Integrating nonstationarity and uncertainty for quantifying flood protection reliability

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Extended Abstract

This presentation outlines novel methods, applications, and a discussion of the implications for incorporating nonstationary flood frequency analysis with uncertainty in flood peak distributions and uncertainty in flow capacity to quantify the distribution of flood protection reliability over a planning horizon. Flood protection reliability of a specific location/feature on the floodplain is typically conveyed as a precisely known value based on a deterministic estimate of the flow magnitude that inundates its elevation and the corresponding annual occurrence probability of that flow. This assumes the flow capacity of the specific location and the flood likelihood is exactly known and static through time. However, deterministic model estimates of reliability mask inherent uncertainties, often assume stationarity, and potentially underestimate communicated failure likelihood (Stephens and Bledsoe, 2022). Alternatively, quantifying the distribution of reliability provides a means to transparently communicate and make decisions based a contextually appropriate level of confidence in flood protection reliability.

Numerous factors impact the distribution of reliability. For instance, flood magnitude-frequency relationships are uncertain and can change through time, which has been documented at a large number of stream gage locations across the US (Barros et al., 2013; Hodgkins et al., 2019; Slater, 2016; Vogel et al., 2011). The flow capacity of rivers and floodplains is also uncertain and may change through time due to aggradation/degradation, land use change, and others (Call et al., 2017; Lee and Mays, 1986; Pinter et al., 2006; Slater et al., 2015). These factors can interact to amplify, reduce, or offset one another in their impacts on the magnitude and frequency of flooding (Slater et al., 2015). Stephens and Bledsoe (2022) quantified the distribution of flood protection reliability by accounting for inherent uncertainties in flow capacity and annual maximum flood (AMF) distributions while accounting for nonstationarity in AMFs.

Here we describe methods for quantifying and mapping the distribution of reliability, present applications and findings at two different study sites, and discuss the implications of our findings. Alternative methods for quantifying the uncertainty in flow capacity are presented, and the nonstationarity of AMF distributions is incorporated into flood protection reliability estimates.

In order to quantify the distribution of flood protection reliability we apply the method developed by Stephens and Bledsoe (2022) that accounts for uncertainty and nonstationarity. Reliability is defined as the probability that the loading on a system will not exceed its resistance over a planning horizon (Tung et al., 2006). Consequently, if loading and resistance are independent random variables, reliability is a function of their joint probability distribution (Tung et al., 2006). In terms of flood protection reliability, the flow capacity of the channel and floodplain below a specific elevation (e.g., crest of a levee) defines resistance, and the distribution of AMFs defines loading. Thus, flood protection reliability over a planning horizon can be quantified by (Stephens and Bledsoe, 2022):

$$R_l = \prod_{t=1}^{n} \left[\int_0^\infty f_r(r)\, F_l(r) dr \right] \tag{1}$$

Where R_l is reliability, n is the planning horizon, $f_r(\cdot)$ is the probability density function (pdf) of flow capacity and $F_l(\cdot)$ is the cumulative distribution function (cdf) of AMFs. In this computation of reliability, the pdf of flow capacity and/or the cdf of the AMFs may change with time (i.e., exhibit nonstationarity). This approach is advantageous because it can account for interacting effects between flow capacity and AMFs that may decrease, amplify, or offset one another in terms of flood risk.

While Equation (1) provides a reliability estimate that accounts for nonstationarity and uncertainty in flow capacity, it does not account for uncertainty in the AMF distribution itself. Therefore, Equation (1) can be implemented in a bootstrap-scheme that incorporates uncertainty in the AMF distribution to provide a distribution of reliability. In other words, Equation (1) is solved a large number of times (e.g., 1000) with each solution providing a reliability estimate based on a sample from the uncertainty distribution of the AMF distribution and the pdf of flow capacity. A specified confidence in reliability may be obtained by the cumulative distribution of reliability estimates. For instance, obtaining 90% confidence that a particular reliability will be equaled or exceeded would require computing the 10th percentile of the reliability distribution populated by the bootstrap-scheme. This scheme can also be used to solve for a design flood magnitude by specifying a desired reliability and confidence level. Evaluating the integral over the pdf of flow capacity and cdf of AMFs within a bootstrap scheme accounts for the entire range of possible intersections between flow capacity and annual exceedance probabilities (e.g., 10% - 1%), as opposed to evaluating a single annual exceedance probability (e.g., 1%).

A spatial map of the distribution of reliability can be obtained by conducting Monte-Carlo simulations of flood hydraulics where the uncertainty distribution of flow capacity and AMFs is sampled. Sampling the uncertainty in flow capacity may involve varying roughness parameters and channel bed elevation or shape. Whereas, sampling the uncertainty in the AMF distribution will involve sampling from magnitude-frequency relationships. A number of flows can be simulated with each sampled flow capacity and magnitude-frequency relationship parameter set to generate a gradient of reliability across the floodplain in a rasterized format. This is repeated a large number of times (e.g., 1000), and metrics from the distribution of reliability (e.g., mean, standard deviation, 90th percentile, etc.) can be quantified at each pixel on the floodplain.

The distribution of reliability was quantified at two separate locations: 1) along the regulatory floodplain boundary at Little Sugar Creek, Charlotte, NC, USA and 2) a levee crest location on the eastern floodplain of the Mississippi River near St. Louis, MO USA. These two sites were selected because they provide contrasting hydrogeomorphic settings where uncertainties may propagate differently to impact the distribution of reliability. For instance, the drainage area of the Mississippi River is much larger than Little Sugar Creek, they have contrasting channel substrates, valley shapes, among other characteristics. A high degree of urbanization exists in the Little Sugar Creek watershed; however, upstream flow regulation is nonexistent. Whereas, the Mississippi River is highly regulated by a series of predominantly run-of-river lock and dams. Selection of the study sites was also motivated by their location relative to nearby USGS gaging stations.

The distribution of flow capacity uncertainty at Little Sugar Creek was quantified by conducting Monte-Carlo simulations of flood hydraulics with a calibrated 1-D, steady flow HEC-RAS model used to delineate the regulatory floodplain boundary. The Monte-Carlo simulations sampled 1000 unique combinations of uncertainty in channel bed elevation and roughness parameters. A nearby USGS gaging station 02146507 (Little Sugar Creek at Archdale Drive), located 3 km upstream, was utilized to define the AMF distribution based on a nonstationary Gumbel model (Stephens and Bledsoe, 2022). The gaging station exhibits a statistically significant increase in AMF since approximately 1945, coinciding with a period of urbanization (Villarini et al., 2009).

At the levee crest along the Mississippi River, we utilized manual USGS field measurements at gaging station 07010000 (Mississippi River at St. Louis, MO) and specific stage analysis (Pinter et al., 2006) to estimate uncertainty in flow capacity. Following this method, a stage-discharge curve was fitted to measurements for each year in the record with sufficient observations. The discharge pertaining to a specific elevation for each year's fitted stage-discharge curve was then determined. This provided a sample distribution of flow capacity pertaining to a certain water level. However, it is imperative to differentiate between out-of-bank flows and water levels that are completely contained within the channel to avoid biasing flood flow capacity with in-channel capacity. Fortunately, a number of flood flow measurements were available. While this approach is limited to data availability and makes some simplifying assumptions, it provides a useful method to empirically quantify the distribution of flow capacity. The distribution of AMF was determined by fitting a nonstationary Gumbel model with the *extRemes* R-package (Guilleland and Katz, 2011) to the observed AMF the USGS gaging station.

Upstream flow regulation was not directly considered in the fitting the pdf of AMFs. However, the close proximity of the gaging station provided an estimate of the pdf that implicitly accounted for those impacts in observed flows. For both the Mississippi River and Little Sugar Creek, systematic observations of AMFs were used, and historic or paleofloods events outside the gaging record were not included.

Results at the two study sites reveal that accounting for uncertainty and nonstationarity substantially reduces flood protection reliability compared to typical estimates that assume stationarity and rely solely on flood annual exceedance probability for computing reliability. In addition, results at Little Sugar Creek reveal that even proximate locations along the regulatory floodplain boundary are characterized by differing distributions of flood protection reliability. This indicates that typical, deterministic estimates of flood protection reliability communicate an optimistic valuation of flood risk and do not capture the spatial variance in confidence.

Results show a marked difference in design flood magnitudes depending on the desired level of confidence in reliability and whether nonstationarity and uncertainty are considered. Design flood magnitudes that account for uncertainty and nonstationarity may challenge current decision making by substantially increasing required resources or accepting a reduced level of confidence in reliability.

Mapping the distribution of reliability further emphasizes its spatially variance, which is due to local channel and floodplain characteristics. Neglecting this fact and ignoring potential nonstationary flood response conceals a location's true flood risk profile. The results can provide valuable information for floodplain management by recognizing and quantifying the spatial distribution of uncertainty in flood reliability and supports evidence for solutions that challenge the status quo of floodplain management.

The methods presented here can serve as tool for flood risk management and design, provide a template for nature-based solutions to reduce flood risk, and aid in the design of resilient infrastructure. Particularly as this computation of reliability considers all possible annual exceedance probabilities a feature may be exposed to over a planning horizon, rather than selecting a single “design AEP” (e.g., 1%). The results highlight the implications of considering uncertainty and nonstationarity on estimates of current and future flood risk.

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