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Record Flooding Risk and Power Outage Restoration

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Abstract: We need to predict the probability of unprecedented flooding of lands and coastlines due to unexpected storms, overflowing rivers, hurricanes, tidal surges and dam failures. This paper addresses new record floods that exceed all prior "historic" levels and are invariably due to extreme or severe weather and/or unexpected precipitation, defeating barriers and causing extensive power system outages. Given their inherently low occurrence, the probabilities of new (rare) record floods are treated as random outcomes and independent events using classical statistical mechanics and related hypergeometric sampling. This analysis straightforwardly replaces tuning or fitting to "normal" precipitation, regular tides and prior flood data and the traditional use of multi-parameter extreme value distributions (EVDs) used for weather-induced flood forecasting and estimating "return periods". The approach is not reliant on geographic computer models, meteorological forecasting, published "flood zone" charts, or hydrological techniques and images. We illustrate the universal applicability of this Bayesian-style approach of solely addressing new records for a wide range of specific flooding case studies for rivers, major hurricanes, quasi-periodic coastal tides, and dam failures. The quantitative link is shown between extreme event extent and power outage duration, and the results impact disaster resilience, infrastructure vulnerability and emergency preparedness measures.

Key words: Floods, planning, rare events, risk, rivers, dams, probability.

1. Introduction: New Record Flood Risk

1.1 The Predictive Need and the Present Approach

We need to predict the probability of unprecedented flooding of lands and coastlines due to unexpected storms, overflowing rivers, hurricanes, tidal surges and dam failures. Known as "extraordinary floods" [1] by its very definition, a new "record" flood exceeds all prior floods in height and extent, and is an "unknown known" and usually results in extended power outages. As suggested by P. C. Oddo (private communication, 2020) this could mean "that our current conception of the future could be fundamentally different from the present or the past". Since extreme flood events will occur, the only question is risk quantification *defined as the inevitable probability of a new record flood.*

The present approach of rare-event risk assessment for the probability of flooding is based on the established statistical mechanics of physical systems. A wide range of specific example case studies include flooding from New Zealand and US rivers, recent major US hurricanes (Harvey, Irma and Florence), high tides in Netherlands, the repetitive tides in the Venice Lagoon, and the occurrence of dam failures. The quantitative link is shown between flooding extent and power outage duration, and a new correlation developed for the probability of extended non-restoration and its duration.

Our primary interest is in predicting the unexpected new record and the subsequent restoration of power system infrastructure due to the occurrence of record floods, to help defining barriers, defenses or controls which focus on disaster resilience and emergency preparedness [2, 3]. As pioneered in the Netherlands [4], we consider flood probability as a measure of the predictive uncertainty, because of the direct impact on disaster resilience, infrastructure vulnerability and emergency preparedness measures for extreme flooding events [5, 6]. Given that all non-record floods are implicitly societally acceptable, for any location the desired final statement sought is of the form: "There is a one in X chance that the next flood

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will exceed existing barrier heights, prevention capacity and/or record water levels within the foreseeable future". So determining the value for X is the recurring question.

Despite clear economic justification, the present work is *not* based on any economic decision making such as cost-benefit trade-off [7], societal risk cost inter-comparisons [8], or funding allocation based on land loss [9, 10]. There have been extensive (and expensive) studies of the financial risk and economic factors for prioritizing river and coastal flood prevention measures, especially in the USA [6, 7, 10, 11]. Enhanced flood prevention measures for just the massive Dutch [4], Venice [12], and New Orleans [13] projects have a cost many $B, and will still need future upgrading.

Humans globally now occupy more floodable lands and coasts exposed to unprecedented events [e.g. 4, 6, 14] while more dams are operating [15, 16]. There is concern that flood and storm magnitudes and frequency are perhaps increasing due to *systematic* climate change, and the excellent review [17], identified 3,173 events in 25 years but states: "we should not assume that this long-term record is the best predictor of the future". This is ample justification for the present study and attempt.

1.2 Previous Methods Used for Floods and Socio-economic Risk

Forecasting weather and flooding is the traditional realm of the established hydrological and meteorological disciplines [1, 17-19; plus water.weather.gov and www.weather.gov]. Past and present river and coast water levels are coupled to weather forecasting using computer modeling and "ensemble" predictions [20] and elaborate statistical curve fitting for the probability of potential flow or height [21]. Being linked to weather forecasting, there are many excellent and key references on models used world-wide for the frequency and magnitudes of historical flooding due to past storms and stream flows (as a sample see Refs. [1, 19-28]).

By definition, new records are "known unknowns" resulting from an unexpected hurricane, tsunami or downpour, and may include failure of existing engineered preventative measures (overloaded levees, pumps, sea walls, storm drainage, etc.). We cannot predict *when* record floods will occur, and it is clearly stated that: "As a rule of thumb, statistical methods should not be used to estimate recurrence intervals in years that are more than twice the number of years of available homogeneous data" [29].

The usual approach is to make the best statistical fits[1] to the prior height or flow data, and all have essentially very similar coefficients of determination or "goodness of fit" parameters [19, 29, 30, 31]. The only justification for their use is they can be tuned to fit the data well even though the adjustable parameters can number three, four, or more, but are not physically distinguishable. The excellent US Geological Survey (USGS) study [21] covered the basic methods and carefully examined nine different fits, showing no unique "best fit" prediction to the tail (Ref. [21], Fig. 9), and the uncertainties in making predictions beyond the data range, in this case above the prior record flow of about 70,000 cfs and below an exceedance probability of 0.01.

The data fits are location and regionally different and specific, and require "regional skewness estimators" (see e.g. the excellent summaries in Refs. [22-24, 32]). Also Bonnin et al. [22] also importantly state: "The current practice of precipitation (and river height and flow) frequency analysis makes the implicit assumption that past is prologue for the future. Furthermore, if the climate changes in the future, there is no guarantee that the characteristics extracted are suitable for representing climate during the future lifecycle of projects being designed". This issue was

[1] The formulae are often termed Generalized Extreme Value Distributions (variously abbreviated as EVD, GED and GEVD), or specifically named, and have three or more adjustable parameters (see Section 3.2 and Table 1).

also pointed out as due to globally and locally changing climate and precipitation patterns [25].

For coastal regions worldwide, there are similar statistical approaches and concerns for predicting flood and storm surges (see Refs. [4, 13, 33-35]). Standard (Monte-Carlo type) statistical sampling has also been used for variations in the arbitrarily chosen fitting parameters, and flooding probabilities or frequencies are often extrapolated outside the data base by ascribing uncertainty bands or assumed "confidence" levels (see below). Coasts have quasi-periodic tidal fluctuations superimposed on potentially record high levels, and are different from inland floods due to "one-off" river overflows. To account for systematic sea level rise, the mean or average tidal sea level data have been adjusted using 3rd order polynomials fitted by arbitrary, which again are highly location and data range specific (see Refs. [7, 11]).

Hence, in summary, it is well known from all this extensive and detailed work that:

(a) Sophisticated distributions fitted to prior data for frequency or number of floods, storm surges or precipitation events are physically arbitrary and multi-parameter, and therefore only strictly applicable *within* the existing data range and may not properly include the tail of random rare events.

(b) The assumption that the future is just like the past historical (prior) data does not account for any systematic or recent shifts or significant changes in weather patterns, precipitation or climate, which have been and are actually observed whether attributed to climate change or not.

(c) Extensive numerical flood depth data are generally not available for intervals longer than 50 to 100 years, are often incomplete, and relevant hydro/paleo/geologic data are scarce.

(d) Modern precipitation analyses, computer models and statistical methods are well developed and tuned to daily, weekly and multi-year weather forecasting, but not to the worst few one-off rare or extreme events (due to unexpected hurricanes, major storms, tidal surges, typhoons etc.) so do not predict unusual flooding events well.

Since the real issue is fitting the few extreme points *at the right tail* of the distribution, past studies try to allow for the resulting greater uncertainty, sometimes referred to as "deep uncertainty", but are inherently biased since they usually retain and the fits are weighted by the bulk of the non-record data forming the peak probability.

In 2012, the UK reported the "wettest winter for 250 years", but despite this new record the flood zones are still defined by yearly occurrence[2], and flood risk delineated by distinct but entirely arbitrary categories [36], viz:

- "—high risk…each year, there is a 3.3% chance or greater;
- medium…each year, there is between a 1% and 3.3% chance;
- low risk…each year, there is between a 0.1% and 1% chance;
- very low risk…each year, there is less than 0.1% chance".

This ranking implies the completely new record was a "low risk" at 0.4% per year (i.e. probability of 0.004 for once in 250 years). We do not use such unsupported relative risk level, empirical classification, yearly "frequency" or rankings; and also reject defining acceptable risk boundaries on the basis of event frequency vs. consequences measured in deaths or money (see Refs. [13, 15, 29, 37]). Using quantitative frequency-versus-deaths (F-N curves) as the risk measure literally allows trades between deaths and frequency for obtaining the same risk, using what is called a "Societal Tolerable Risk Limit" boundary. For example, for existing dams a failure frequency of one in a million dam-years resulting in a cut-off limit of 1,000 deaths is the same tolerable "risk" as one

[2] Equivalently, a 0.1% chance in a year is a frequency of 10^{-3}/year or the apocryphal one-in-a thousand years' event.

death for a failure of one every thousand years. As justification, the USBR report [37] simply states: "(Bureau of) Reclamation defines this risk as Annualized Life Loss, and uses a guideline of 0.001 fatalities per year to address this measure of risk"; while economic losses and impacts "may be important considerations in the decision-making process". Working backwards, the "statistical value" or cost-of-a-life lost varies widely [38] being somewhere in the range of \$1-10 M, so 0.001 implies only a completely negligible financial/societal risk exposure of \$1-10,000 per death per year. Only if more than 1,000 are killed is the lost value greater than \$1 M which is still "tolerable", but surely negligible compared to the likely \$Bs of infrastructure damage and repair costs.

Using geographic - hydrographic - socioeconomic computer modeling, about 40 M people and \$3 T are estimated to be at future or potential risk to a "once-in-a-hundred year flood" in the US alone [26], comparable to the cost of a major viral pandemic. The past cost of US flooding risk has been estimated as \$90 B and over 700 deaths during 2004-2014, and will likely become worse [6]. In England there are about 5 million properties at risk of any type of flooding, with an annual insurance cost of more than \$3 B, with 14% or 7,000 sites of the electrical infrastructure at risk [36]. The fiscal and societal risk is actually huge.

1.3 Present Scope and Objective

Pragmatically, we only seek the probability of *exceeding* the previous record flood in some (unknown or chosen) future and treat all record floods as random outcomes or events, subject to statistical and physical constraints. Support to the present approach is also in USGS Bulletin 17C p. 21: "In general, a time series of annual peak-flow estimates may be considered to be a random sample of independent, identically distributed random variables" [1]. We simply extend this concept to describe the occurrence of new record (extraordinary) floods that do *not* follow standard statistical distributions; or occur at any known variance, multiple standard deviations or moments from some average, median or central value. In addition, systematic changes in "normal" water levels and geology/geography can affect long-term predictions.

We first briefly discuss existing predictive and flood risk analysis approaches and develop the new approach based on the established statistical mechanics of physical systems. We then provide test cases, and link to power outage extent and probability.

2. Probability and Rate of Record Floods: Theory and Comparison of Predictions

To attempt to inform this problem, we adopted simple sampling of observations based on standard assumptions, physical reasoning and traditional statistical mechanics theory for observing random outcomes. To illustrate the long-standing and well-known fitting and consequent predictive problem we compared three different approaches to quantify the "tail" uncertainty: (a) the usually plotted Extreme Value Distribution (EVD) and weighted Pearson Type III curves; with (b) the hypergeometric and statistical sampling estimates; and to (c) standard Excel Add Trendline or weighted TableCurve 2D mathematical fitting routines.

2.1 Traditional Generalized EVDs

Typically, arbitrary three or more parameters "Generalized Extreme Value Distributions" (GEVD) and Pearson type are used for floods [7, 19, 26, 30, 31] and also for power outages [39]. The only justification for their use is they can be tuned to fit the data well even though the adjustable parameters can number three, four, or more. Not physically distinguishable, the EVDs have been written with many different symbols for the various constants and the zero-offset, μ (for a range of examples, see Ref. [40]) and are exponential functions of similar general form.

Table 1 Typical EVD fitting parameters.

Distribution	Ψ	α	β	ζ
Gumbell	1	0	$e^{-\theta}$	1
Frechet	1	$(\xi-1)/\xi$	$-1/\xi$	ξ
Weibull	1	$(1-\xi)/\xi$	$-1/\xi$	ξ
Pearson III, IV	1	ξ	1	$\Gamma(\xi)$
Modified Gaussian	$e^{-\theta/4\psi}$	1	1	1

Typical popular variants are compared in Table 1, where α, β, ζ, ξ, Ψ and ψ are the adjustable fitting parameters, and setting $\theta \equiv \left(\frac{M_F-\mu}{\psi}\right)$, so $p(M_F) = \frac{\Psi\theta^{\alpha}}{\psi\zeta} e^{-\theta\beta}$.

These types plus some 3,000 other formulae (including high-order polynomials) are available using the commercial curve fitting software TableCurve 2D [41]. While Ockham's Razor suggests using the simplest hypothesis or method, the reader is of course free to adopt whatever best suits the purpose and represents appropriately the physics, available data and logic of the situation. For the present rare or record event case, we seek the "best" fit to just the "tail" record events, not to the overall distribution as usual; and must avoid extrapolating EVD fits outside the basic data range, as extensively described and shown by Asquith et al. [21].

2.2 Hypergeometric Sampling

Since the occurrence of any past or new record flood is purely random, we retain the original Laplace "equally possible" definition of probability being the ratio of numbers observed, n, to the total possible, N [42]. Each flood event is completely independent but part of some overall population, which may be subject to local, regional and global shifts in geography, geology, meteorology, oceanography and hydrology. Observed record, n_F, or non-record, m, floods are random independent events, out of total (sample) populations of, N, and, M, respectively, and can occur or be observed at any (unpredictable) moment and represent our prior information or history. Therefore, the *probability* of observing the outcomes, $p(n_F)$, of, n_F, record floods occurring randomly among non-record floods, m, is always determined from and by the classic hypergeometric sampling distribution function (see Ref. [43], pp. 52-55, and 68-69), and is:

$$p_F(n_F) \equiv p_F(n_F, N, m, M) = \frac{\binom{N}{n_F}\binom{M}{m}}{\binom{N+M}{n_F+m}} \qquad (1)$$

As an example of this standard combinational notation, ${}^{N}C_{n_F} \equiv \binom{N}{n_F} = \left(\frac{N!}{n_F!(N\text{-}n_F)!}\right)$, with the total number of, N, possible record floods being observed (or occurring) n_F at a time among, m, the possible total non-records, M. Evaluation of the hypergeometric probability, $p_F(n_F)$, for any n_F, m, N and M values can be performed using the Excel HYPERGEOMDIST function routine[3]. Self evidently, the future risk does indeed depend on the past propensity for record flooding, and is based on knowing the uncertainties and duration span of the historical record itself, or what is often termed the "prior information" [43]. In Bayesian terminology, the likelihood of the next flood is $1/n_F$, which may or may not be identical to the prior ones so the Posterior probability is $1/N$, for any future risk exposure.

2.3 Classical Statistical Mechanics Theory

The rate of outcomes, λ, is the change in the number of outcomes observed during an incremental variation of the risk exposure. Now, N, is the total number of record floods, so in terms of the observed number of (record flood) events, n_F, of magnitudes, M_F, the frequency/rate,

$$\lambda(M_F) = \frac{1}{(N-n_F)}\frac{dn_F}{dM_F} \qquad (2)$$

and

$$p_F(M_F) = \frac{n_F(M_F)}{N} \qquad (3)$$

[3] To check the mathematical results, we obtained complete numerical agreement between the hypergeometric cases evaluated in and by Jaynes [43] with those same cases using the Excel 14.7.7 HYPERGEOMDIST routine.

The flood magnitude, M_F, can be a volumetric flow, Q_F, or tidal height or river depth, H_F, depending on measurement type and location.

Not applied to flooding before, the *distribution* of the number, n_F, of random events (in this case observed floods as a function of magnitude, M_F) can be derived by applying and adapting the well-known classic methods and physically-based constraints of statistical mechanics [44-46]. Specifically for flood events, these are that:

- record and non-record floods occur randomly and are counted in some past and present observational interval as distinct independent outcomes and are some systematic function of the risk exposure (flood flow or height, or operating dam-years);
- probability of purely random record floods (past, present and future) is derivable from the total possible number, N, of all occurrences;
- being random, many possible distributions of the observed flood outcomes or number of dam failures are equally likely;
- distribution of the number of flood events recorded or observed as a function of magnitude is the most likely because that is the one that actually occurred;
- number of possible distributions of *all* observed outcomes (floods and dam failures), given by $N!/\Pi n_F!$ allows the standard use of Stirling's factorial approximation[4] [44].

For any observed sample of floods these constraints result in distribution formulae that are *always* simple exponential forms [44, 45]. The number of random flood events, n_F, is [3, 46, 47]:

$$n_F(M_F) = n_m + (N - n_m)e^{-\gamma M_F} \quad (4)$$

The naturally arising constants to be determined are the e-folding characteristic, γ, and the minimum number, n_m, being the lowest attainable or actually observed. From Eqs. (3) and (4) the probability of observing any flood is,

$$P_F(M_F) = p_m + (1 - p_m)e^{-\gamma M_F} \approx p_0 e^{-\gamma M_F} \quad (5)$$

The standard Excel Add Trendline fitting routine contains this exponential form, which is just a working hypothesis at this stage to be validated by data.

3. Comparisons of Theory to Data: Predicted Probability and Uncertainty of New Record Floods

To illustrate the general methodology and address differing flooding scenarios, we select and focus on: (a) extreme or rare event occurrences; (b) where non-records are either present or absent in the observations; and (c) disparate causes due to river flows, coastal surges, hurricane rain and winds, plus dam overtopping and failures. Often the data are only available/published in graphical form so had been hand transcribed[5], but the slight errors incurred (5-10%) are not important for demonstrating the principles of the predictive methods. The typical examples that follow cover the whole panoply of differing flood "types" but with similar data base challenges and predictive uncertainty.

Once again, we emphasize that the real issue is fitting these extreme points *at the right tail* of the distribution, not just the bulk of the data forming the peak probability. Therefore, whenever possible we compared: (a) the hypergeometric estimates (Eq. (1)); (b) the plotted weighted Pearson Type III or EVD curves (as in Table 1); (c) Excel Add Trendline or weighted TableCurve 2D fitted exponentials (Eq. (5)).

3.1 Record Tokomairiro River Flooding

The first demonstration and intercomparison is for local *record* floods, being the simple case of volumetric flow rate data, Q_F, for N = 115 floods of the Tokomairiro River in New Zealand for 1961-2002

[4] By illustration, the possible number of combinations or occurrence sequences is $W = N!/\Pi n_F!$ and W = 3,628,800 just for n_F = 1 record flood observed randomly among a total possible of only, N = 10.

[5] Whenever possible, we requested or gained access to original data files for the published plots, and where granted the source is acknowledged or referenced in the text.

[48] which flooded the City of Milton in 2006, 2007 and 2010 [49], with local flash flooding in 2017. As conventionally, the flood count, n_F, has been compared against multi-parameter GEV/EVD type distributions, so we transcribed the flood number data[6] from the original graph (Fig. 3 in Ref. [48]). Converting to probability by dividing the total count, N = 115, and taking the magnitude of the flood as equivalent to the flow, Q_F, Fig. 1 shows that simple exponentials fit the data well, at least based on the coefficient of determination[7], for $M_F = Q_F$ in m^3/s, using AddTrendline with $R^2 = 0.973$,

$$p_F(Q_F) = 0.79e^{-0.075Q_F} \quad (6)$$

or using TableCurve 2D with $R^2 = 0.995$.

$$p_F(Q_F) = 0.0023 + 0.82e^{-0.081Q_F} \quad (7)$$

TableCurve 2D also provided the Weibull, GEV and Pearson VII fits which have R^2 ~0.998 by adjusting the Table 1 parameters.

The above simple exponential fits in Fig. 1 align more smoothly and better than the three GEV types shown in Fig. 3 of Ref. [48]; but more importantly can still capture the "right tail" minimum of the physical distribution caused by the rarer record floods. The correct probability method is the hypergeometric "probability of exceedance", p_F (n_F, m, N, M) based on knowing the historical record itself, as well as postulating the future risk exposure.

If the total record and non-records, ($N + M$), is taken as a measure of our total *future* risk exposure or experience, the total number of non-outcomes, M, clearly could have the effect on reducing the perceived or apparent outcome probability, $n_F/(N + M)$. This trend is also exactly what we see reflected in the data, and on reflection is trivial and obvious. Re-examining the Tokomairiro River case discussed above [48], since there were 115 floods observed already the probability of the very next flood equaling or exceeding the prior record flood of Q_F = 65 is p_F (1, 1, 1, N) = (1, 1, 1, 115) = 0.008695. This result confirms the assumption of randomness as it is precisely the LaPlace-Bayes-Jaynes uniform posterior value, $p_F = 1/N = 1/115$, but some 40% more than p_F (Q_F > 65) = 0.0062 derived from the fitted equation.

3.2 Record Big Sandy River Flooding

This test case has both non-record and record data, being the typical and traditional example in the FEMA Flood Risk Assessment course ([29] Fig. 4.1) showing the standard probability plot of flowrate (discharge) Q, versus the probability, p_F (> Q). For this Big Sandy River specific case, there are non-flood points (m = 44) for 1930-1973, and three (n_F = 3) largest historical record flows observed during 1897-1973 and the FEMA fit to the data is stated to be a usual "weighted Log Pearson Type III". Because the Pearson line is extrapolated beyond the database, strictly all we can say is the new record flow magnitude, Q_F, will be greater than the last record, or more than about 28,000 cfs.

Consider further the all-important "right tail" caused by just having three rare record floods with an average probability of p_F (Q_F > 18,000) = 0.025.

The hypergeometric probabilities for these three record data points, n_F = 1, 2, 3, are p_F (1, 1, n_F, 47). For example, having observed the three records out of $n + m$ =47 prior observations, the hypergeometric probability of the next flood being a record is p_F (Q_F > 28,000) = p_F (1, 1, 3, 47) = 0.064, which again is trivially identical to $n_F/47 = 3/47 = 0.064$.

The weighted TableCurve 2D fitted exponential is,

$$p_F(Q_F) = 0.001 + 1.28e^{-0.0021Q_F} \quad (8)$$

This typical comparison is shown in Fig. 2, where the three different estimates (a-c) have an average probability p_F (Q_F > 18,000) ~0.03 for the three record points, a difference of 30%.

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[6] Mohsson [48] used the terminology "frequency" to describe the flood number count, n_F, in discrete ranges or "bins" of flowrate, Q_F.

[7] Note the usual goodness of fit parameters (R^2, Fstat, moments etc.) is not the best or most sensitive measures for fitting a few "tail" data points, being heavily influenced by the vast majority of "normal" data, and barely at all by the few rare records at the "tail".

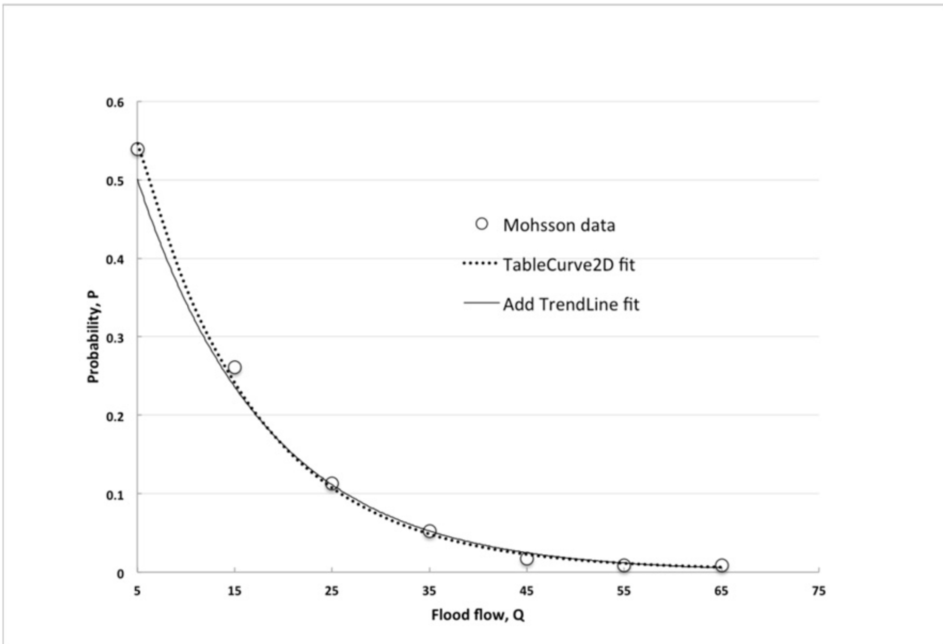

Fig. 1 Probability of flood flows for Tokomairiro River and the theoretically based fits.
Source: data from Ref. [48].

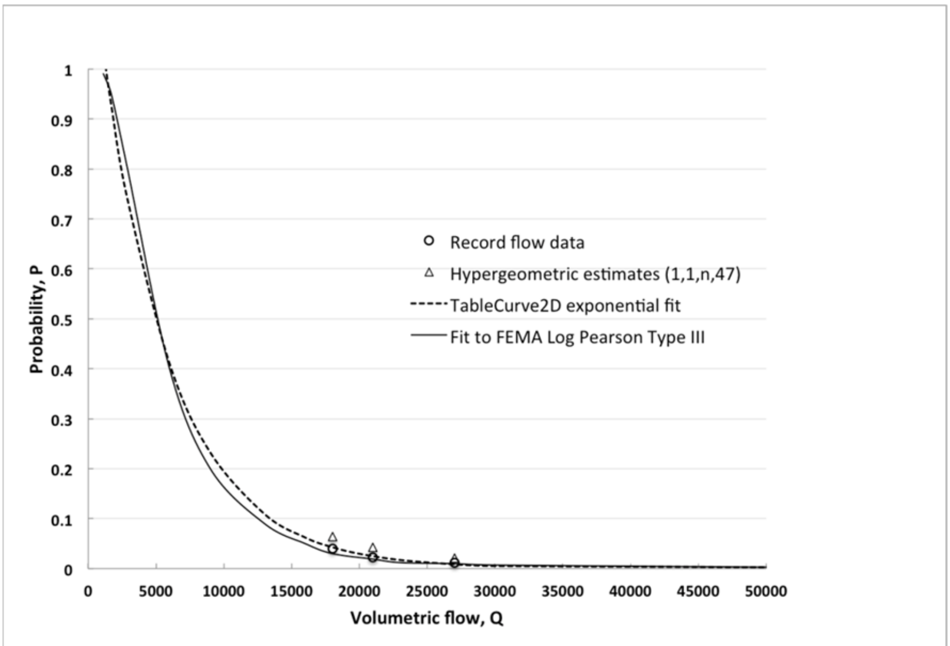

Fig. 2 Illustration of alternative estimates for the probabilities and "tail" for the FEMA Flood Risk Course standard example.
Source: Fig. 4.1 of Ref. [29].

3.3 Record Hurricanes Induced Floods

For unexpected major storms, we found new flood gauge records in the extensive river "stage height" graphs for Hurricane Florence [50]. As stated: "Florence analysis confirms extreme 3-day rainfall amounts exceeded 0.1% probability event expected in given year, or was a 'once in 1,000-year' event" [51]. A typical gauge example[8] for the Little River showed

[8] Of the gauge locations with totally new record floods, in the spirit of this study this record history was chosen at random from among those that had a prior NWS magnitude distribution *and* a listing of historic prior floods.

a *new* record flood where the prior historic record was for 1929-2016 (87 years), so was indeed almost the one-in-a-hundred-years flood. For this Little River example case, on the National Weather Service (NWS) past probability graph [50] there were $(m + n_F) = 63$ prior data points (8 records and 55 non-records over the 87 years) with, of course, $n_F = 1$, the one new "extraordinary" record beyond the prior listed total past record or peak floods at this specific location. As a reality check, the hypergeometric *past or prior* probability, p_F (n_F, 8, 63, 71) has a peak value ~0.4; and the CDF probability, $\Sigma_n\, p_F\, (n_F)$, of having the observed 8 record events is indeed unity. The concomitant record flooding also damaged the electric power system.

For coastal record floods due to extreme precipitation not sea surges, Hurricane Harvey (Category 4) made landfall at Corpus Christi in Texas, and then stalled over Houston in Texas, causing the worst rainstorm in U.S. history. The precipitation rate was 10" (254 mm) per day with massive concomitant local flash flooding of inland rivers, creeks, and bayous that entirely swamped the surrounding suburban areas and the city. From 25 August to 28 September 2017 we downloaded rainfall and water level data for selected flood warning stations [52], and estimated the frequency from the period or number of years, y, since a flood event last occurred or has not occurred, i.e. $\lambda \sim 1/y$. The startling observation is the factor of ten underestimations of the frequency of occurrence for a flood depth expected and known to exceed the bank heights for the same bayous and creeks, and excluded the delayed and necessary release of excess water from overwhelmed flood control dams.

3.4 Record Venice Tidal Flooding

In total contrast, we examined aperiodic tidal flooding having entirely different origins from that due to sudden major storms or overflowing rivers. For Venice, Italy, the *acqua alta* data, H_F, are available on-line [12], where the floods are ascribed to tides coupled to variations in atmospheric pressure and winds, plus the systematic subsidence of the Venetian Lagoon [53]. Being tidal in nature, the peak floods generally last for about 3 hours, are quasi-repetitive, and have been extensively modeled using geographic and statistical methods to inform the design and operation of new flood control and prevention barriers [53].

We substantiated the random nature of the peak flood levels using the data for 52 years (1966-2018) in which there was a total, $N = 5{,}986$, measurements of flood levels, H_F, greater than 80 cm listed in 10 cm increments (or bins), n_F, up to the record of 190 cm [12]. As shown in Fig. 3, the listed flood level frequency distribution, $\lambda(H_F) = n_F/52$ per year, follows almost exactly the symmetric Gaussian or "normal" distribution about an average flood value as:

$$\lambda(H_F) = \lambda_m + (\lambda_0 - \lambda_m)e^{-0.5(H_F-\overline{H_F})^2} \quad (9)$$

The values derived using Tablecurve 2D are, with $R^2 = 0.994$ and for $H_F > 80$ cm,

$$\lambda(H_F > 80) =$$
$$0.029(0.69 - 0.029)e^{-(0.5(H_F-127)^2/10.33)}$$

Note the implied "tail" rate value of $\lambda_m = 0.029$ per year (one in 34 years), and the mean flood level $\overline{\mathrm{M_F}} = 127$ cm. Since the data follow a normal distribution this confirms our fundamental hypothesis that the flood levels are statistically random occurrences, as also shown by the data point for the latest "near record" flood in November, 2019.

The probability analysis of these same 1966-2016 data gives a different perspective. The probability, $\mathrm{p_F(H_F)} = \frac{\mathrm{n_F}}{\mathrm{N}}$, of a flood at any level, H_F, is shown in Fig. 4, and compared to both using hypergeometric sampling and the exponential best fit values from TableCurve 2D, with an almost perfect $R^2 = 0.9998$ for the entire data set,

$$p_F(H_F) = p(1, n_F, 1{,}5986)$$
$$\text{or} \quad p_F(H_F) = 0.00016 + 810e^{-(0.09H_F)}$$

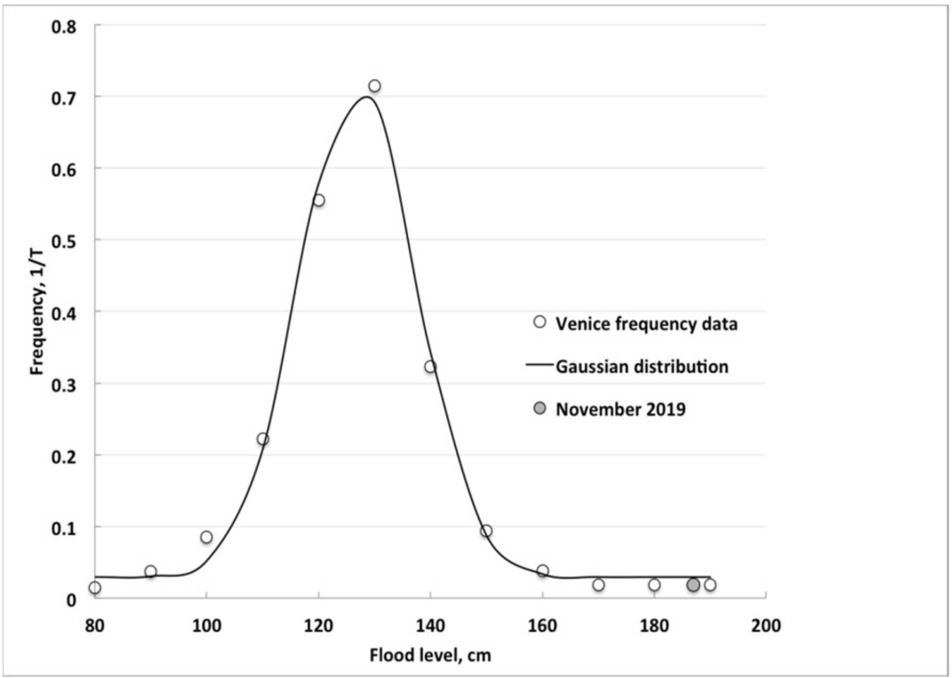

Fig. 3 Normal frequency distribution for tidal flood heights in Venice.
Source: data from Ref. [12].

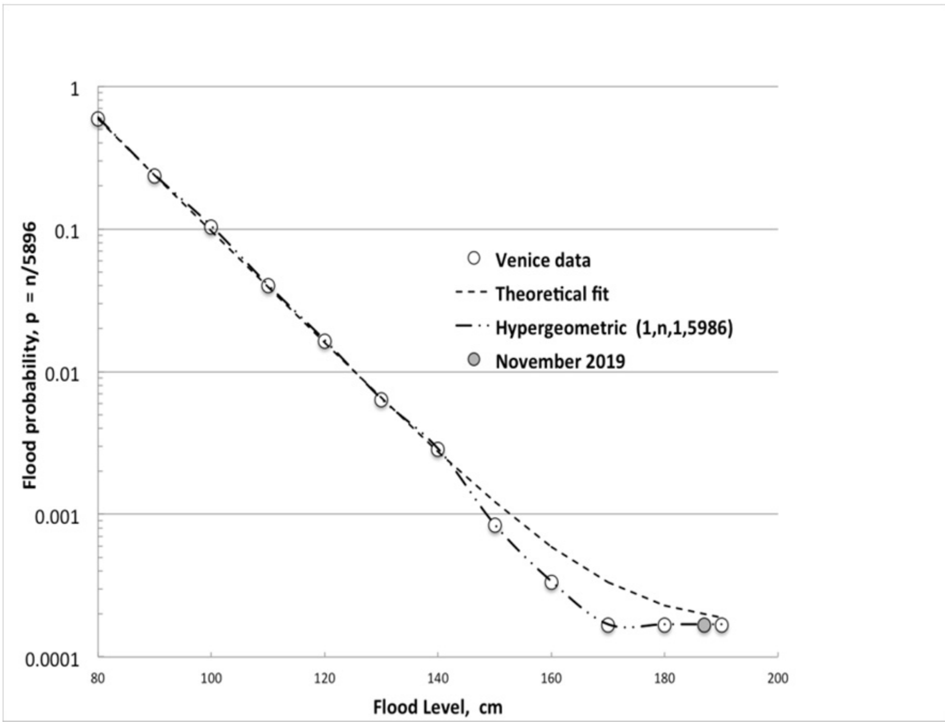

Fig. 4 Declining "tail" probability of flood levels for Venice and theoretical fits.

The hypergeometric result is exact, whereas the best exponential statistical fit again deviates slightly at the "tail" of the lowest probabilities for the rare events. Naturally, the uncertainty for this "rare tail' or record event is because of the few data points, and the new 2019 data point has a probability of $1/(N + 1) = 1/5{,}987 = 0.000167$, a small but important 6% difference from the value predicted by the exponential fit.

The hypergeometric analysis *assumes* no changes in flood control measures or weather patterns. For Venice in 1966-2018 having already had one all-time record, M_F > 190 cm out of N = 5,986 floods, the chance that the very next one will be also > 190 cm is, p_F (1, n_F, 1, N) = p_F (1, 1, 1, 5,896) = 0.00017, or one in 5,896, exactly the estimate based on the LaPlace probability, $p_F = n_F/N$ = 1/5,986 = 0.00017, for the event count. Simply assuming a uniform occurrence probability over the last fifty-two years, there is an average of λ = 5,986/52 = 115 flood events of > 80 cm per year. Trivially, on average another record H_F > 190 cm can be expected within the next fifty-two years (i.e. 5,896/115). Note that the new Venice MOSE barrier is designed to handle floods up to 3 m (9.8 feet) from which any projected systematic or overall level rise perhaps should be subtracted.

3.5 Record Floods and Systematically Increasing Sea Levels (Climate Change)

To examine changing the threshold for exceeding a flood of any given height is the case of systematic (or climatic induced) sea level rise. For example, Venice having already observed the 10 out of 5,986 floods with levels, M_F >140 cm, the chance that of the next 10 floods there will be one > 140 cm is, p_F (1, 10, 10, 5,896) = 0.017, or about 1 in 58, or about ten times (10×) the risk as having one new all-time record. The difference between one in 52 and 34 years for the normal vs. hypergeometric risk estimates, respectively, is one possible measure of the uncertainty in the prediction of having a new record.

Methods to include such future sea level rise trends for coastal floods have been introduced (e.g. Refs. [4, 11]). As part of a risk-benefit study, using one Netherlands gauge station, the peak tidal level frequency for a 137-year gauge record has been fitted by a simplified GEV (Ref. [7], Fig. 2). We were kindly supplied the original data file[9], and instead of frequency, calculated the occurrence probabilities for every 5 m height over the range 210 < H_F < 260 m. The probability of one record peak, n_F = 1, among the M = 137 prior non-peaks, P (1, n, 1, 137) is,

$$p_F(n_F) \equiv p_F(n_F, N, m, M) = p_{M_F}(1, n(H_F), 1{,}137)$$

The results show that the probability of occurrence of any new peak height is actually normally distributed (cf Venice Fig. 3), and the best fit is the simple Gaussian distribution (dotted line) shown in Fig. 5. This result confirms again that the peak levels occur randomly with a normal probability distribution centered on circa 286.5 m.

The fit suggests the new record flood probability is 0.01174, but within the range 1/137 < p < 3/137 spanned by the data points at the "tail" of 0.0146. Hence there is about a 1.5% chance of a new record flood.

3.6 Dam Failures and Flooding

Finally, we examine dam failures which are also usually caused by unexpected precipitation or other natural events and presumably cause locally record flooding. Being a rare but perceived societal hazard, guidelines for evaluating dam safety risk management exist from Federal Emergency Management Agency (FEMA) [15] and the US Bureau of Reclamation [37]. Prior and future risk exposure is measurable by the time in dam-years, *Dy*, spent actually holding water, analogous to aircraft accumulating flight-miles, trains the train-miles traveled, or the number of patient-operations of surgeons. For all dam types and failure modes, the US National Bureau of Reclamation (NBR) has data with accumulated experience of over 100,000 dam-years (*Dy*) including the oldest earthen dams [54]; and the National Performance of Dams Program (NPDP) of some 1.7 million dam-years for all US dams [16].

[9] We are extremely grateful to P. C. Oddo for supplying these data and for further technical remarks regarding the present analysis.

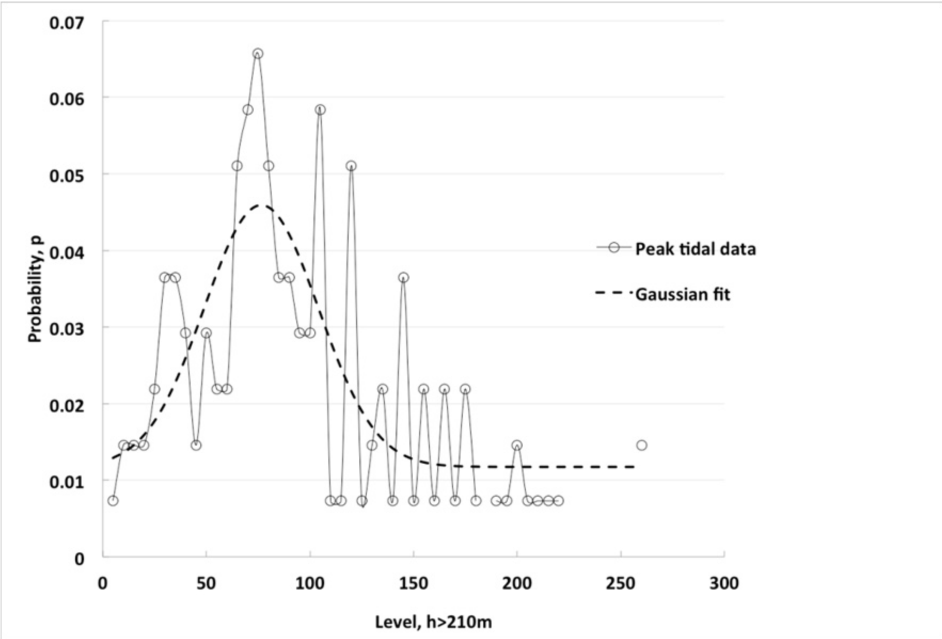

Fig. 5 Fitted normal probability distribution (dashed line) of flood surge heights (open circles) in Netherlands over 137 years.
Source: data from Ref. [7].

Using the exponential Eq. (5), the statistical fitting routine TableCurve 2D gave a *minimum* dam failure rate for the NBR dams of order three per 10,000 dam-years, or a rate of 0.0003 dam failures each year [42]. For the 90,000 dams in the US NPDP database, there were about n_F ~2,296 failures over the last 120 years or so, or about 20 per year and have an overall average past/prior failure rate of about n_F/Dy = 2,296/1.7 M ~0.001 per operating dam-year, by far the lowest found failure rate for any technology or human-made structure.

The probability of dam failure was calculated using the available NPDP subset data base[10], as a function of individual dam operating age, "binned" in yearly intervals so $p_F = n_F\,(Dy)/N(Dy)$, for any given age (in years). The result was bathtub shaped analogous to many mechanical components, decreasing during wear-in and then increasing due to wear-out (see Fig. 6) presumably due to the deleterious effects of aging and increasing accumulated risk exposure.

While completing the original analysis, another unexpected major flooding occurred due to overtopping failure of a 96-year old dam at Edenville, Michigan [55]. This data point is shown shaded in Fig. 7 as a *new record* flood for either Michigan (with N = 2,600 dams) or nationally (N = 90,000). Depending on which national or state dam population group this failure is believed or attributed to belong, the failure probability is $0.00005 < p_F$ (Edenville) < 0.0004. This new result implies an order of magnitude predictive uncertainty in general accord with the overall prior 1900-2020 historic trend, and still very unlikely.

4. Results and Predictive Summary

A summary of the cases studied in Sections 3.1-3.6 is given in Table 2, plus for the recent flooding of the Red River, providing alternative estimates for many disparate locations with individual case estimates differing by factors of up to 10. Being totally independent events with, $0.00016 < p\ (M_F) < 0.04$, strictly we cannot combine or "pool" the results. The naive generalization is that the event probability is about a one in a few hundred chances of a future flood exceeding existing barrier heights, prevention capacity and/or record water levels within the foreseeable

[10] We are extremely grateful to Professor M. W. McCann of NPDP for compiling and supplying these original, comprehensive and most useful data.

Table 2 Example "new" record flood probability comparing Pearson or EVD, hypergeometric and exponential predictions.

Location/flood case	Data span (y)	Total prior #	Pearson or EVD	Hypergeometric P (n, m, N, M)	Exponential
NZ/Tokomairiro R	40	115	0.0086	0.009	0.0023
USA/Big Sandy R	43	47	0.01	0.064	0.001
USA/Potomac R	35	100	0.004	0.032	
USA/Rariton R	31	103	0.001	0.032	0.002
USA NC/Little R	87	63	0.018	0.04	0.01
USA AK/Red R	74	116	0.017	0.036	0.018
Italy/Venice	83	5,986	N/A	0.00016	0.029
Netherlands	137	137	N/A	0.014	0.012
USA/Houston TX	23	9	N/A	0.1	0.015
US dam failures	120	575	N/A	0.0001	0.0001

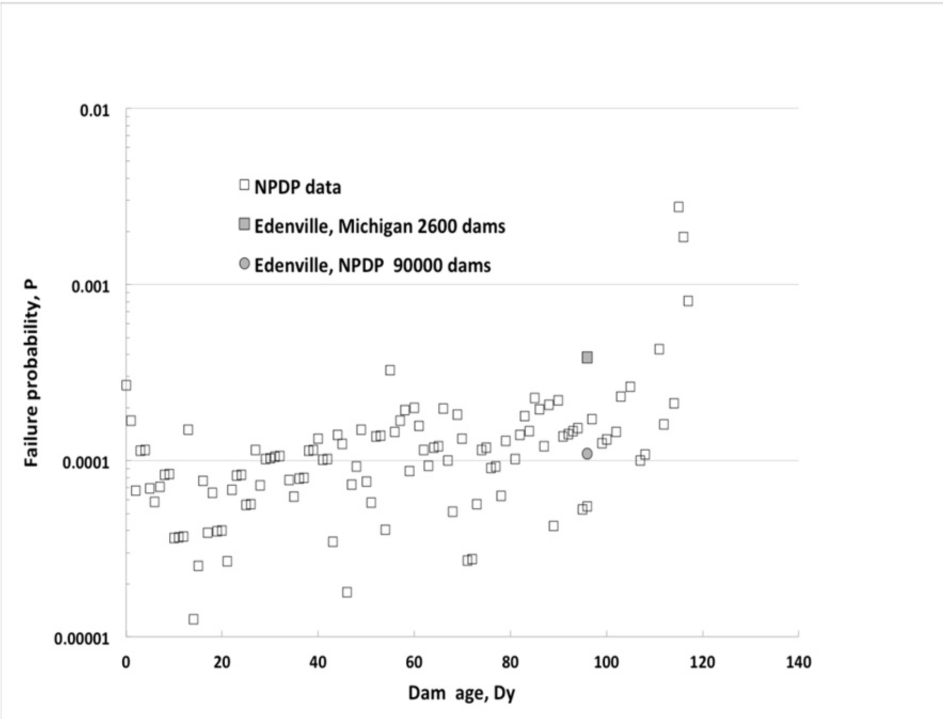

Fig. 6 Bathtub failure probability for US dams and the recent Edenville failures.

future, while flooding due to dam failures is at least a factor of ten less likely, with individual locations showing a predictive uncertainty of a factor of three to ten.

There is no advantage in endlessly debating or statistically examining which arbitrary equation is the "best fit" to the overall data distribution(s) if it is only relevant to "normal" and non-record conditions. To determine the future risk, we must distinguish between the past (statistically, the known prior) and the future (statistically, the unknown posterior), which includes the somewhat controversial arena of prediction using statistical reasoning, a subject addressed in great detail elsewhere [43].

Rather the efforts should be directed to determining the uncertainty in making rare new record predictions and to gain more predictive insights. This changes flood prediction from being purely a statistical exercise to a social decision-making and risk management activity. We next consider examples of recent power outages due to new record flooding.

5. The Link of Flooding Extent to Power Outage Restoration

Parts of the power system may be above "flood level" or not affected by rising water, and some delay occurs before water depths affect the electric distribution, circuit connections, substations, facilities and infrastructure, typically peaking 50-100 hours after storm onset [3, 47]. Extensive data show the probability distribution in the USA of exceeding a large multi-MW(e) outage size, Q^*, as a fraction of the probable average of the data set, is similar but not identical to EVD types (as in Table 1), being a double exponential with a learning theory constant, k [56], where,

$$P(Q^*) = (1 - e^{-\frac{1}{kQ^*}\{1 - e^{-kQ^*}\}}) \quad (10)$$

The largest outage events are always extreme weather related so the infrastructure and property "degree of damage" should be related to the area or extent of flooding. For Venice, the data for percentage, D, of the city flooded [12] show the linear (proportional) correlation with flood height, H_F, with $R^2 = 0.939$, for $H_F > 86$ cm, as

$$D(\%) = 0.91\, H_f - 79 \quad (11)$$

The excellent on-line USGS/NWS system has over 100 gauge records distributed in the region impacted by Hurricane Florence flooding [50, 51]. Assuming a random gauge distribution in the most flood prone regions, an indirect indication of flooding extent is defined by the fraction or probability of river gauges showing flooding as given by, $P(g) = g/G$, where g is the number of gauges showing flooding out of the working total, G. The relation between this probability of flooding, $P(g)$, and power outage non-restoration, $P(NR)$ for storm Florence is shown in Fig. 7. The flooding peak occurred after some 70 hours, or 30 hours after the peak in power outages, reaching a 30% chance before declining. Flooding persisted as drainage and recovery took longer, and some 70% of power system restoration occurred after the flooding peaked at $h = h_0$, presumably as defenses were progressively restored.

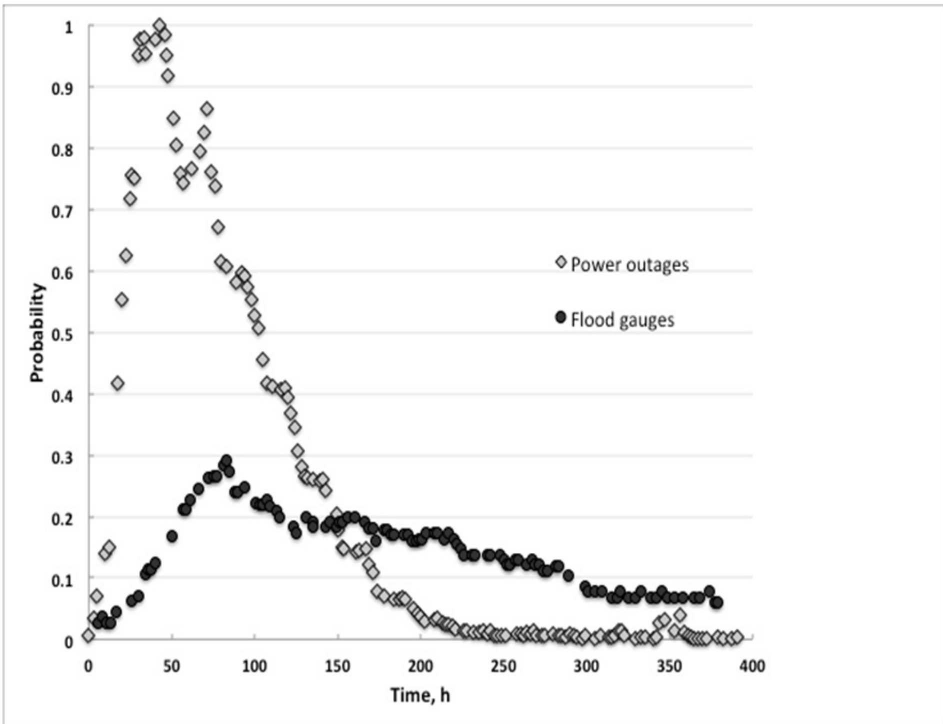

Fig. 7 The observed relation of gauge flooding to power system outages during hurricane Florence.

Comparable to Venice, one plausible assumption is that the probability of power non-restoration due to flooding, $P(F^*)$, *after the peak*, $h > h_0$, is conditionally dependent on and/or directly proportional to the extent represented by the probability of (river) gauge flooding. Symbolically, we already know the probability of power non-restoration, $P(NR)$, is exponential in form [3]. The probability of power outage non-recovery solely due to flooding is, from Fig. 7 for Hurricane Florence, the best fit to the data with an $R^2 = 0.94$,

$$P(F^*)_{h>h_0} = 0.25\, e^{-0.022(h-h_0)} \qquad (12)$$

This implies of course that a maximum of some 25% of the persistent outages are directly attributable to the difficulties caused by flooding. Lacking other evidence or alternative, this relation or something similar is assumed to be generally applicable to any power system susceptible to flooding. The parameter values in Eq. (12) are presumably dependent on the specific factors of flood zone geography, topology, hydrology, power system design, and unique gauge locations and distribution. The overall restoration rate remained largely unaffected [3], being essentially the same for Hurricane Irma as for Hurricanes Florence and Harvey because of the dominant access difficulties caused by flooding.

6. Conclusions

Despite many studies and masses of data, the past frequency of floods is not the future probability of a completely new record flood occurring that will overwhelm our defenses. Therefore, in the present pragmatic approach, we focus on estimating the probability of exceeding the previous record(s) or having a rare "extraordinary" flood. The key point is that new record floods do *not* necessarily follow the statistical distributions of more frequent events that have been previously adopted for meteorological forecasting, or extreme value distributions fitted to past peak precipitation and stream flow data. What we have learned has national as well as systems engineering implications.

Present predictive models, systems methods and statistical techniques used are subject to great uncertainty because:

- The occurrence of new record rare events is random, so it is difficult to adequately include in standard hydrological and meteorological models that are tuned to a multitude of prior historical data;
- By definition, a record flood is greater than anything in the past but is rare, random and unexpected, so it is difficult to demonstrate existing mitigation and control measures will not be overwhelmed;
- The impact on vital infrastructure like power systems is at present barely included in present flood risk assessments since the focus is on property damage, cost and protection.

For widely disparate flood types for rivers, tides, hurricanes and dam failures, we applied differing approaches to predict new records, compare traditional empirical fits to a theoretical exponential based on statistical theory and to random hypergeometric sampling. Addressing our objective, a naïve generalization is that for *naturally occurring* rare new record flooding the statement is: "There is about a one in a few hundred chance of a future flood exceeding existing barrier heights, prevention capacity and/or record water levels within the foreseeable future, while flooding due to dam failures is at least a factor of ten less likely, with individual locations having a predictive uncertainty of a factor of three to ten".

Instead of debating or statistically examining which arbitrary equation is the "best fit" and really only relevant to "normal" and local conditions, efforts should be directed to determining the uncertainty in making such rare new record predictions. We need to continually examine rare event limits to gain more predictive insights, since the link exists between extreme event extent and power outage duration. By illuminating the uncertainties, the results impact disaster resilience, infrastructure vulnerability and emergency preparedness measures, and assist in communicating the realities of extreme flood prediction.

References

[1] England, J. F., Cohn, T. A., Faber, B. A., Stedinger, J. R., Thomas, W. O., Veilleux, A. G., Kiang, J. E., and Mason, Jr. R. R. 2018. *Guidelines for Determining Flood Flow Frequency—Bulletin 17C: U.S. Geological Survey Techniques and Methods*, Book 4, Chapter B5, p. 148, doi/10.3133/tm4B5.

[2] US Department of Homeland Security, DHS. 2017. *Outage Incident Annex (POIA) to the Response and Recovery Federal Interagency Operational Plans, Managing the Cascading Impacts from a Long-Term Power Outage*. June 2017. www.fema.gov/media-library-data.

[3] Duffey, R. B. 2019. "Power Restoration Prediction Following Extreme Events and Disasters." *Int J Disaster Risk Science* 10 (1): 134-48. doi: 10.1007/s13753-018-0189-2.

[4] Jorissen, R., Kraaij, E., and Tromp, E. 2016. "Dutch Flood Prevention Policy and Measures Based on Risk Assessment." In *Proc 3rd Eu Conf on Flood Risk Management*.

[5] NIAC. 2018. *Surviving a Catastrophic Power Outage*. President's National Infrastructure Advisory Council, Washington, DC. Accessed Aug. 14, 2019. http://www.dhs.gov/national-infrastructure-advisory-council.

[6] National Academies of Sciences, Engineering, and Medicine (US NAS). 2019. *Framing the Challenge of Urban Flooding in the United States*. Washington, DC: The National Academies Press.

[7] Oddo, P., Lee, B. S., Garner, G. G., Srikrishnan, V., Reed, P. M., Forest, C. E., and Keller, K. 2012. "Deep Uncertainties in Sea-Level Rise and Storm Surge Projections: Implications for Coastal Flood Risk Management." *J Risk Analysis* 40 (1): 153-68. doi: 10.1111/risa.12888.

[8] Starr, C. 1969. "Social Benefit versus Technology Risk." *Science* 165 (3899): 1232-8.

[9] Barnes, S., Bond, C., Burger, N., Anania, K., Strong, A., Weilant, S., and Virgets, S. 2015. *Economic Evaluation of Coastal Land Loss in Louisiana*. LSU and Rand Corporation Report, Coastal Protection and Restoration Authority of Louisiana (CPRA), Baton Rouge, LA, USA. Accessed Nov. 22, 2019. http://www.coastal.louisiana.gov.

[10] Louisiana State. 2017. *Louisiana's Comprehensive Master Plan for a Sustainable Coast, Investing in Our Future: Building a Coastal Protection and Restoration Strategy for the Next 50 Years*. Coastal Protection and Restoration Authority (CRPA), Baton Rouge, LA, USA. Accessed Nov. 22, 2019. http://www.coastal.louisiana.gov.

[11] Lempert, R., Sriver, R. L., and Keller, K. 2012. *Characterizing Uncertain Sea Level Rise Projections to Support Investment Decisions*. Energy Commission Report CEC-500-2012-056. Sacramento, CA: California Energy Commission, USA.

[12] Citta di Venezia. 2019. *Centro Previsioni e Segnalazioni Maree, Dati e statistiche*. Accessed May, 2019. http://www.comune.venezia.it/it/content/dati-e-statistiche.

[13] US Army Corps of Engineers (US ACE). 2006. *Performance Evaluation of the New Orleans and Southeast Louisiana Hurricane Protection System*, Volumes I to VIII, Engineering and Operational Risk and Reliability Analysis, Interagency Performance Evaluation Task Force, US ACE Digital Library. https://usace.contentdm.oclc.org/digital/collection/p266001coll1/id/2844/.

[14] Stevens, A. J., Clarke, D., and Nicholls, R. J. 2016. "Trends in Reported Flooding in the UK: 1884-2013." *Hydrological Sciences Journal* 61 (1): 50-63. doi: 10.1080/02626667.2014.950581.

[15] US Federal Emergency Management Agency (FEMA). 2019. *Guidance for Flood Risk Analysis and Mapping: Dams/Reservoirs and Non-dam Features*. U.S. Department of Homeland Security, Document 101, November.

[16] McCann, M. W., and Lundqwist, B. A. 2017. *Development of F-N Curves for Public Safety Risks Associated with Dam Failures in the U.S.* Association of State Dam Safety Officials, Inc., Lexington, KY, USA.

[17] Kundzewicz, Z. W., Pinskwar, I., and Brakenridge, G. R. 2012. "Large Floods in Europe, 1985-2009." *Hydrological Sciences Journal* 58 (1): 1-7. doi: 10.1080/02626667.2012.745082.

[18] Groeve, T. D., Brakenridge, R. G., and Paris, S. 2015. *Global Flood Detection System: Data Product Specifications*. European Commission, Joint Research Centre, Institute for the Protection and Security of the Citizen, Ispra, Italy. https://ec.europa.eu/jrc.

[19] Demargne, J., Limin, W., Satish, K., Regonda, J., Brown, D., Haksu, L., He, M., Seo, D.-J., Hartman, R., Herr, H. D., Fesch, M., Schaake, J., and Yuejian, Z. 2014. "The Science of NOAA's Operational Hydrologic Ensemble Forecast Service." *Bull Am Met Soc* (Jan.): 1-20. doi: 10.1175/BAMS-D-12-00081.1.

[20] Adams, T. E. 2015. "Verification of the NOAA/NWS

MMEFS Operational Hydrologic Ensemble Forecasting System in the Ohio River Valley." In *Proc. World Environmental and Water Resources Congress: Floods, Droughts, and Ecosystems*. doi: 10.1061/9780784479162.

[21] Asquith, W., Kiang, J., and Cohn, T. 2017. *Application of At-Site Peak-Stream Flow Frequency Analyses for Very Low Annual Exceedance Probabilities*. Scientific Investigations Report 2017-5038, US Geological Survey, DSOI: 10.3133/sir20175038.

[22] Bonnin, G. M., Martin, D., Bingzhang, L., Parzybok, T., Yekta, M., and Riley, D. 2006. *Precipitation-Frequency Atlas of the United States, Volume 2 Version 3.0: Delaware, District of Columbia, Illinois, Indiana, Kentucky, Maryland, New Jersey, North Carolina, Ohio, Pennsylvania, South Carolina, Tennessee, Virginia, West Virginia*. U.S. NOAA Atlas 14, Department of Commerce, National Oceanic and Atmospheric Administration, National Weather Service, Silver Spring, Maryland.

[23] Garrett, G. G. 2011. *Understanding Floods: Q & A*. Queensland Government, Australia. http://www.chiefscientist.qld.gov.au/publications/understanding-floods/chances-of-a-flood.

[24] Perica, S., Martin, D., Pavlovic, S., Roy, I., St. Laurent, M., Trypaluk, C., Unruh, D., Yekta, M., and Bonnin, G. 2013. *Rainfall frequency Atlas of the United States for Durations from 30 Minutes to 24 Hours and Return Periods from 1 to 100 Years*, Technical Paper No. 40, NOAA Atlas 14, Precipitation-Frequency Atlas of the United States, U.S. Department of Commerce, National Oceanic and Atmospheric Administration, National Weather Service, Silver Spring, Maryland, USA.

[25] DeGaetano, A. T. 2009. "Time-Dependent Changes in Extreme-Precipitation Return-Period Amounts in the Continental United States." *J. App. Meteorology and Climatology* 48: 2086-99. doi: 10.1175/2009JAMC2179.1.

[26] Sandoval, C. E., and Raynal-Villaseñor, J. 2008. "Trivariate Generalized Extreme Value Distribution in Flood Frequency Analysis." *Journal Hydrological Sciences* 5 (3): 550-67. doi: 10.1623/hysj.53.3.550.

[27] Shukla, R. K., and Trivedi, M. K. 2010. "On the Proficient Use of GEV Distribution: A Case Study of Subtropical Monsoon Region in India." *Anale. Seria Informatică*, 81-92. https:// arxiv.org/pdf/1203.0642.pdf.

[28] Wing, O. E. J., Bates, P. D., Smith, A. M., Sampson, C. C., Johnson, K. A., Fargione, J., and Morefield, P. 2018. "Estimates of Present and Future Flood Risk in the Conterminous United States." *Environ. Res. Lett.* 13: 034023. doi: org/10.1088/1748-9326/aaac65.

[29] FEMA. 2019. *Floodplain Management: Principles and Current Practices*, *Chapter 4 Flood Risk Assessment*. Academic Emergency Management and Related Courses (AEMRC) for the Higher Education Program, FEMA Emergency Management Institute. https://training.fema.gov/hiedu/aemrc/courses/coursetreat/fm.aspx.

[30] Alam, M. A., Emura, K., Farnham, C., and Yuan, J. 2018. "Best-Fit Probability Distributions and Return Periods for Maximum Monthly Rainfall in Bangladesh." *Climate* 6: 9-25. doi: 10.3390/cli6010009.

[31] Langat, P., Langat, K., Kuma, L., and Koech, R. 2019. "Identification of the Most Suitable Probability Distribution Models for Maximum, Minimum, and Mean Streamflow." *Water* 11: 734-58. doi: 10.3390/w11040734.

[32] Franz, K. J., and Sorooshian, S. 2002. *Verification of National Weather Service Probabilistic Hydrologic Forecasts*, Final Report, Department of Hydrology and Water Resources, The University of Arizona, Tucson, Arizona, Grant Number 40-AA-NW-217447.

[33] Matczak, P., Wiering, M., Lewandowski, J., Schellenberger, T., Trémorin, J.-B., Crabbé, A., Ganzevoort, W., Kaufmann, M., Larrue, C., Liefferink, D., and Mees, H. 2016. *Comparing Flood Risk Governance in Six European Countries: Strategies, Arrangements and Institutional Dynamics*. Report No. D4.1, STAR-FLOOD Consortium, Utrecht, The Netherlands.

[34] Emanuel, K. 2017. "Assessing the Present and Future Probability of Hurricane Harvey's Rainfall." *Proc. Nat. Ac. Sci*. 114 (48): 12681-4. doi: 10.1073/pnas.176222114.

[35] COMRISK. 2006. *Common Strategies to Reduce the Risk of Storm Floods in Coastal Lowlands*. EU Project www.umweltbundesamt.de/en/topics/climate-energy/climate-change-adaptation/adaptation-tools/project-catalog/comrisk.

[36] UK Environment Agency (UK EA). 2009. *Flooding in England: A National Assessment of Flood Risk*. Bristol, UK. https://assets.publishing.service.gov.uk/government/file/292928/.

[37] US Bureau of Reclamation (USBR). 2011. *Interim Dam Safety Public Protection Guidelines*. US Department of Interior, Dam Safety Office Denver, Colorado.

[38] Krupnick, A. 2008. "Cost-Benefit Analysis, Tolerable Risk and the VSL." Presented at Tolerable Risk Workshop, Resources for the Future, March 18.

[39] Espinoza, S., Panteli, M., Mancarella, P., and Rudnick, H. 2016. "Multi-phase Assessment and Adaptation of Power Systems Resilience to Natural Hazards." *Electric Power Systems Research* 136: 352-61. doi: 10.1016/j.epsr.2016.03.019.

[40] US National Institute of Standards (US NIS). 2020. *Engineering Statistics Handbook*, 1.3.6.6 Gallery of Distributions. http://www.itl.nist.gov/div898/handbook/

eda; and http://www.mathwave.com/help/easyfit/html/analyses/distributions/.

[41] Systat Software Inc. 2002. *Table Curve 2D User's Manual*. Richmond, CA, USA.

[42] Laplace, P. S. 1814. "Essai philosophique sur les probabilities." Extracted as "Concerning Probabilities." In *The World of Mathematics*, edited by Newman, J. R. 2: 1327. New York: Simon and Schuster.

[43] Jaynes, E. T. 2003. *Probability Theory: The Logic of Science*. Cambridge University Press.

[44] Rushbrooke, G. S. 1949. *Introduction to Statistical Mechanics*. London, UK: Oxford University Press.

[45] Greiner, W., Neise, L., and Stocker, H. 1995. *Thermodynamics and Statistical Mechanics*. NY: Springer.

[46] Duffey, R. B., and Saull, J. W. 2008. *Managing Risk*. UK: J. Wiley and Sons.

[47] Duffey, R. B. 2019. "The Risk of Extended Power Loss and the Probability of Emergency Restoration for Severe Events and Nuclear Accidents." *J. Nuc Eng Rad Sci*. ASME NERS-18-1122, doi: 10.1115/1.4042970.

[48] Mohsson, M. 2008. "An Insight into Flood Frequency for Design Floods." *WIT Transactions on Ecology and the Environment* 118. doi: 10.2495/FRIAR080161. www.witpress.com/Secure/elibrary/papers/FRIAR08/FRIAR08016FU1.pdf.

[49] Goldsmith, M., and Brass, M. 2012. *Milton 2060 Flood Risk Management Strategy for Milton and the Tokomairiro Plain*. Otago Regional Council (ORC), Dunedin, New Zealand. www.orc.govt.nz.

[50] US National Weather Service (US NWS). 2018. *River "Stage Height" Graphs for Hurricane Florence*. water.weather.gov/ahps2/hydrograph.

[51] US National Weather Service (US NWS), and NOAA. 2018. http://nws.noaa.gov/oh/hdsc/aepstormanalysis/index.html#Florence.

[52] Harris County Flood Warning System (FWS). 2017. Accessed Aug. 25-Sep. 28, 2017. www.harriscountyfws.org/GageDetail/Index/.

[53] Mel, R., and Lionello, P. 2014. "Storm Surge Ensemble Prediction for the City of Venice." *Weather and Forecasting* 29: 1044-57. doi: 10.1175/WAF-D-13-00117.1.

[54] Tatalovich, J. 1998. *Comparison of Failure Modes from Risk Assessment and Historical Data for Bureau of Reclamation Dams*. Department of Interior Report DSO-98-01, Dam Safety Office, Materials Engineering and Research Laboratory, USBR, USA.

[55] www.damsafety.org/article/awareness/failure-edenville-and-sanford-dams-michigan, May 20, 2020.

[56] Duffey, R. B. 2020. "Predicting Power System Reliability and Outage Duration Including Emergency Response." *Dependability* 20 (3): 3-14. https://doi.org/10.21683/1729-2646-2020-20-3-3-14.