval in excess of 100 years, imperviousness is relatively unimportant in terms of runoff efficiency and volume.

Many of the studies examining the presence of trends in annual maximum flood peak records have not found statistically significant trends in watersheds without extensive changes in water regulation or land-use change. Lins and Slack (1999) focused on 395 stream gage stations that are relatively free of human modifications (e.g., construction of dams, land-use changes). While nearly 30% of these stations exhibited significant increasing/decreasing trends in annual median discharge, less than 10% of the stations exhibited a statistically significant trend in extreme (90th percentile) flows (Figure 5-3). Lack of statistically significant trends in flood flow was also documented by Douglas et al. (2000) and Small et al. (2006). Villarini et al. (2009b) focused on 50 stream gage stations over the continental United States with a record of at least 100 years, and found that the presence of trends was often due to artifacts related to the presence of abrupt changes in the flood peak distribution. Similar results were obtained by Villarini and Smith (2010, 2013) and Villarini et al. (2011a), who performed detailed analyses at the regional scale, with particular emphasis on the eastern and central United States and Texas. Mallakpour and Villarini (2015b) showed that the most widespread signal of change over the central United States is in the frequency rather than in the magnitude of flood events.

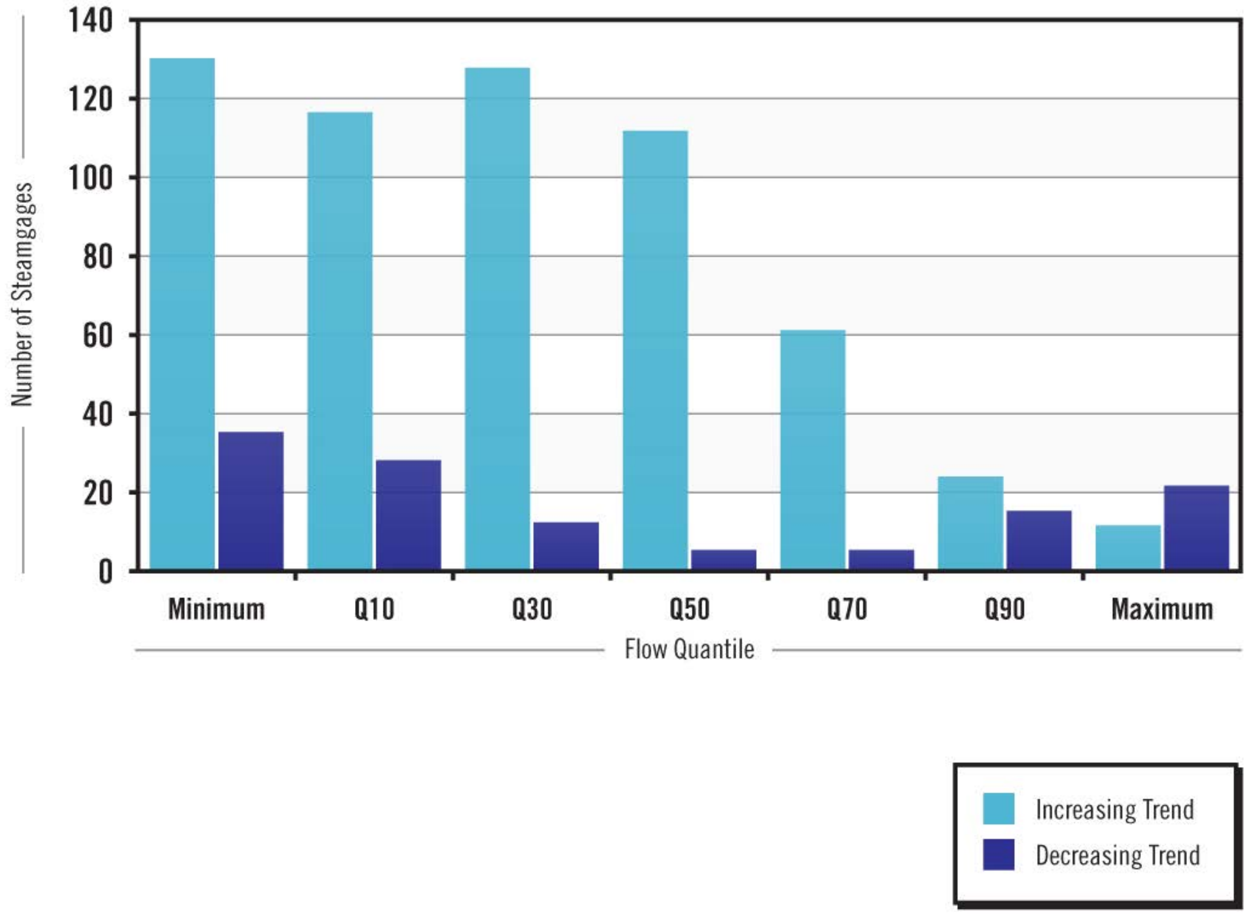


Figure 5-3: Number of stream gages with statistically significant trends in different flow metrics over the second half of the 20th century. Note the drop in number of statistically significant trends for more extreme flow metrics (after Lins and Slack 1999).

There are some regions of the U.S. for which it is possible to identify spatially consistent patterns of change. For instance, based on an analysis of 200 long-term (85–127 years of record) stream gages, Hirsch and Ryberg (2012) found decreasing trends in annual peak streamflow in the southwestern United States, possibly related to a drying of the region. Some areas of the northeastern U.S. (from the northern Appalachian Mountains to New England) have exhibited increasing trends in annual peak flood records (Collins 2009, Hodgkins 2010, Smith et al. 2010), possibly related to changes in snow pack (earlier melting and changes in the rain/snow ratio (Hodgkins et al. 2003). However, the spatial coherency of this signal is weaker than for the southwestern United States (Hirsch and Ryberg 2012).

In addition to changes in land use, the high natural variability associated with peak flood records can cause issues in detecting a change, because extremes are by definition rare. Thus, trends are very difficult to distinguish from the persistence inherent in most flow records (Cohn and Lins, 2005). Larger changes, on the other hand, have been detected in studies examining lower quantiles of the flood peak distributions. Lins and Slack (1999) found a widespread increase in flow quantiles, from annual minimum to median flow. Similar conclusions were reached by

McCabe and Wolock (2002) (see Figure 5-4), who also found that these increases were generally abrupt rather than gradual. They also related these increases in the 1970s to increases in precipitation in the eastern United States (Karl and Knight 1998).

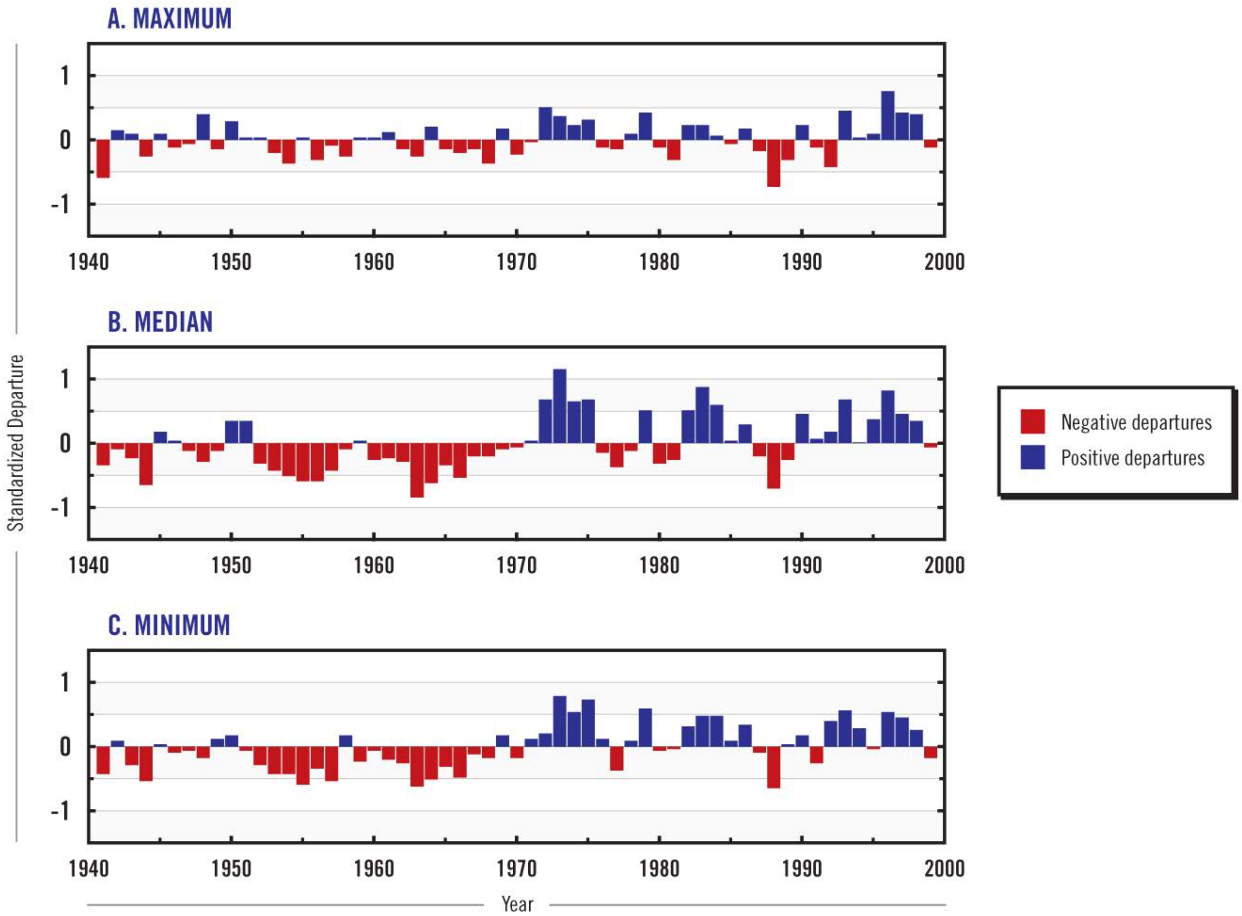


Figure 5-4: Departures from historical flow metrics over the second half of the 20th century for maximum, median, and minimum flows at 400 stream gaging sites. Note the increased coherence of a signal for lower-magnitude flow events (after McCabe and Wolock 2002).

In their review of trend studies on the European continent, Madsen et al. (2014) reported that several studies from regions dominated by snowmelt-induced peak flows found decreases in extreme streamflow and earlier spring snowmelt peak flows, likely caused by increasing temperature. Madsen et al. (2014) also reviewed existing guidelines in Europe on design flood and design rainfall estimation; only a few countries have developed guidelines that incorporate a consideration of climate change impacts.

5.4 Challenges in Hydrologic Trend Detection

Adaptation planning in the context of flood management in a nonstationary world depends critically on trend detection; hence, it is important to first understand the limitations and concerns surrounding tests of statistical significance of trends. As summarized above, studies that seek to identify trends in flood series are now widespread. All of the previous flood studies we have reviewed have employed a null hypothesis H_o that there is no trend, and most have chosen an associated significance level of $\alpha = 0.05$ (i.e., if there truly is not a trend, errors will be reported 5% of the time). This is termed a type I error, an "over-preparedness" error. The practical implication of a type I error in adaptation decisions for flood management is overinvestment in flood risk reduction measures.

However, potentially more severe consequences may occur if a trend actually exists but is not identified, termed a type II error, or an "under-preparedness" error. The physical repercussions of a type II error could be major flood damages or public safety issues due to underinvestment in flood risk reduction measures. Although most trend detection problems focus on the probability of a type I error, the consequences of a type II error could be much more significant because they imply no societal response is necessary when one is actually warranted. Rosner et al. (2014) introduced a methodology for incorporating both types of errors into a risk-based approach to flood management under nonstationarity conditions (Figure 5-5). This approach is described in more detail in Section 7.

	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 5-5: Decision matrix for the general trend detection decision problem, with null hypothesis H_o and alternate hypothesis H_A shown. α is the probability of a type I error, whereas β is the probability of a type II error. Modified from Vogel et al. 2013.

Examples of papers on power studies for trend detection based on linear regression are common in the medical sciences (Dupont and Plummer 1990, 1998). Analytical power studies are less common in the water literature, although there are some notable examples (Lettenmaier 1976, Bowling et al. 2000, Ziegler et al. 2003 and 2005, Vogel et al. 2013, Prosdocimi et al. 2014, Rosner et al. 2014). Lettenmaier (1976) first introduced analytical expressions for the power of a hypothesis test based on an 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. Another notable example is Ziegler et al. (2005) who used GCMs to project trends in annual precipitation on the Mississippi basin, and then performed Monte Carlo simulations to determine the minimum length of record that would be needed to detect trends of those magnitudes. They found that between 82 to 143 years would be required to detect the trend corresponding to type I and II error probabilities of $\alpha = 0.05$ and $\beta = 0.10$, respectively.

Fewer studies exist of the power of nonparametric trend tests. Yue et al. (2002), Onoz and Bayazit (2003), Yue and Pilon (2004), and Morin (2011) examined the power of the Mann-Kendall test and other non-parametric techniques. Yue et al. (2002) performed an extensive analysis of the power of the Mann-Kendall and Spearman tests by means of a Monte Carlo simulation. They found that both tests have similar power, and that β depends not only on α and the sample size but also on the variability in the records and the trend magnitude. A more general discussion on power and nonparametric tests can be found in Chandler and Scott (2012, pp. 55–56), who wrote, "… power calculations typically require precise specification of the form of the trend as well as the distribution of the observations: therefore they are not readily adapted to the nonparametric tests described above [Mann-Kendall], except under some precisely specified parametric model that serves as a benchmark."

Vogel et al. (2011), Prosdocimi et al. (2014), and Rosner et al. (2014) employed a simple nonlinear model (fit using linear regression) to characterize trends in flood levels. More complex trend analyses are possible by incorporating other covariate predictors of the trend such as climatic indices (Kwon et al. 2008) and/or trends in other moments (Villarini et al. 2009a, 2009b). Vogel et al. 2011 (see appendix) and Prosdocimi et al. (2014) found that a nonlinear model 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 United States and the United Kingdom, respectively. Even for highly nonlinear trends, OLS regression can often provide a good approximation by employing the ladder of powers to "linearize" the relationship (Helsel and Hirsch 2002). Helsel and Hirsch (2002) provided a good background on trend tests and how to improve their power, given the tremendous challenges associated with distinguishing among trends, seasonality, and persistence.

There are also considerable challenges in distinguishing trends from natural hydrologic persistence (Klemes 1974, Potter 1976, Cohn and Lins 2005, Matalas and Sankarasubramanian 2003, Koutsoyiannis 2006) (see Figure 3-1). Under LTP, abrupt changes and trends can be interpreted in such a way that similar events would tend to cluster, compatible with fluctuations over decadal, multidecadal, and longer time scales. Using this information in trend detection could result in a better way of characterizing patterns observed in hydrologic records (Koutsoyiannis 2003 and 2006, Koutsoyiannis and Montanari 2007, Lins and Cohn 2011). The presence of LTP is examined by computing the Hurst exponent H (Hurst 1951). The Hurst exponent ranges between 0 and 1, with a value larger than 0.5 indicating LTP. Tan and Gan (2015) calculated Hurst exponents for a series of gaging stations in Canada and demonstrated strong LTP in more than half of these rivers. Several different estimators of the Hurst exponent have been proposed, based on the aggregated variance method, differenced variance method, the rescaled range statistic (R/S) method, and the Whittle method. Montanari et al. (1999) and Serinaldi (2010) provided a review of these different estimators.

The decision of whether to include LTP when characterizing the temporal changes in observational records could have large impacts on the outcome of the analyses and interpretation of the results (Matalas and Sankarasubramanian 2003, Cohn and Lins 2005, Koutsoyiannis 2006, Lins and Cohn 2011). Cohn and Lins (2005) analyzed the influence of LTP on the statistical significance of observed trends for different statistical tests. Thirty-five Monte Carlo experiments were conducted with sample sizes ranging from 100 to 2,000 and fractional differencing values (*d*), an indicator of LTP, ranging from 0 to 0.4. The fractional differencing values were selected based on previous studies to ensure that the simulated populations would be representative of all ranges of hydroclimatical records. Multiple statistical methods were applied: (1) the OLS regression model was fitted and statistical tests focused on whether the fitted slope coefficient differed from zero, (2) two forms of the maximum likelihood (ML) approach were used to estimate the slope coefficient and the statistical significance was based on the likelihood ratio test (LRT), and (3) an adjusted likelihood ratio test (ALRT) was applied to improve the type I error in the presence of LTP. The tests were applied to samples without a trend as well as to observed surface air temperatures for the northern hemisphere. The results showed that as *d* increased, all tests were more likely to detect a statistically significant trend; however, ALRT provided the lowest occurrence of type I errors, and the OLS approach provided the highest occurrence of type I errors. Therefore, the presence of LTP can result in the false detection of a statistically significant trend if the wrong test is used. These results emphasize the importance of methods for accounting for LTP in trend testing and selecting the appropriate statistical test to avoid over- or under-estimating the statistical significance of a detected trend. Matalas and Sankarasubramanian (2003) provided analytical expressions for correcting the significance of trend tests based on regression for various forms of LTP.

Lins and Cohn (2011) emphasized the importance of understanding the characteristics of long-term hydroclimatic processes to inform water management decisions. They discussed the importance of selecting statistical tests that satisfy the characteristics of the data, to avoid inaccurate levels of statistical significance. They also showed the sensitivity of statistical tests to the start and end point within a data series being tested (see Figure 5-6). These issues make it difficult to detect nonstationarity within a data series. Therefore, Lins and Cohn (2011) suggested that stationarity and nonstationarity may be statistically indistinguishable in most scenarios. Based on these findings, they suggested that humility and caution are important factors in water management decision making. Another complicating factor with analyses of

LTP is that large sampling uncertainties are associated with the estimators of the Hurst exponent (Maraun et al. 2004, Rea et al. 2009), even using long flood series (e.g., more than 75 years) (Villarini et al. 2009a, 2011c). These difficulties in detecting values of H different from 0.5 at an α significance level do not allow for a clear distinction between LTP and nonstationarity.

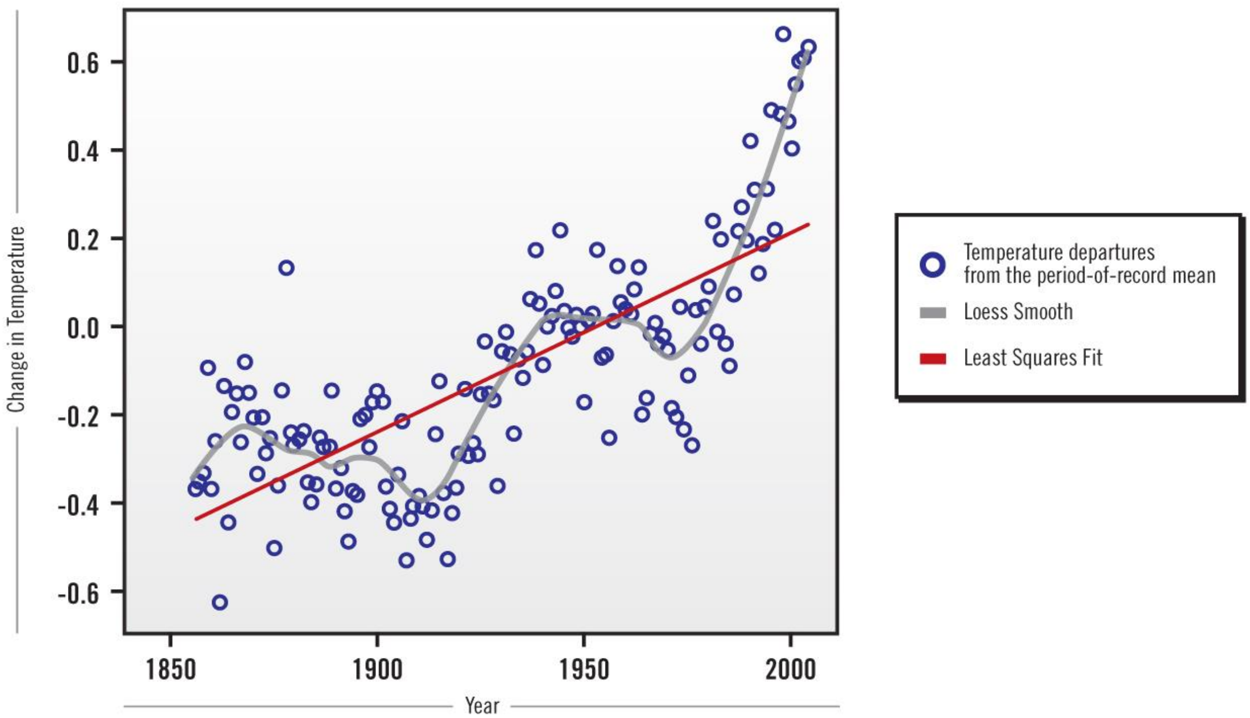


Figure 5-6: Northern hemisphere temperature trends 1856–2004. Note that the long-term trend (red line) may be missed if shorter portions of the record were selected (after Lins and Cohn 2011).

6. Characterizing Functional Nonstationarity for Engineering Analyses

Recall from Section 2.1 that for the purpose of water resources engineering and management, we introduced the concept of "functional" nonstationarity, which refers to the behavior of a data set (not a population) that does not appear to behave as we would expect a series of IID variables to behave over a limited time period. The purpose of fitting a probability distribution to annual peak streamflows is to make probabilistic statements about flood characteristics for a future planning horizon or project lifetime in a functional engineering environment. If a population is stationary in the statistical sense (see Section 2.1), but the data set is in the middle of a decades-long excursion due to internal climate dynamics, traditional frequency analysis methods need to be extended to consider paleoflood or other climatic information to properly constrain and/or interpret the estimates (See Section 5.4). Similarly, if a watershed has undergone urbanization over several decades, followed by restoration efforts thereafter, traditional frequency analysis methods need to be extended to consider information about the impacts of such urbanization and restoration efforts to properly model future flood frequency relationships.

In addition to the detection of change, methods have been developed to describe "functional" models of nonstationarity. One approach is to adjust a nonstationary streamflow record to stationary conditions (e.g., using a rainfall-runoff model to reflect changes in the watershed over time). A flood frequency analysis can then be applied to the adjusted record to develop a stationary flood frequency model for the time period represented by the model. Other approaches to model nonstationary flood frequency aim to model the nonstationarity found in the distribution parameters, moments, or the hydrologic variable of interest. Examples of both of these approaches are reviewed in this section.

6.1 Adjusting a Nonstationary Record to Stationary Conditions

USACE and others have developed methods to account for the effect of watershed changes on the stationarity of flood data. For example, many studies have tried to associate indicators of urbanization derived from existing geographic information system (GIS) and remote sensing (RS) sources with increased flooding[7] (Beighley and Moglen 2003, Villarini et al. 2009b), but data constraints have often limited these studies to a few decades. Moglen and Shivers (2006) investigated how to adjust rural peak discharges in an urban environment based on the percentage of imperviousness, while others have performed greater flood frequency analyses based on watershed characteristics. USACE (1994) recommended the use of a rainfall-runoff model to adjust a nonstationary flood record to stationary conditions to account for urbanization within a watershed and for the addition of flood storage. A stationary flood frequency analysis could then be performed based on the adjusted flood record.

Other studies describing methods to adjust nonstationary records to stationary conditions include Beighley and Moglen (2003), Boughton and Droop (2003), Gilroy and McCuen (2012), and Ahn et al. (2014). Boughton and Droop (2003) review the application of rainfall-runoff models to flood frequency analysis. Judging from the rapid increase in the application of rainfall- runoff models for flood frequency analysis, an updated review will be needed before 2020.

6.2 Distribution Characterization

Other approaches to model nonstationarities in flood frequency attempt to develop statistical models of the nonstationarity observed in the probability distribution parameters, moments, or the hydrologic variable of interest. Three general types of approaches are described in this section. In the first set of approaches (Section 5.2.1), the nonstationarity is modeled simply as a

[7] Vogel, personal communication, 2017.

function of time. These models seek to detect trends in the underlying data, generally by fitting a distribution or a curve through the data. In the second set of approaches (Section 5.2.2), one or more physical covariates are used to explain past variations in flood frequency based on our knowledge of the physical processes involved (e.g., urbanization, climate). Projected future changes in these covariates can then be used to model future changes in the hydrologic variable of interest. Finally, some methods (Section 5.2.3) use observational data to estimate the parameters of an underlying statistical distribution. Summaries and examples of all of these approaches are reviewed in this section.

6.2.1 Time Varying Parameters

Vogel et al. (2011) and Prosdocimi et al. (2014) found that a relationship between the logarithm of annual maximum streamflows and time can provide an excellent representation of historical nonstationary (and stationary) flood behavior in the United States and United Kingdom, respectively. They combined this simple exponential model of the mean annual flood with a lognormal model of the annual maximum floods to obtain a generalized nonstationary lognormal model. The focus of fitting such models is to simply understand historical variations in flood magnitudes and frequencies, not to provide extrapolations into the future. Others have found a simple two-parameter nonstationary lognormal (LN2) model to be useful for increasing understanding of risk, reliability, and return periods under nonstationary conditions (Prosdocimi et al. 2014, Read and Vogel 2015).

Gilroy and McCuen (2012) fit a similar exponential model to the location parameter of the GEV distribution for annual maximum precipitation and applied this trend to a rainfall-runoff model for estimating future flood risk. Obeysekera and Salas (2014) illustrated how a modeled trend in the location parameter of the GEV distribution for flow could be used to estimate future design flood magnitudes and uncertainty for Assunpink Creek in New Jersey (Figure 6-1). It is important that the statistical models that represent changes in the distribution moments or parameters are credible in a statistical sense, so that proper statistical inference can be performed, such as inclusion of prediction intervals, statistical significance testing of model parameters, as well as estimates of the probability of type I and II errors (Hecht 2017).

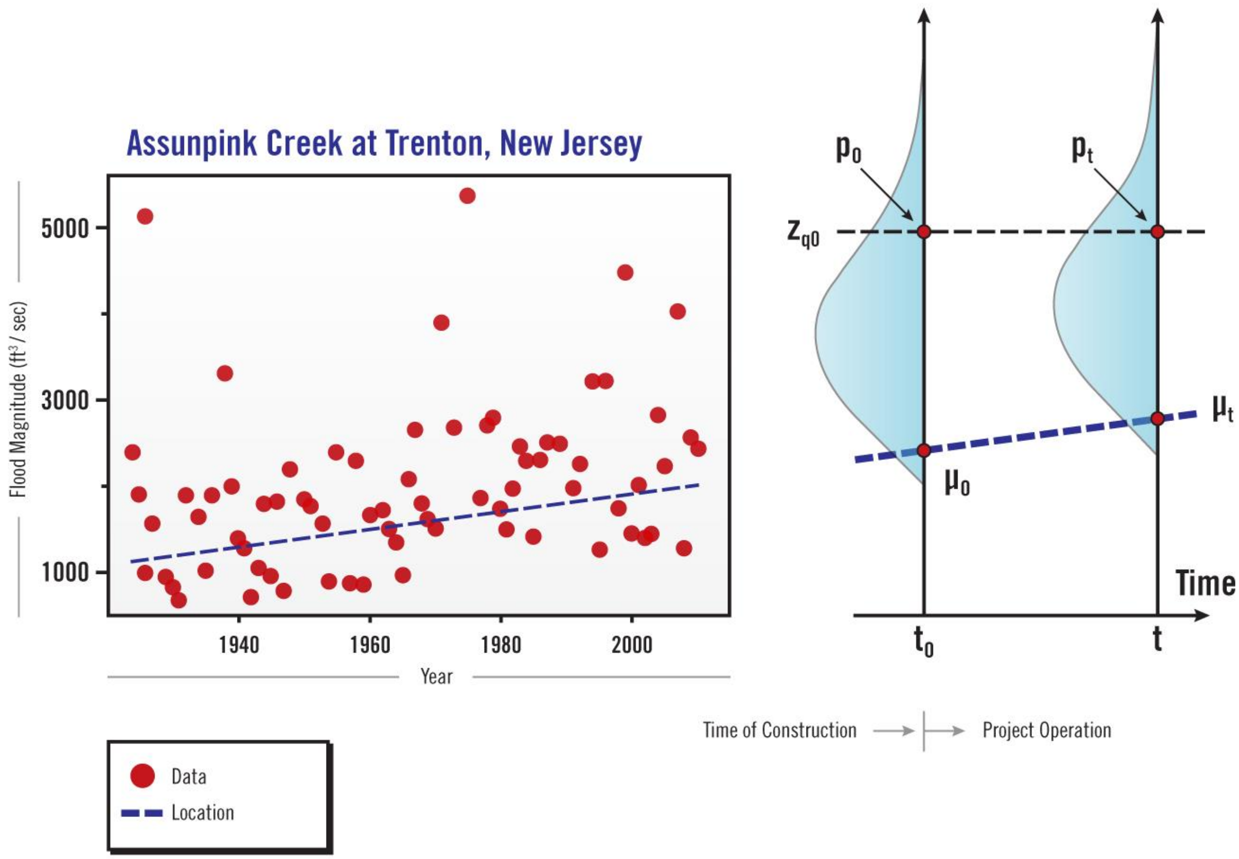


Figure 6-1: Schematic showing how a modeled trend in the location parameter of the GEV distribution can be used to project future probability of design flood magnitude over the lifetime of an infrastructure project (after Obeysekera and Salas 2014).

Generalized software packages are now available for selecting and fitting nonstationary flood frequency distributions (Martins and Stedinger 2000, Villarini et al. 2009a and 2010). Stedinger and Griffis (2011) presented extensions of the Log Pearson III distribution with time-dependent parameters, including mean, variance, and skew. They also compared a flood distribution with a trend term and a stationary low-order autoregressive moving average (ARMA) process. The rationale is that many hydrologic sequences exhibit systematic deterministic trends as well as stochastic persistence due to natural processes. Although the use of time-varying parameters of a probability distribution is simple mathematically, Stedinger and Griffis (2011) emphasized that it is entirely unclear how to project trends into the future. They also noted that flood distributions can also be conditioned on climate indices, such as ENSO, so that in any given year the flood distribution conditioned on a climate index may differ from the unconditioned flood risk.

Strupczewski and colleagues discussed two different approaches to incorporate nonstationarity into flood frequency modeling (Strupczewski and Kaczmarek 2001, Strupczewski et al. 2001a, 2001b). These methods include the identification of distribution and trend (IDT) method, in which either linear or parabolic time-dependent functions are fit to the first and second moments of a probability distribution (Strupczewski et al. 2001a); and the weighted least squares (WLS) method, which assumes both the mean and variance are time dependent and the functional form of the change in the variance is calculated (Strupczewski and Kaczmarek 2001). In both of these methods, the optimal combination of distribution and trend functions is identified based on the Akaike Information Criterion (AIC).

Strupczewski et al. (2001b) compared the IDT and WLS methods and applied each method to 39 flood records from Polish rivers to evaluate nonstationarity. Four classes of time trends were analyzed for the WLS method, including (1) a trend in the mean, (2) a trend in the standard deviation, (3) a trend in both the mean and standard deviation related by a constant coefficient of variation, and (4) an unrelated trend in both the mean and standard deviation. Trend models 2 and 3 were the optimal models for the majority of the flow records studied. In addition, a comparison between models 1 and 2 suggested that incorporating a time-varying standard deviation in a trend model is more important than incorporating a time-varying mean, at least for the flood records analyzed. For the IDT method, the lognormal distribution was most commonly selected as the best fitting distribution, followed by the Log Pearson III distribution. The results showed that the distribution selection noticeably influenced the trend estimated by the ML method. Comparison between the two methods suggests that different trend models may be identified for the same records. The overall results showed a decreasing trend for both statistical moments in the majority of flood records analyzed.

Cunderlik and Burn (2003) proposed a second-order, nonstationary pooled flood frequency analysis. The method divided the nonstationary pooled quantile function into two components: (1) a local time-dependent component, and (2) a regional time-independent component, based on the assumption of second-order nonstationarity. A local trend analysis of the time-dependent components was conducted. Regional changes were also assessed based on a regional trend analysis conducted through a regional bootstrapping algorithm. The ability of the method to detect changes in the location and scale parameters was assessed through a Monte Carlo experiment. The method was applied to homogeneous catchments in the mountains of southern British Columbia. O'Brien and Burn (2014) extended this method to evaluate spatially dependent trends in annual maximum streamflow for different regions of Canada.

Cunderlik and Ouarda (2006) defined the components of a regional nonstationary flood-duration-frequency model. Time-dependent model parameters were identified on a regional basis through a linear trend analysis. The model assumes temporally and spatially constant nonstationarity and can be used to estimate future flood quantiles. The model was applied to a hydrologically homogeneous region in Quebec, Canada. The results showed that significant bias in flood quantiles may result if nonstationarity is ignored.

Roth et al. (2012) presented a GEV/GPD-based approach to modeling regional peak over threshold processes with time-varying parameters. They applied the method to seasonal gridded daily precipitation extremes in the Netherlands and noted an increasing trend in the incidence of threshold crossings. Cheng and AghaKouchak (2014) used a Differential Evolutionary Monte Carlo algorithm to model differences in precipitation intensity-duration-frequency (IDF) curves from historical precipitation records under stationary and nonstationary assumptions and demonstrated that ignoring nonstationarity in IDF curves can substantially underestimate the risk of extreme events.

6.2.2 Covariate Analyses

Villarini et al. (2009a, 2010), López and Francés (2013), and Villarini and Strong (2014) used the Generalized Additive Models for Location, Scale, and Shape (GAMLSS) parameters to model nonstationary time series based on covariates. GAMLSS is a flexible modeling tool for time series under nonstationary conditions. It can be applied for a variety of distributions and models multiple distribution parameters simultaneously (e.g., location, scale, or shape parameters of a GEV distribution). Likewise, the user can select different functions to model each parameter, such as a linear, nonlinear, parametric, and/or additive nonparametric function (Villarini et al. 2009a, 2010).

Villarini et al. (2009a) developed a flood-frequency analysis framework based on the semi-parametric additive formulation of GAMLSS. Four two-parameter distributions were analyzed: (1) Gumbel, (2) gamma, (3) lognormal, and (4) Weibull. The parameters were modeled as a function of time based on the cubic spline smoothing technique, in which the cubic splines were optimized based on AIC and BIC. Population density and urbanization were added through a stepwise approach and assessed with BIC to determine whether the covariates improved the model. The method was applied to annual maximum peak discharge records for Little Sugar Creek in Charlotte, North Carolina. The results showed that population density and rainfall were significant covariates for the location parameter, while population density was a significant covariate for the scale parameter. Villarini et al. (2010) used a similar approach to assess the importance of AMO, NAO, and the Mediterranean Index on seasonal rainfall and temperature in Rome, Italy. The results showed that the Mediterranean Index was a statistically significant predictor regardless of the season, and the NAO was a statistically significant predictor for the winter season.

Villarini and Strong (2014) used the GAMLSS method to describe the changes in discharge (from low to high flow) in an agricultural watershed in Iowa. They used rainfall and combined harvested corn and soybean acreage as predictors and showed that the entire discharge distribution can be well characterized by these simple models. These models were then used by Villarini et al. (2015) as a way of projecting changes in discharge over this area. Other applications of the GAMLSS method include Xiong et al. (2014) and Zhang et al. (2014, 2015).

El-Adlouni et al. (2007) demonstrated a quantile estimation method for the GEV distribution in the presence of nonstationarity. They assumed parameters are either time dependent or dependent on other covariates. Parameter estimation was done with the generalized maximum likelihood (GML) estimation method, developed by Martins and Stedinger (2000). The GML method is similar to the ML estimation method; however, prior information is integrated into the shape parameter for the GML method. The Markov chain Monte Carlo (MCMC) method was used to generate estimators for the GML method. El-Adlouni et al. (2007) conducted a simulation study to compare the performances of GML and ML methods based on four GEV models: (1) stationary GEV model, (2) nonstationary case where the location parameter is linearly dependent on covariates, (3) nonstationary case with quadratic dependence on covariates, and (4) nonstationary case where both the location and scale parameters have linear dependence on covariates. The covariates analyzed included time and the Southern Oscillation Index (SOI) (

Figure 6-2). The results showed that the GML performed better than the ML method for the studied cases with respect to bias and the root mean squared error of design flood quantiles. El Adlouni et al. (2007) recommended additional research be conducted in the future, including (1) perform a distribution that depends on more than one covariate, (2) evaluate other statistical distributions and different nonstationarity structures such as trends in the variance of the series (scale parameter), and (3) develop a new framework for risk assessment in the case of nonstationarity.

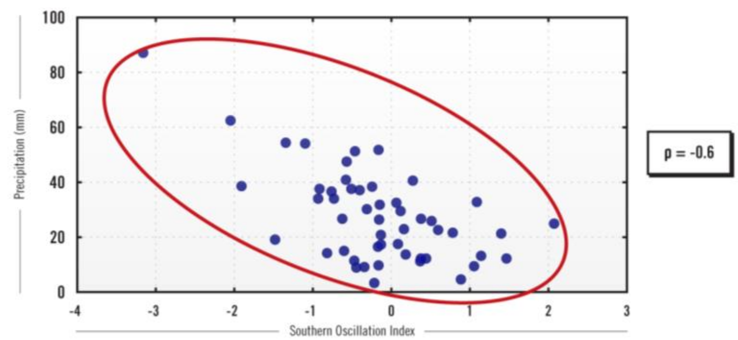


Figure 6-2: Relationship between annual maximum precipitation and the SOI for Southern California (after El Adlouni et al. 2007).

6.2.3 Bayesian Methods

Bayesian methods seek to estimate the parameters of an underlying distribution based on the distribution of observed values. Bayesian methods are well suited to integration of prior information concerning the behavior of probability distribution parameters, including covariate information. They integrate our knowledge of prior uncertainty of an event with our current observations to create an informed opinion balanced by the two.

Kwon et al. (2008) demonstrated a hierarchical Bayesian climate-informed flood frequency analysis model dependent on multiple factors that affect extreme flood events in Montana, including sea surface temperature (SST), predicted GCM precipitation data, climate indices, and snowpack depth. The climate information was implemented to update estimates of probability distribution parameter values for the Gumbel distribution, which was used to represent annual maximum flood data. The MCMC algorithm was used to simulate the updated flood risk prediction parameters based on climate conditions. The method was applied to the Clark Fork River in Montana to estimate the 1% exceedance flood from 1930 to 2005. The results showed a statistically significant link between the peak discharge and the SST indices, snowpack depth, and GCM seasonal precipitation data, which suggests that climate indicators can be used to predict flood risk.

Renard et al. (2006a) proposed a regional flood frequency model with time-varying parameters for a homogeneous region to improve trend detection through appropriate pooling of data from multiple stations in the region. A Bayesian framework was used to develop posterior probability distributions for the parameters and carry uncertainty information across the model chain. Renard et al. (2006b) used a Bayesian framework to account for nonstationarity in extreme events. Three probabilistic models were demonstrated: (1) stationary, (2) step change, and (3) linear trend. Four extreme value distributions were discussed: (1) exponential, (2) generalized Pareto, (3) Gumbel, and (4) GEV. Regional prior knowledge was used to develop prior distributions. Posterior distributions were calculated from the prior distributions and available data on extreme events. Frequency analyses were developed for peak-over-threshold extreme events, which take into account uncertainty in the prior and posterior distributions.

Lima and Lall (2010) developed a hierarchical Bayesian model to quantify the uncertainty in hydrologic scaling relationships as well as potential nonstationarity within data. Bayes' theorem, combined with watershed characteristics, was used to determine distribution parameters for ungaged sites or sites with small data samples. The Gumbel distribution was selected to represent annual maximum flood series. For the prior distribution, a log-log linear relationship was assumed between the scale and location parameters and drainage area based on empirical as well as physical modeling results. The MCMC method was then used to simulate values for the variables in the posterior distribution. The method was applied to 40 reconstructed inflow series from 40 hydropower sites in Brazil. The results showed that the model successfully estimated parameter values for sites not included in the development of the model. To account for nonstationarity, the model was modified to assume that all of the data used to estimate the time-varying parameters come from the same distribution and are stationary; however, additional variation that is dependent on time can be incorporated based on a hierarchical model. The random variation may be purely random, if the data are stationary, or may show a trend in time. Lima and Lall's results showed a statistically significant trend in the added variation, which suggests that nonstationarity exists within the data. Lima and Lall (2010) commented that an extension of this study would include climate predictors or trend-informing variables within the developed model to provide forecasting capabilities.

Ouarda and El-Adlouni (2011) used a Bayesian approach to nonstationary flood frequency analysis. The authors considered different GEV distribution models with location and/or scale parameters as functions of time or low-frequency climate indices. The functions that were considered were linear or quadratic. The GML method was used to estimate the nonstationary parameters, and a Beta distribution was used as the prior distribution for the model parameters.

The MCMC method can be used to estimate the empirical posterior distribution of the parameter vector and the marginal distributions of the parameters.

Renard et al. (2013) provided a comprehensive example of the application of Bayesian and hierarchical Bayesian models to the estimation of at-site and regional nonstationary probability distributions for climate extremes. Spatial copulas are used to model regional dependence and a strategy for inference across space and time using covariates is offered. Objective and subjective priors for the Bayesian estimation for the stationary case are addressed, as are hierarchical Bayesian regression formulations for estimating regional flood/precipitation frequency in the presence of a finite set of covariates. The use of MCMC methods for parameter estimation is also clarified. Examples for monotonic and step trend analysis in this framework, as well as prediction using covariates, are provided.

Gelati et al. (2010) developed a method to stochastically model nonstationarity within runoff time series. The method consists of a Markov-modulated autoregressive model with exogenous input (MARX) to produce runoff based on climate conditions. The method was applied to inflow time series for the Daule Peripa reservoir in Western Ecuador, where El Niño results in high SSTs and heavy rainfall events. The climate state is determined based on a first-order Markov chain. The current climate indices are used to determine the state transition probability, and the state transition probability formula contains a nonstationary component modeled by the kernel of a multivariate Gaussian distribution. Inflow anomalies are then modeled through an autoregressive model in which the parameters are dependent on the generated climate state. Multiple ENSO indices were analyzed to identify the indices that are most correlated to the inflow time series. The model components were selected based on the BIC. The results showed that the MARX model successfully simulates positive inflow anomalies during El Niño events. However, the model is unable to simulate significant decreases in inflow anomalies, most likely because the ENSO indices were weakly correlated with low-inflow anomalies for the reservoir.

6.3 Using Historical Trends to Project Future Trends

It is difficult to assess whether an observed historical trend is truly a monotonic trend that will continue into the future, or whether it is part of a multidecadal episodic pattern with only the upward or downward leg apparent in the data. Trends can also be confused with change points (Khaliq et al., 2006) and can be confounded by both short- and long-term natural hydrologic persistence (Cohn and Lins 2005). The presence of statistically significant trends and/or change points is often dependent on the time period used in the analysis. Thus, while some methods may appear successful for modeling observed changes in the distribution of flood series, they should be used with great caution when projecting future changes.

For example, the time-varying moments approach consists of modeling changes in the distribution parameters over time based on observed records. However, extrapolating these time-dependent models to a future design year requires the assumption that factors influencing the data, such as climate change and urbanization, will continue to have the same effect under future conditions. This may not be a realistic assumption, as land-use changes alone can occur gradually or abruptly over time. The incorporation of covariates enables a more realistic representation of changes in flood characteristics to be represented by changes in specified indices, such as climate and urbanization indices. Therefore, knowledge of future conditions for these indices provides a more realistic approach for projecting changes in flood conditions.

The covariate models reviewed here are often based on urbanization indices and possibly other indices linked to climate patterns such as ENSO and PDO. As described in Section 3, studies have linked ENSO and other patterns with an increased or decreased probability of flooding when the climate pattern is in a particular phase. The conditional probability of flooding for a given climate index can be used in a covariate analysis. Such models may be directly useful for planning and operation of flood-control facilities, and for incentivizing change through the pricing of financial instruments such as flood insurance rates for business loss of use. For design purposes, the use of climate covariates could improve estimates of the long-term variations in flood risk, including the potential persistence attributes. A stochastic simulation model using the climate variables could then inform the over-design/under-design probabilities for floods through a better characterization of the estimation uncertainty and its persistence.

6.4 Incorporating Paleoflood Information

In many cases, historical records may be inadequate for detecting nonstationarities in hydrologic variables. This is particularly true for the extreme, low-probability events that are commonly of greatest interest for hydrologic design. To fill these gaps in historical records, paleohydrologic information can often be used to inform decision making.

USACE developed guidance for incorporating paleoflood information into hydrology and hydraulics decision making (USACE 2014). In general, this guidance suggests that it is appropriate to use paleoflood information when the return period of interest is more than twice as long as the available hydrologic records and identifies regions where this information is appropriate for use. A number of studies have outlined ways to use paleoflood information for reconstructing discharges prior to gaging records (Stedinger and Baker 1987, Baker 2008). For example, geologic deposits such as gravel terraces and slack-water deposits can be used to estimate the extent and/or the magnitude of paleofloods. Provided that this information is appropriately applied, this information can be used to increase the effective length of the hydrologic record.

In addition to the flood records preserved in geologic deposits, proxy records from tree rings (dendrochronology) have shown significant promise for extending hydrologic records beyond the observational record. Razavi et al. (2015) described a method for evaluating regional consistency in growth history from tree rings, which they propose as a proxy for hydrologic variability. Although this information may not be used directly for estimating changes in hydrologic parameters of interest, their analysis demonstrates that historical variability in hydrology can be substantially greater than what is preserved in observational records. Furthermore, this analysis demonstrates that although streamflow or other hydrologic parameters may appear nonstationary from short-term records, a paleo perspective may demonstrate longer term stationary with a larger variance.

Caution should be exercised, however, when applying paleoflood information where channels and watersheds have not remained stable over time. Additional details and references are provided in USACE (2014).

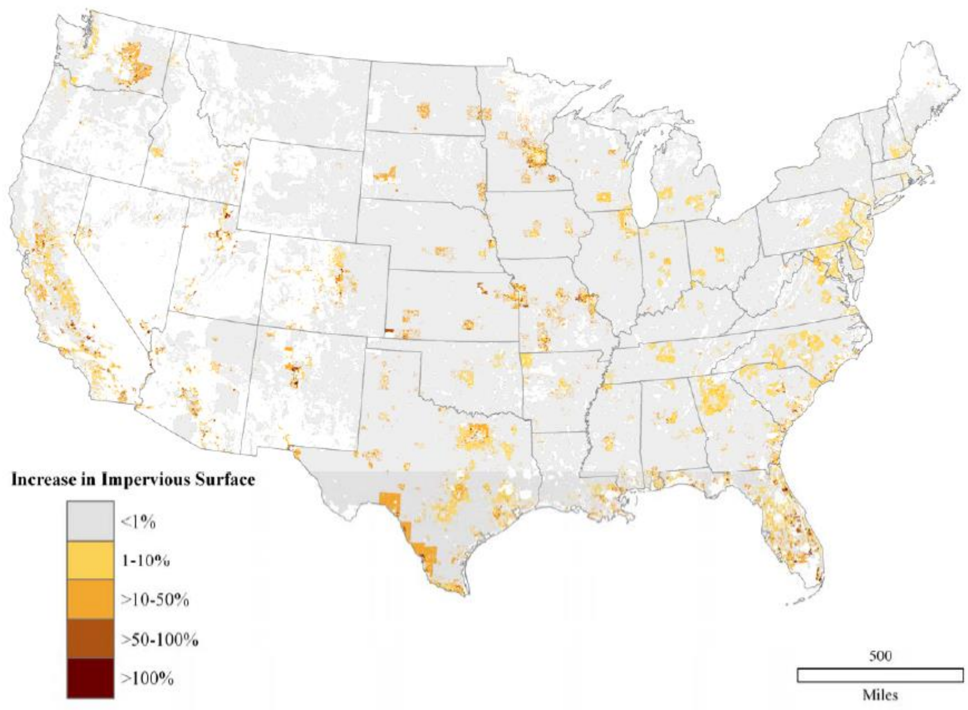
7. Projections of Future Change

Numerous sources of change can affect future hydrologic risk. Among these are changes to land cover, land use, population, and climate that impact hydrology. If these future conditions can be adequately characterized, projections of changes to the hydrologic system can then be linked by physical system models to directly estimate future flood potential over a given time horizon.

7.1 Land Use and Population Projections

Changes in land use are known to alter the hydrologic regimes of watersheds. Deforestation (Brath et al. 2005) as well as urbanization (Wheater 2006) can increase the magnitudes of floods, given similar rainfall inputs. Many municipalities produce projections of demographics within the context of their long-range planning efforts. Such projections can be used to estimate future urbanization in regions of interest. These projections can be coupled with projections of land-use change (Veldkamp and Lambin 2001) to make quantitative projections of future land conditions.

There are also more generalized approaches to projecting land-use changes, and various models that can be employed to assess future systems. For example, the U.S. Environmental Protection Agency's (EPA) Integrated Climate and Land-Use Scenarios (ICLUS) project provides projections of U.S. population growth and economic development that can be used to bracket future land-use changes in different regions of the U.S. (U.S. EPA 2009). These ICLUS scenarios were originally developed to be consistent with the Intergovernmental Panel on Climate Change (IPCC) Special Report on Emissions Scenarios (SRES) storylines. For each storyline, mathematical and statistical models were used to simulate migration of populations within the United States, and associated changes in impervious surface area resulting from residential development (U.S. EPA 2009) (Figure 7-1).



Source: U.S. EPA, 2009.

Figure 7-1: ICLUS projected change in impervious surface area based on SRES A1 storyline. (U.S. EPA 2009).

7.2 Climate System Projections

The climate science research community regularly combines its work in a series of experiments to test and explain current representations of climate processes in the global Coupled Model Intercomparison Projects, the current version of which is the fifth (CMIP5) (Taylor et al. 2012). The GCMs exercised in CMIP5 were initialized with outputs from integrated assessment models using storylines of future global socio-economic changes to derive future levels of GHGs and radiative forcings.

The scale at which GCMs operate are coarse compared to the scale of flood-generating atmospheric, topographic, and orographic conditions that underlies observations (Dettinger et al. 2004, Dettinger 2005, Maurer 2007, Cayan et al., 2008a, 2008b). Downscaling methodologies can be employed to simulate finer scale processes important to the generation of precipitation and flooding, using a variety of analytical and modeling techniques (Wood et al. 2004, Wigley

2004, IPCC 2007, Brekke et al. 2009). The two primary categories of downscaling techniques are statistical and dynamical downscaling:

1. **Statistical downscaling.** In statistical downscaling techniques, large-scale climate features generated by GCM hindcasts are related statistically to historical finer scale on-the-ground weather observations. The statistical relationships developed from these historical comparisons are assumed to hold true for future climate conditions, which allows coarse, future GCM outputs to be translated into finer scale projections. Although some authors have challenged the assumption of time invariance in the bias correction (Velazquez et al., 2015), statistical downscaling methods have been applied in studies of nonstationarity in hydrology (e.g., Wood et al. 2004, Maurer et al. 2010, Abatzoglou and Brown 2012, and Pierce et al. 2014).

2. **Dynamical downscaling.** In dynamical downscaling, fine-scale physical models of the region of interest are modeled using regional climate models (RCM). The boundary conditions for these regional models are driven by coarser scale GCMs. This approach directly represents local terrain and weather processes for the region of interest. Some examples include Moglen and Vidal (2014), who employed a suite of GCM/RCM pairs to estimate changes in precipitation intensity and impacts on stormwater design for the Washington, DC, area.

Climate projections and downscaling are rapidly evolving at this time. Practitioners must carefully assess the particular methods and their applicability to the particular water resources management planning and engineering problems being addressed.

7.3 Linking Projections to Hydrologic Risk

The flood-generating information available from climate models includes a variety of hydrologic information in addition to temperature and precipitation. This information, coupled with information about land surface conditions and other changing conditions, can be evaluated through hydrologic modeling to gain insight into future flood magnitudes. Various methodologies and model techniques have been employed (Cameron et al. 2000, Hirabayashi et al. 2008, Raff et al. 2009, Das et al. 2011). These methods often rely on well-calibrated models for the area of interest, which can include the Variable Infiltration Capacity (VIC) model (Maurer et al. 2002, Wood et al. 2005, Wood and Lettenmaier 2006), the topography-driven hydrologic model (TOPMODEL), or the National Weather Service (NWS) River Forecast System Sacramento Soil Moisture Accounting (NWSRFS-SAC-SMA) model (Burnash et al. 1973). Similarly, land-use studies have also used proven hydrologic tools (Brath et al. 2005), and current federal guidance within the USACE provides a basis to employ rainfall-runoff analysis when land use can be projected (USACE 1994). Additional work is ongoing to evaluate the effects of differences in models and model parameterizations on routed climate hydrology (Mendoza et al. 2014, Mizukami et al. 2014, Newman et al. 2015a).

Many of these hydrologic models have been shown to accurately reproduce observed flood frequency curves for an antecedent period (Raff et al. 2009, Das et al. 2011). It is, of course, unknown how well these models reproduce future flood potential because there is no viable means of validation today.

8. Use of Functional Nonstationarity for Risk-Based Engineering Design

For USACE, the ultimate goal of characterizing nonstationarity in historical and future flood distributions is to use this information to inform engineering design and minimize flood risk. In many cases, steps can be taken to achieve this goal regardless of whether the detection or attribution of change has been perfectly characterized. In this section we describe the practical applications of nonstationarity analysis for risk-based engineering design.

8.1 Probabilistic and Risk-Based Approaches to Hydrologic Design

To provide a review of current probabilistic and risk-based approaches to hydrologic design under nonstationary conditions, it is necessary to first provide a background and nomenclature corresponding to existing approaches commonly used for stationary analyses. Nonstationarity introduces additional uncertainty into the process of decision making, and we show that most existing approaches may be adapted for use under nonstationary conditions.

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. Most existing hydrology texts and handbooks provide a review of hydrologic design procedures assuming stationary conditions. Normally, hydrologic design is based on some random variable x, with stationary probability distribution function (pdf) denoted by $f_x(x)$, and cumulative distribution function (cdf) denoted by $F_x(x)$. Consider some hydrologic design problem in which a structure is built to protect against an event with an annual nonexceedance probability, $p=F_x(x)$. The design event for such a structure is computed as simply the inverse of the cdf so that the design event is the pth quantile of x denoted as x_p, which is the value of x with nonexceedance probability p. Under stationary conditions, the nonexceedance probability p, and its converse, the exceedance probability $q = 1\text{-}p$, are both constant in time. Under nonstationary conditions, the sequence of future exceedance probabilities, corresponding to the probability of a flood exceeding a fixed threshold design event, is likely to change. Fuller (1914) and Gumbel (1941) first introduced the idea of the average return period. We emphasize here that in spite of the widespread usage of return period nomenclature in hydrology, there are good reasons to temper its use as a metric of communicating flood risk (Serinaldi 2015, Read and Vogel 2015).

8.2 Key Concepts in Hydrologic Design Under Stationary Conditions

8.2.1 Reliability

The concept of reliability is one of the most widely used design criteria in water resources. In their now classic paper introducing the concepts of reliability, resilience, and vulnerability to the field of water resources, Hashimoto et al. (1982) defined reliability as the probability or likelihood that a system remains in a satisfactory state. Reliability is usually defined as the opposite of risk or probability of failure, which we have defined above as the exceedance probability of an event q. Thus, if the annual risk or probability of failure is defined as q, then the annual reliability $R_a = 1-q = p$. Hashimoto et al. (1982) emphasized that neither risk nor reliability reflects the consequences of an extreme event. The notions of resiliency and vulnerability are needed to reflect the consequences associated with an extreme event.

It is very important to distinguish between the various definitions of reliability and risk in the literature. Most hydrology textbooks contain expressions that relate the reliability of a water project over an n-year planning horizon, R_n, to its annual reliability R_a, using the fact that $R_n = R_a^n$. Risk of failure over an n-year period is related to the design average return period T_{avg} $Risk_n = 1 - \left(1 - \left(1/T_{avg}\right)\right)^n$. The relationships between the annual reliability and the reliability over an n-year planning period were first introduced by Gumbel (1941) and Thomas (1948) and further analyzed by Yen (1970). Those nonparametric relationships depend on the fundamental assumption that flood flows are IID variables. These relations are in widespread use as evidenced by their inclusion in hydrology handbooks (Chow 1964, IACWD 1982, Stedinger et al. 1993, Tung 1999), and 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 2013).

8.2.2 Failure Risk

Analogous to the conditional and unconditional return periods discussed earlier, the failure risk $Risk_n$ can be defined using either a conditional or an unconditional approach. Fernandez and Salas (1999) and Douglas et al. (2002) used a two-state Markov model to derive expressions for the unconditional n-year failure risk $Risk_n$, for events that exhibit serial persistence. Similarly, Sen (1999) used a two-state Markov model to derive expressions for the conditional n-year failure risk $Risk_n$, for events that exhibit serial persistence.

8.2.3 Risk-Based Decision Making

Risk-based decision making (RBDM) is a well-established methodology that determines appropriate levels of infrastructure investment based on the expected damages avoided versus the cost of the infrastructure required to avoid them (USACE 2000, Tung 2005, Yoe et al. 2017). Figure 7-1 illustrates typical expected costs versus net benefits. A RBDM process may lead to protection against an event either larger or smaller than an event with a specified nonexceedance probability.

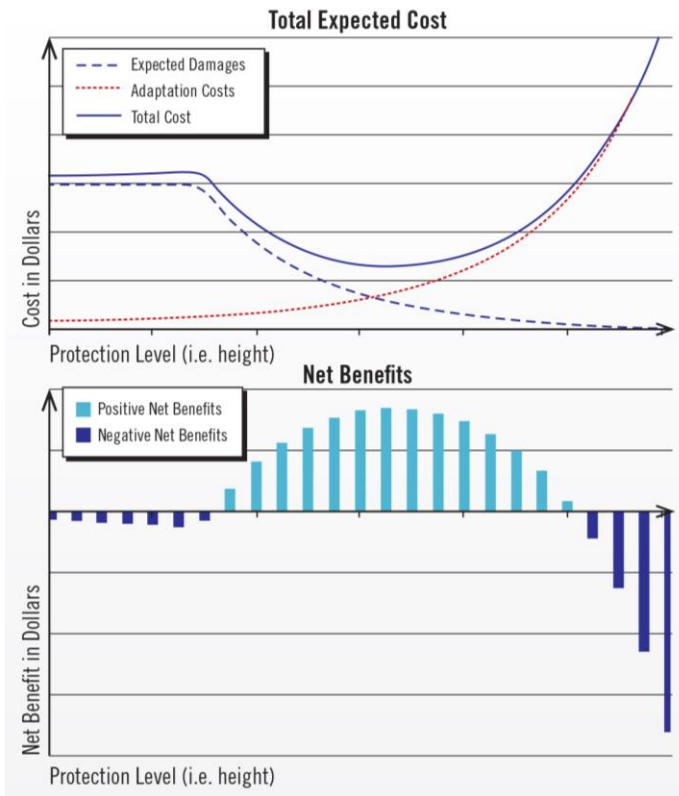


Figure 8-1: The risk-based design method for flood management (after Tung 2005).

Yoe et al. (2017) present a number of qualitative and quantitative approaches to performing risk-based decision making for water resources, among which are multicriteria decision analysis, fault trees, event trees, scenario approaches, expert elicitation, and Bayesian approaches. Nonstationarity can increase the complexity of decision processes and require some adjustments. However, numerous approaches have been taken depending on the decision, its consequences, and the quality of the underlying data (e.g., Borgomeo et al. 2014, Rosner et al. 2014, Spence and Brown 2016).

8.3 Methods for Hydrologic Design Under Nonstationarity–Probabilistic Approaches

Compared to the rich literature on frequency analysis of extremes under nonstationary conditions described in the Sections 4–6, extension of the traditional hydrologic notions of risk, and reliability to nonstationary conditions have received little attention in the water resources literature. Olsen et al. (1998) first described ways to apply the theoretical properties of the hydrologic design indices discussed in the previous section to nonstationary conditions. He extended the ideas of Wigley (1988, 2009) with a more rigorous mathematical treatment. Several investigators have sought to extend the results of Olsen et al. (1998) to nonstationary conditions. Cooley (2013) provided an overview of the various definitions of risk and return period introduced by Olsen et al. (1998). Salas and Obeysekera (2013) and Read and Vogel (2015) provided further extensions to the work of Olsen et al. (1998) and Cooley (2013).

8.3.1 Exceedance Probability of Design Events Under Nonstationary Conditions

Recall from the previous section on stationary methods that we defined the annual nonexceedance probability associated with a particular flood event as $p = Fx(x)$, along with its associated exceedance probability $q = 1\text{-}p$. If flood magnitudes are nonstationary and increase (decrease) through time, the exceedance probabilities q will correspondingly increase (decrease) over time to form the series q_1, q_2, q_3, $\ldots q_t$. Under nonstationary conditions, the time to the occurrence of the next flood T, forms a nonhomogeneous geometric random variable, which is completely analogous to the homogeneous geometric variable under stationary conditions.

Salas and Obeysekera (2013, 2015) point out that two separate cases must be described independently, one in which magnitudes of floods are increasing and one in which they are decreasing. The expressions given by Olsen et al. (1998) and Salas and Obeysekera (2013, 2015) for the expected return period and the risk over the planning horizon under nonstationary conditions are far more complex than the analogous expressions under stationary conditions. In particular, there are significant computational challenges associated with the resulting summations. To reduce such computational burdens, 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 the nonstationary nonexceedance probability $F(t)$ from $F(t\text{-}1)$. Mandelbaum et al. (2007) also showed how their recursive expression can be used to define the structure of future sequences of nonexceedance probabilities that arise from various structures of the pdf $f(t)$ and cdf $F(t)$. A promising area of research might be to explore the various structures of future sequences of exceedance probabilities q_t, which arise from various hydrologically realistic nonstationary flood frequency models. For example, if one substitutes the pdf and cdf corresponding to a realistic nonstationary flood frequency model, what form do the resulting series of exceedance probabilities take?

8.3.2 Risk and Reliability Under Nonstationary Conditions

Relationships among the annual failure risk q, the n-year failure risk Risk_n, and the annual reliability R_a described earlier, are in widespread use in hydrology under stationary conditions. Thus one expects that analogous relationships would be useful under nonstationary conditions. Salas and Obeysekera (2013) provided expressions for the risk of no failure over the first n years, termed the n-year failure risk under nonstationary conditions. Read and Vogel (2015) described such general relationships for the case of a nonstationary lognormal model. It should be of considerable interest for future research to explore the behavior of the n-year failure risk and the n-year reliability under various plausible nonstationary models of flood frequency**.** Such analyses could help us better understand the risk posed by floods under nonstationary conditions.

8.4 Risk-Based Approaches to Flood Management Under Nonstationary Conditions

Flood management decisions in a nonstationary world are inherently sequential decisions that depend on the uncertainty inherent in future projections of flood scenarios and their corresponding consequences. There are numerous approaches to adaptation planning under both uncertainty and nonstationary conditions that do not depend on probabilistic approaches (Herman et al. 2015). Fiering and Matalas (1990) provided one of the earliest examples of a sequential statistical decision process for evaluating various alternatives in the context of nonstationarity due to climate change. Chao and Hobbs (1997) gave a brief history of decision analysis applications to climate change and applied a mathematical version of a decision tree, known as a stochastic dynamic program, to evaluate breakwater adaptation to possible climate change impacts on Lake Erie. Hobbs et al. (1997) applied a decision-tree approach to water resources management under climate change. More recently, staged adaptation strategies have been considered, which offer much more flexible and adaptive responses to potential future climate change (Gersonius et al. 2013, Haasnoot et al. 2013, Kirshen et al. 2014).

A critical challenge in the application of decision trees to the problem of RBDM in a nonstationary world involves estimating the necessary probabilities associated with various outcomes (branches of the decision tree). Hobbs et al. (1997) demonstrated the 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) described a Bayesian analysis consisting of aggregating predictions from suites of model predictions from GCMs or RCMs.

Rosner et al. (2014) introduced a RBDM decision-tree approach for use in a nonstationary world, with the outcome probabilities based on type I and type II error probabilities associated with the outcomes for the statistical hypothesis test for trend. Their approach integrates the uncertainty inherent in the trend detection process with the natural uncertainty and 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.

8.5 Methods for Hydrologic Design under Nonstationarity–Non-Probabilistic Approaches

In some situations, there may be insufficient information to incorporate the probabilities of foreseeable future hydrologic conditions into long-term flood planning and management decisions. In some cases, the possible failure of infrastructure due to rare events may be so catastrophic that a single worst-case scenario is predicted and then planning decisions are based on that lone worst-case scenario (i.e., a predict-then-adapt approach) (Gersonius et al. 2013). In other cases, the robustness of planning decisions to a wide range of possible hydrologic futures is of paramount importance. In this context, minimizing under- and over-design regrets to extreme scenarios is of greater concern. In yet other cases, expectation decision making is desired, but there is insufficient information with which to assign probabilities to a set of distinct and possibly plausible climatic, or hydrologic, futures.

Even if there is insufficient information to specify particular probability distributions, there may be enough information to identify a plausible range of uncertainty. The challenge of assigning plausible probabilities to climate change projections, along with increased interest in identifying adaptation solutions robust to a wide range of climate futures, have prompted numerous efforts to devise methods that acknowledge the deep uncertainty of climate change, as well as efforts to review and categorize them (Hallegate et al. 2012, Herman et al. 2015). Adaptation methods profiled in these two reviews include robust decision making (RDM) (Lempert 2002); the information gap, a.k.a. Info-Gap (Ben-Haim 2004); decision scaling (Brown et al. 2012, Spence and Brown 2016); and many-objective robust decision making (MORDM) (Kasprzyk et al. 2013). Many of these approaches first aim to identify conditions under which water resources may be vulnerable now and subsequently determine how climate impacts may change vulnerability. One key feature of these robust decision-making frameworks is that a wide range of possible climate states is considered, as opposed to methods that consider only specific model-generated outputs.

Although robust decision-making approaches avoid some of the challenges of incorporating imprecise and/or deeply uncertain information that characterize approaches in which probability-weighted GCMs are used to optimize adaptation planning decisions, many RDM methods do take probabilistic information into account in the latter stages of their analysis (Hallegate et al. 2012).

We have previously discussed regret-based decision making using probabilistic information about the relative likelihood of “trend” and “no trend” hydrologic futures. Regret-based criteria can be employed to identify solutions that are robust to foreseeable climate changes without assigning probabilities to particular climate or hydrologic scenarios. In particular, the minimax regret criterion (Savage 1951), which aims to minimize the regret incurred across a range of potential adaptation solutions, has been used in water resources planning for over half a century to make decisions without information about the relative likelihood of different future conditions (Maass et al. 1962, Yoe et al. 2017). Recently, it has been used to identify decisions that are robust to a wide range of plausible climate outcomes for numerous environmental management applications, including GHG mitigation (Loulou and Kanudia 1999), water supply and wastewater planning (Kang and Lansey 2013), and water quality management (Faraji et al.

2015). Efforts to apply this criterion to floodplain management are emerging as well but are still under development (van der Pol et al. 2015).

There are two basic approaches for carrying out minimax regret analysis when stakeholders are concerned about minimizing worst-case impacts. The first approach involves comparing the performance of a small set of pre-specified alternatives under a small set of alternative future scenarios. A payoff matrix is constructed to determine the regrets associated with selecting a given alternative for a scenario other than the one for which it is most preferable (Revelle et al. 2003, Faraji et al. 2015). The maximum regret for each alternative is computed and that alternative whose maximum regret is the lowest is selected. However, as Herman et al. (2015) observed, considering only pre-specified management alternatives inhibits the identification of other solutions, including ones that may not be optimal under any single climate change scenario but may be preferable when considering their robustness to a wide range of scenarios. Instead, it is promising to first identify solutions that may be optimal for individual scenarios and then run a subsequent optimization model to search for a single set of decisions that minimizes the maximum regret across all scenarios considered (Kang and Lansey 2013). This approach runs the risk of communicating a false precision while producing an inaccurate result if the small set of alternative future scenarios is wrong.

In some situations, non-probabilistic decision criteria other than minimax regret may be preferable. For instance, Herman et al. (2015) observed that, in a multiobjective context, minimax regret may lead to the recommendation of a strategy that has a mediocre performance for some objectives in order to avoid a severe underperformance in a single objective. The minimum total regret criterion, which Faraji et al. (2015) employed, may offer a remedy for this problem. Revelle et al. (2003) also presented other pessimistic and optimistic decision criteria that can be used when the likelihood of future states, or scenarios, cannot be specified adequately, such as the maximin and maximax criteria. However, to the best of our knowledge, these criteria have not been employed in flood management, considering the additional uncertainty associated with the nonstationary behavior of future floods.

Finally, one major challenge with climate change adaptation planning has been the ability to incorporate new information into decision making with a long time horizon, such as water resources infrastructure. Recent studies demonstrate that it may be possible to dynamically optimize adaptation plans as new information emerges, even when there is insufficient probabilistic information about the likelihood of these updated scenarios materializing (Beh et al. 2015, van der Pol et al. 2015). While difficulties in assigning probabilities to GCM-driven climate change scenarios have motivated the use of non-probabilistic methods, scenarios of hydrologic change analyzed with non-probabilistic decision criteria could ostensibly include two or three alternative statistical models of future peak flows derived from observed streamflow data (e.g., different types of trend models). The rapid development of methods for making flood management decisions under deep uncertainty should aid our ability to make flood adaptation decisions robust to plausible ranges of uncertainty of future flood projections from multiple models, even when the likelihood of each of the projections is difficult to determine.

9. Recommendations and Future Work

This report focused on the complexities associated with nonstationary hydrologic processes, as well as decision-oriented approaches for hydrologic design under nonstationary conditions. Over the past few years, there has been a tremendous increase in the research literature devoted to nonstationary hydrologic processes, particularly within the areas related to climate change, urbanization, and flood frequency analysis. Because of this growth in literature, it is difficult to reach consensus, or to provide guidance, concerning recommended methods of flood frequency analysis and adaptation planning under nonstationary conditions. Instead, this report has attempted to provide an overview of the state of our knowledge in this emerging field.

There are numerous areas of research that could lead to improvements in our current flood frequency analysis approach. For example, many hydrologic frequency analyses have concentrated on a single design variable such as river discharge, in spite of the now numerous studies that have shown the need to consider several variables such as volumes, peaks, and possibly channel capacity. Changes due to land use, urbanization, climate, and infrastructure are likely to influence both the magnitudes of flood volumes and peaks as well as the geomorphic capacity of river channels and floodplains; thus, our methods of design must account for these interacting influences. Methods of attribution require further exploration and evaluation.

Hydrologic rainfall-runoff models are widely used to convert observed rainfall data to runoff, and for subsequent application in a very wide range of water resource investigations. Such models are routinely used in hydrologic design because they are easily adapted to account for changes in climatic and land-use conditions (Gilroy and McCuen 2012). However, these models may exhibit less variability than observed discharge data (Kirby 1975), which could lead to systematic downward bias in the calculated design flood events. There is a need to evaluate such models for their ability to account for the numerous additional sources of uncertainty that arise when calibrating, validating, and applying such models in practice. Fortunately, USACE and its partners have been examining these issues for several years (e.g., Gutmann et al. 2016, Mizukami et al. 2016, Wood et al. 2016, Clark et al. 2015, Mendoza et al. 2015a and 2015b, Newman et al. 2015a and 2015b, Mizukami et al. 2015, Maurer et al. 2014, Moss et al. 2013).

Each topic area in this report provides a potential opportunity to improve the existing flood frequency analysis method under nonstationary conditions. Consider the analogy between the development and evolution of flood frequency methods under stationary conditions. In the 1970s, there was a great deal of attention given to new methods of flood frequency analysis.

Most of the attention was given to the problems of distribution selection and model parameter estimation. Such studies were able to document, for example, that the use of annual maximum series was often preferred to the use of partial duration series. Next, in the 1980s, attention focused on the use of regional versus at-site information, with a large literature showing clearly that regional methods of flood frequency analysis are to be preferred to at-site methods, because they often lead to more precise (lower root mean square error) estimates of design flood quantiles. Over the years, innovations in flood-frequency analysis addressed the use of historical flood information, handling both low and high outliers, construction of confidence intervals, estimation of regional skewness, and in the use of generalized least squares hydrologic regression procedures.

By analogy, the field of flood frequency analysis under nonstationary conditions is in its infancy. Most of the literature reviewed has concentrated on detection of trends and incorporation of rather simplistic statistical models of such trends into existing flood frequency models. The most important issues addressed in the field of flood frequency analysis include the incorporation of regional information into flood frequency analysis and the precision of resulting design flood estimates. Additional attention should be devoted to the range of issues mentioned above, which led to improvements in flood frequency analysis under stationary conditions, because they are likely to lead to similar improvements under nonstationary conditions.

10. Works Cited

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