Hydrologic Design under Nonstationarity

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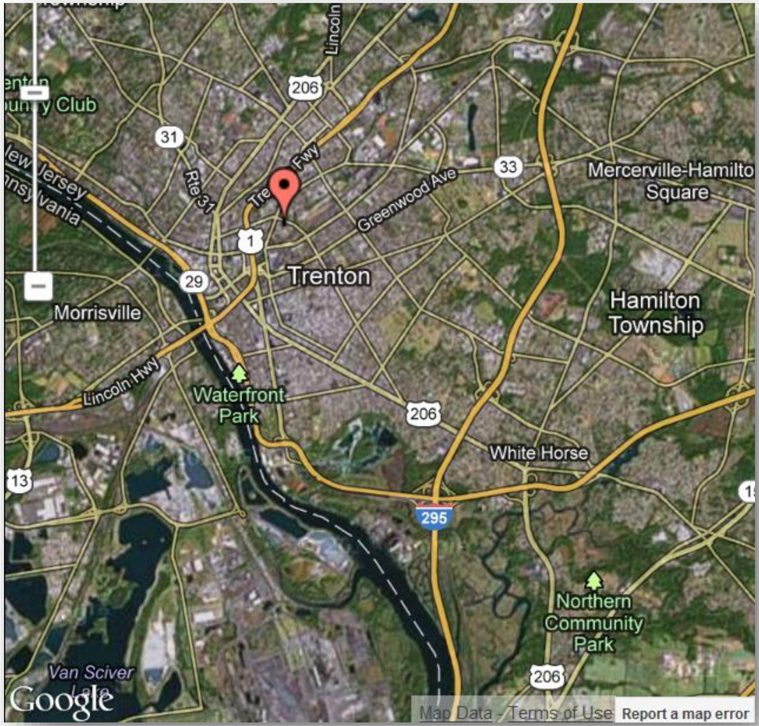
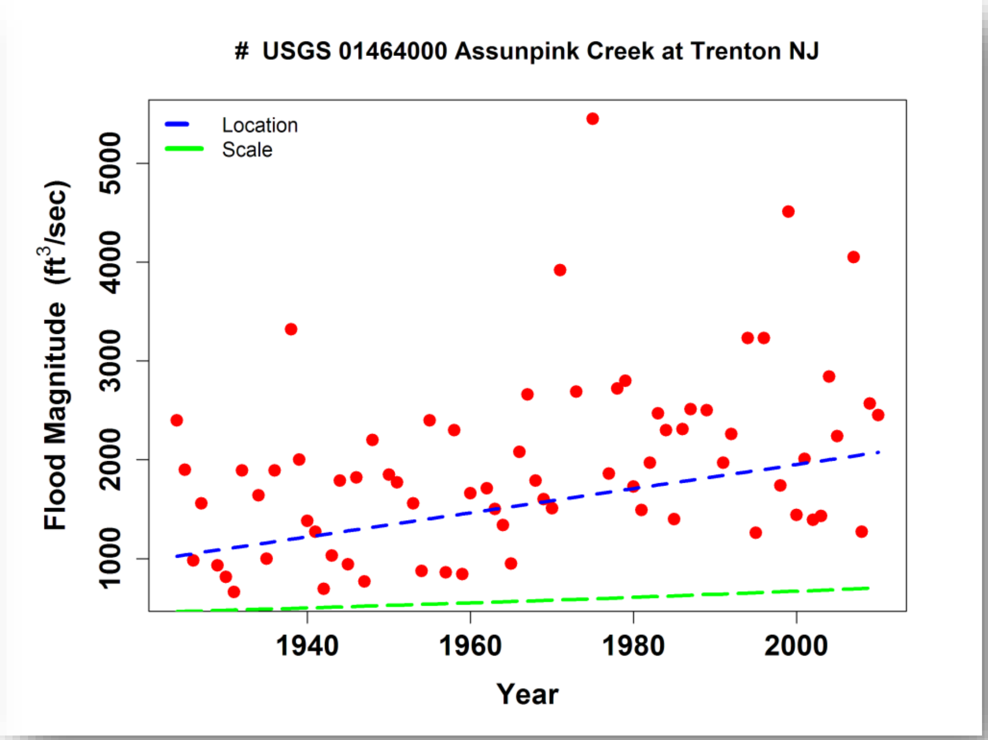
Introduction

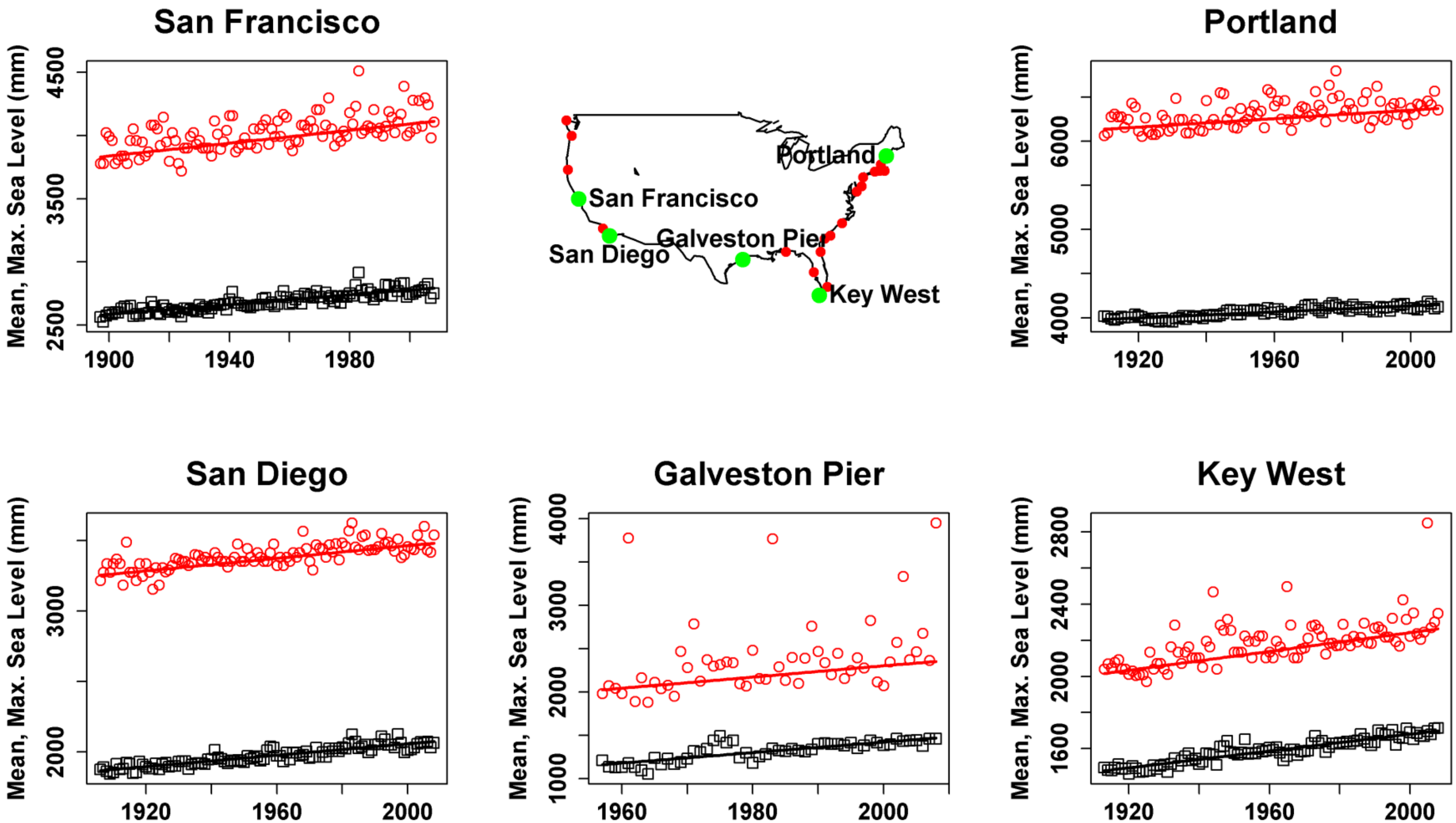
- Recent evidence that dynamics of the hydrologic cycle of river basins have been changing due to human intervention and climate variability/change
- Number of articles arguing that the hydrological processes have become nonstationary
- While a lot of controversy exists, significant developments on methods have been made (Olsen et al. 1998; Wigley 2009; many others)
- This presentation will provide information on the potential approaches that could be used for hydrologic designs considering nonstationarity and discuss challenges ahead.

Example: Annual Maximum Floods, Assunpink Creek, NJ

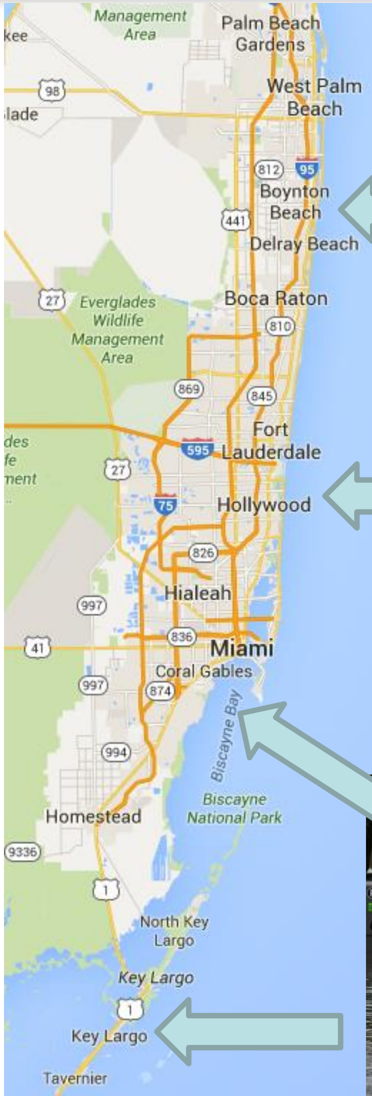


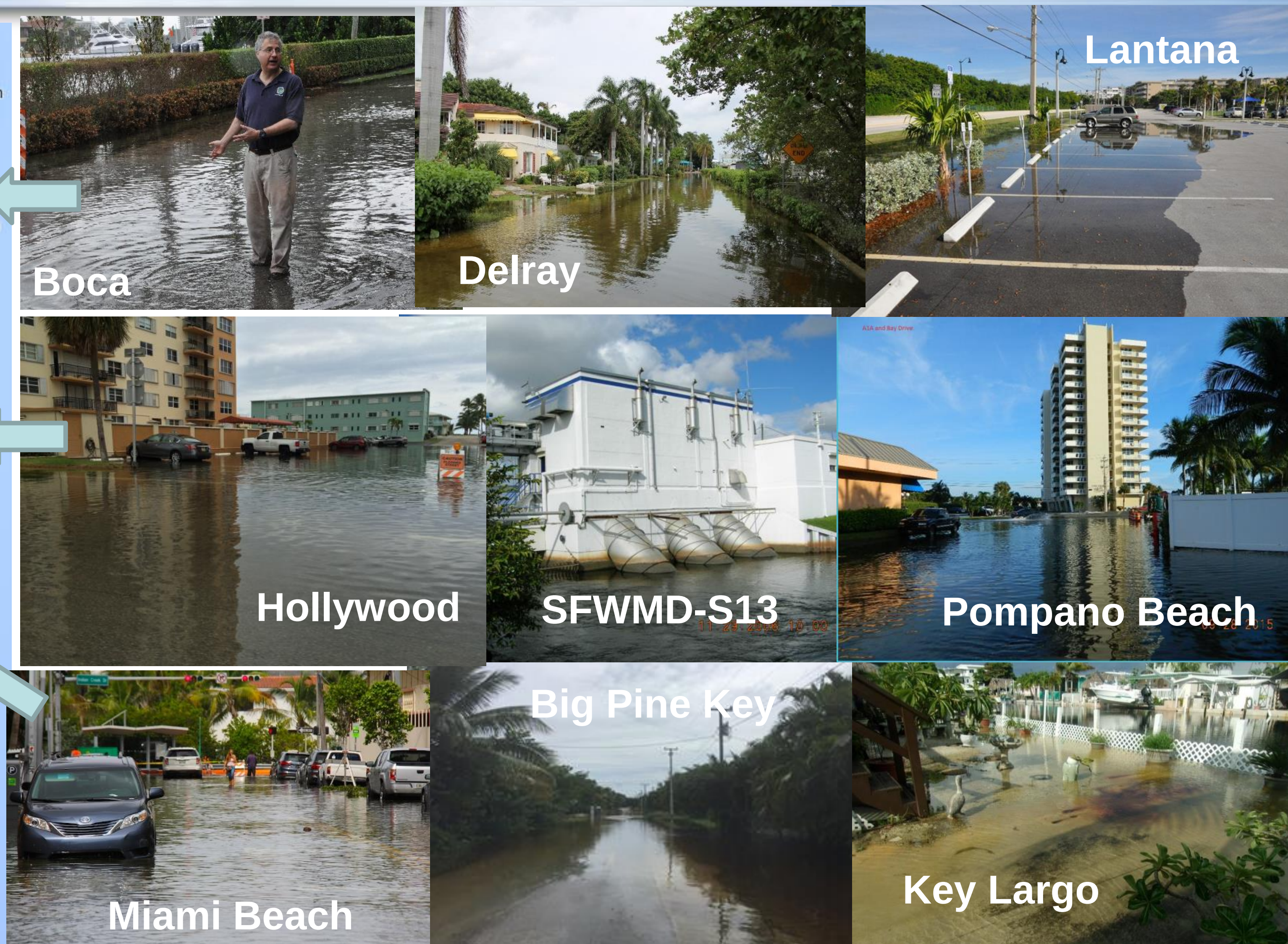


Example: Extreme (and Mean) Sea Levels



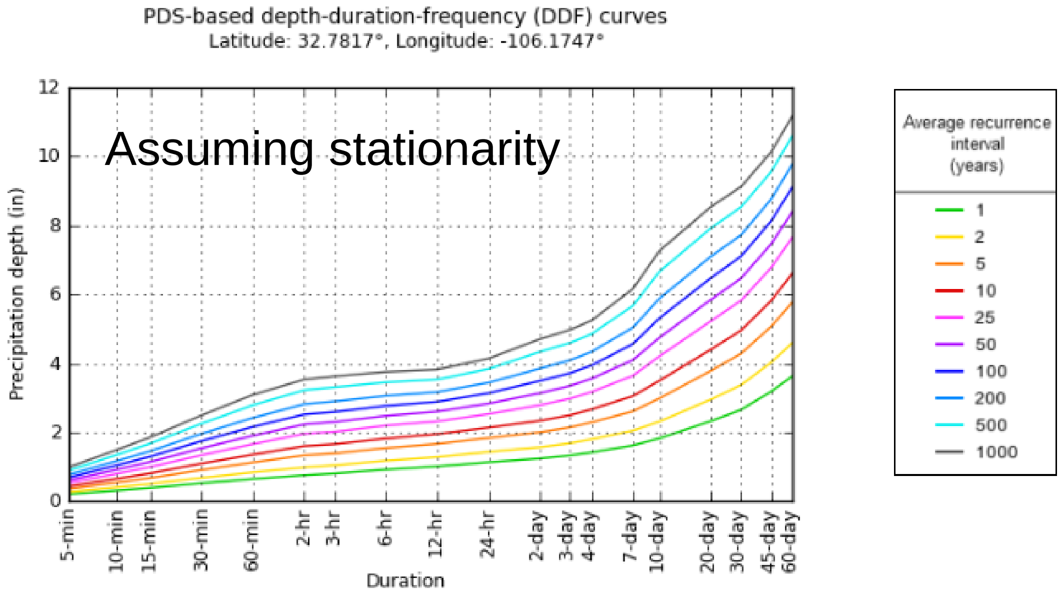
Example: Sunny Day Flooding in South Florida (2015)

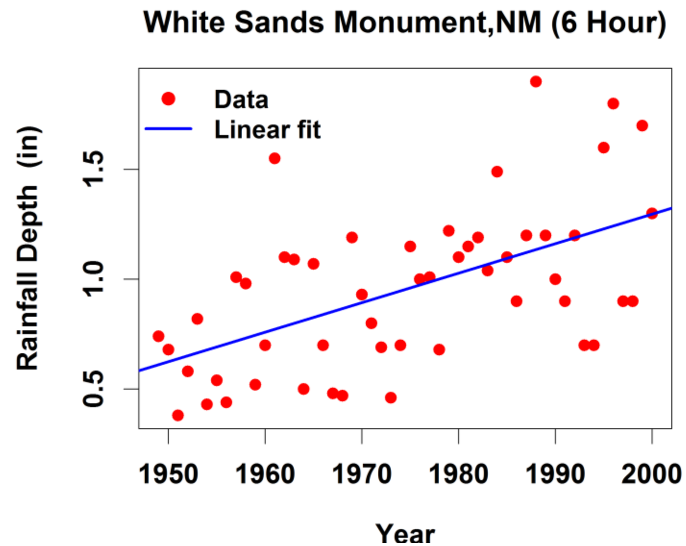


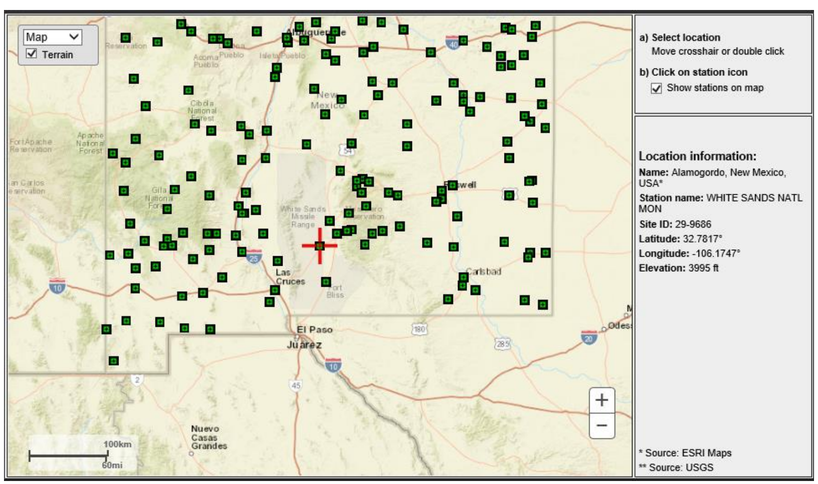


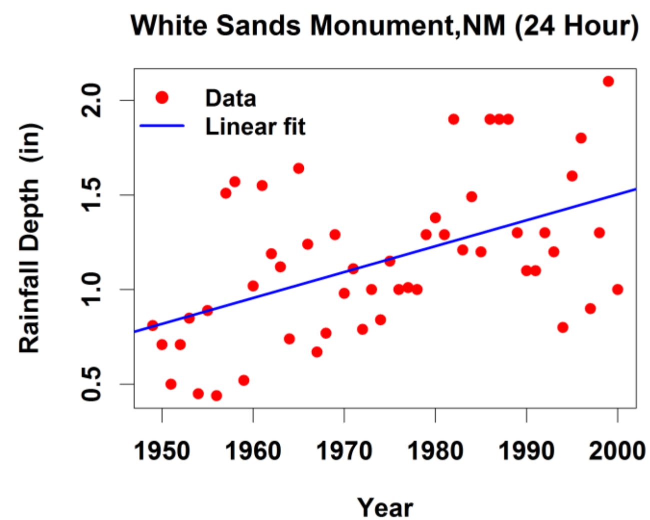
Credits: Rhonda Haag, Jennifer Jurado, Natalie Schneider

Example: Depth-Duration-Frequency of extreme precipitation (NOAA Atlas 14)









Data suggested by Cheng and AghaKouchak (2014)

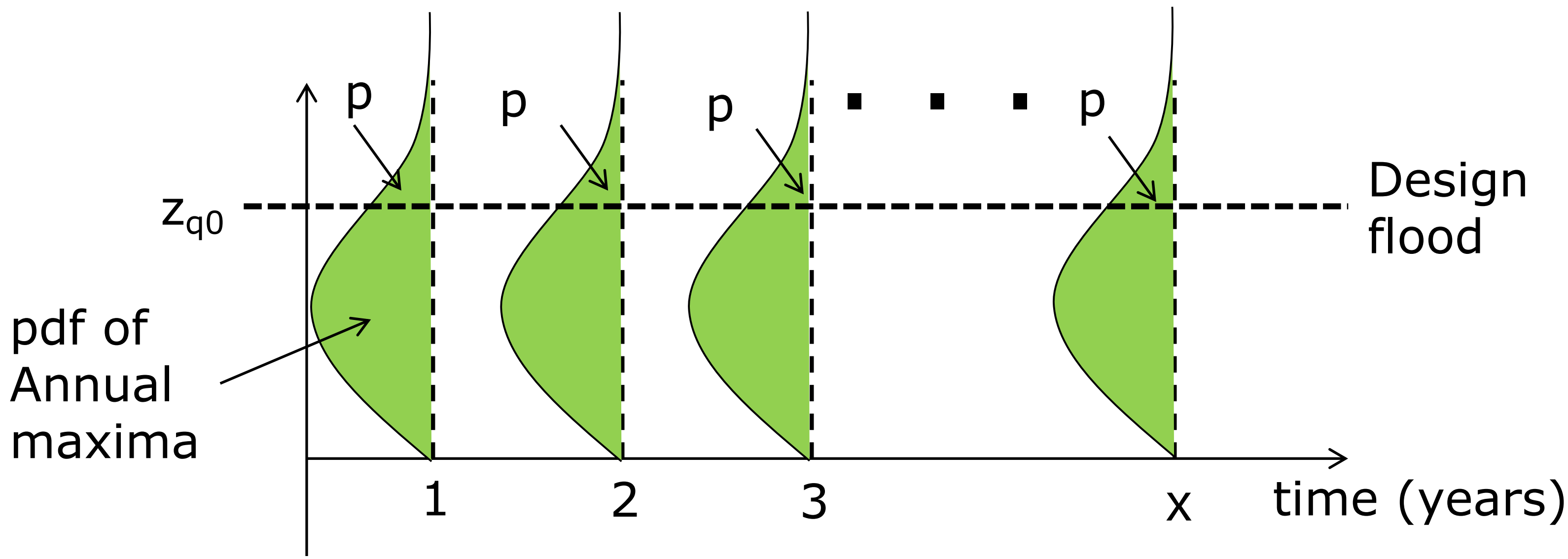
Nonstationarity Debate

- **“Nature’s Style: Naturally Trendy”,** Cohn and Lins (2005)
- **“Stationarity is Dead”** (Milly et al, 2008)
- **“Stationarity: Wanted Dead or Alive?”** (Lins & Cohn, 2011)
- **“Comments on the Announced Death of Stationarity”** (Matalas, 2012)
- **“Negligent Killing of Stationary”** (Koutsoyiannis and Montanari, 2014)
- **“Stationarity is Immortal”** (Montanari & Koutsoyiannis, 2014)

Probabilistic Modeling of Annual Extremes under Nonstationarity

- Two approaches: Block Maxima & Peaks Over Threshold (Coles, 2001)
- Most work uses GEV / GPD with parameters linked to covariates
- Software: R packages (extRemes, gamlss)
- “Return Period” & Risk based on
    - Expected Waiting Time (EWT)
    - Expected Number of Events (ENT)
    - Design Life Level (DLL)
    - Average Annual Risk (AAR)

A brief review – Stationary Case



Return Period $\frac{1}{p} = \frac{1}{p} = \frac{1}{p} \; . \; . \; . \; = \frac{1}{p} = T_0$

Return Period as "Expected Waiting Time"

- X = Waiting Time for the first occurrence of a "flood" (a random variable)

  $f(x) = P(X=x) = (1-p)^{x-1}p \qquad x=1,2..$

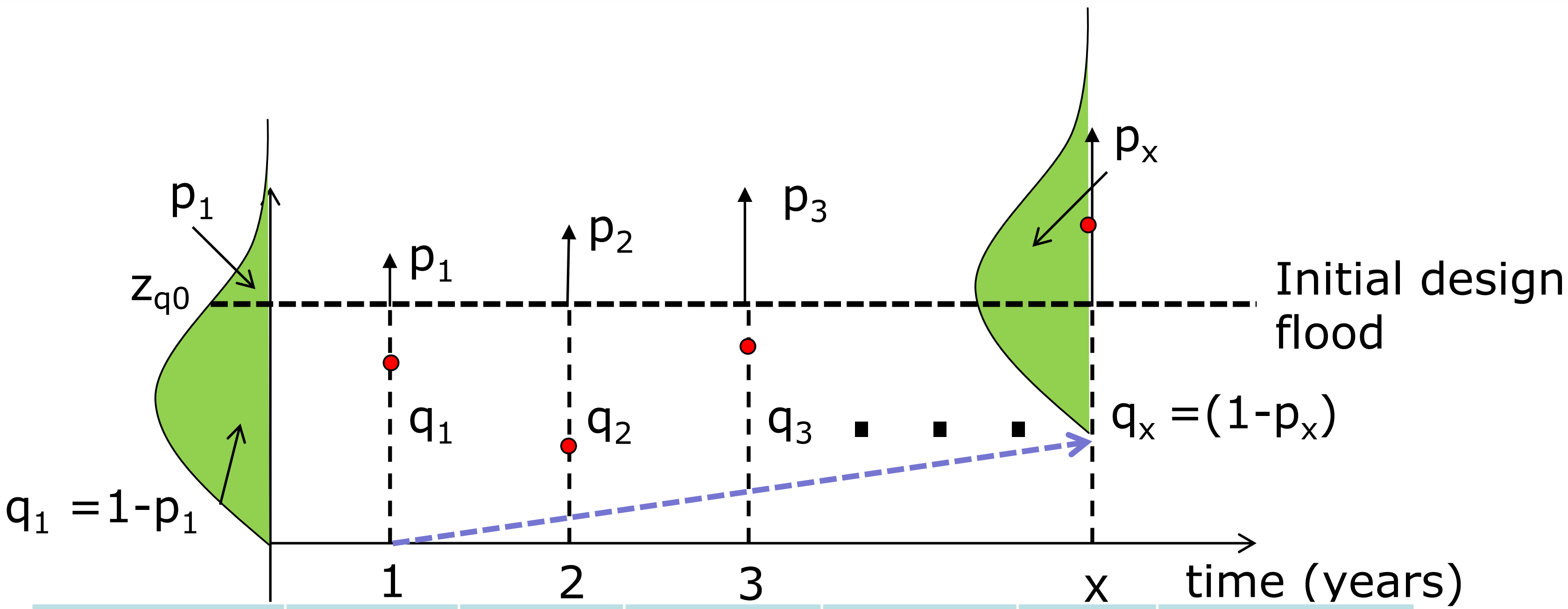
- This is the well known Geometric Distribution for Bernoulli Trials to get one success

- Expected Value of X:

$$E(X) = \sum_{x=1}^{\infty} xf(x) = \sum_{x=1}^{\infty} x(1-p)^{x-1}p = \frac{1}{p} = T$$

- T = Expected Waiting Time for the first occurrence of the exceedance!

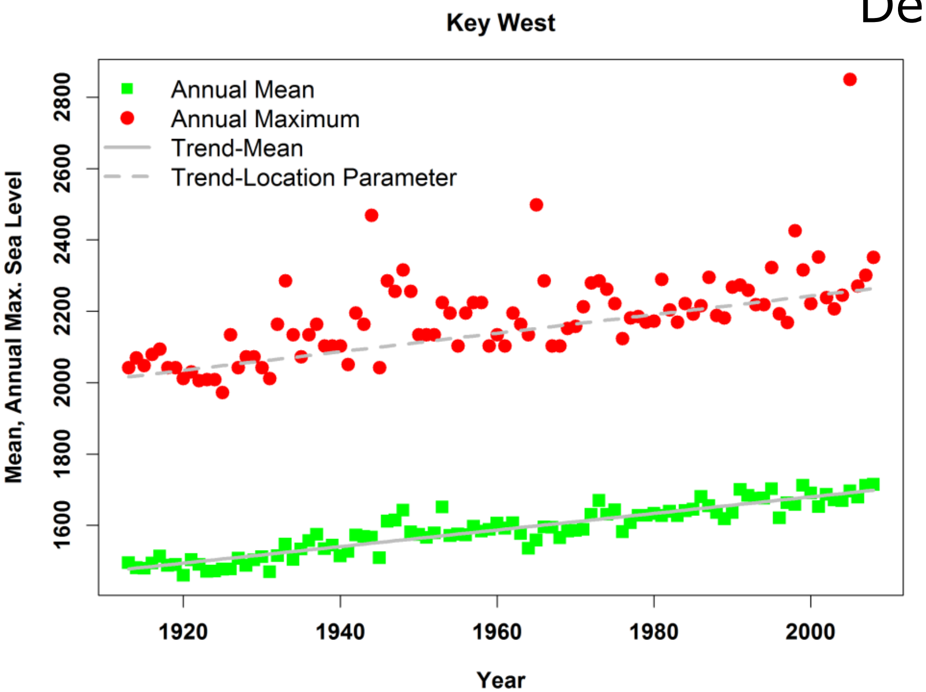
Nonstationarity – A New Paradigm

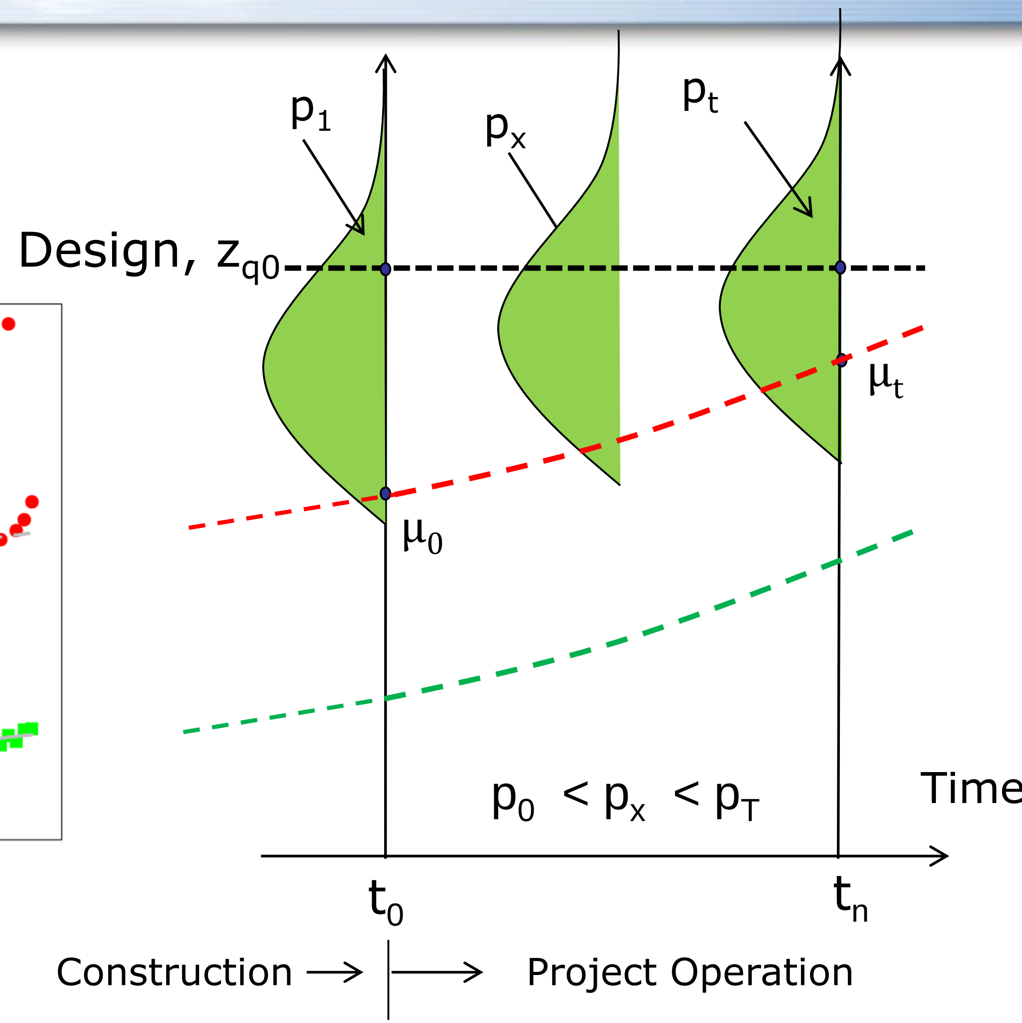


Event	NF	NF	NF	...	F	
Probability	$1-p_1$	$1-p_2$	$1-p_3$	...	p_x	

$$T_0 = \frac{1}{p_1} > \frac{1}{p_2} > \frac{1}{p_3} \;\; . \;\; . \;\; . \;\; > \frac{1}{p_x}$$

Sea Level Rise Case





Probability Distribution of Waiting Time
(Salas & Obeysekera, 2014 and others)

- Probability distribution of waiting time

$$f(x) = P[X = x] = (1 - p_1)(1 - p_2)(1 - p_3)\ldots(1 - p_{x-1})p_x$$

$$f(x) = p_x \prod_{t=1}^{x-1}(1 - p_t) \quad x = 1, 2.. \; with\; f(1) = p_1$$

- Non-homogeneous geometric (Mandelbaum et al.2007)
- CDF

$$F_X(x) = \sum_{i=1}^{x} f(i) = \sum_{i=1}^{x} p_i \sum_{t=1}^{i-1}(1 - p_t) = 1 - \prod_{t=1}^{x}(1 - p_t)$$

"Return Period" Under Nonstationary

- Return Period is defined as the "expected time for the first exceedance (waiting time)"

$$T = E[X] = \sum_{x=1}^{\infty} x f(x) = \sum_{x=1}^{\infty} x p_x \prod_{t=1}^{x-1} (1 - p_t)$$

- Coley (2013) provides a nice simplification:

$$T = E[X] = 1 + \sum_{x=1}^{\infty} \prod_{t=1}^{x} (1 - p_t)$$

Note: Since p_t is a function Z_{q0} (initial design or p_0), this can also be used to find Z_{q0} for a given T

Risk and Reliability Under Nonstationary

- Risk

$$\boldsymbol{R = \sum_{x=1}^{n} f(x) = \sum_{x=1}^{n} p_x \prod_{t=1}^{x-1} (1 - p_t) = 1 - \prod_{t=1}^{n} (1 - p_t)}$$

- Reliability:

$$\boldsymbol{R_\ell = \prod_{t=1}^{n} (1 - p_t)}$$

Specific Models

- For GEV:

$$p_t = 1 - exp\left\{-\left[1 + \xi\left(\frac{z_{q_0} - \mu(t)}{\sigma(t)}\right)\right]^{-1/\xi}\right\}$$

Modeling Non-stationarity

$$\mu(t) = \beta_0 + \beta_1 t;\ \sigma(t) = \sigma; \xi(t) = \xi$$

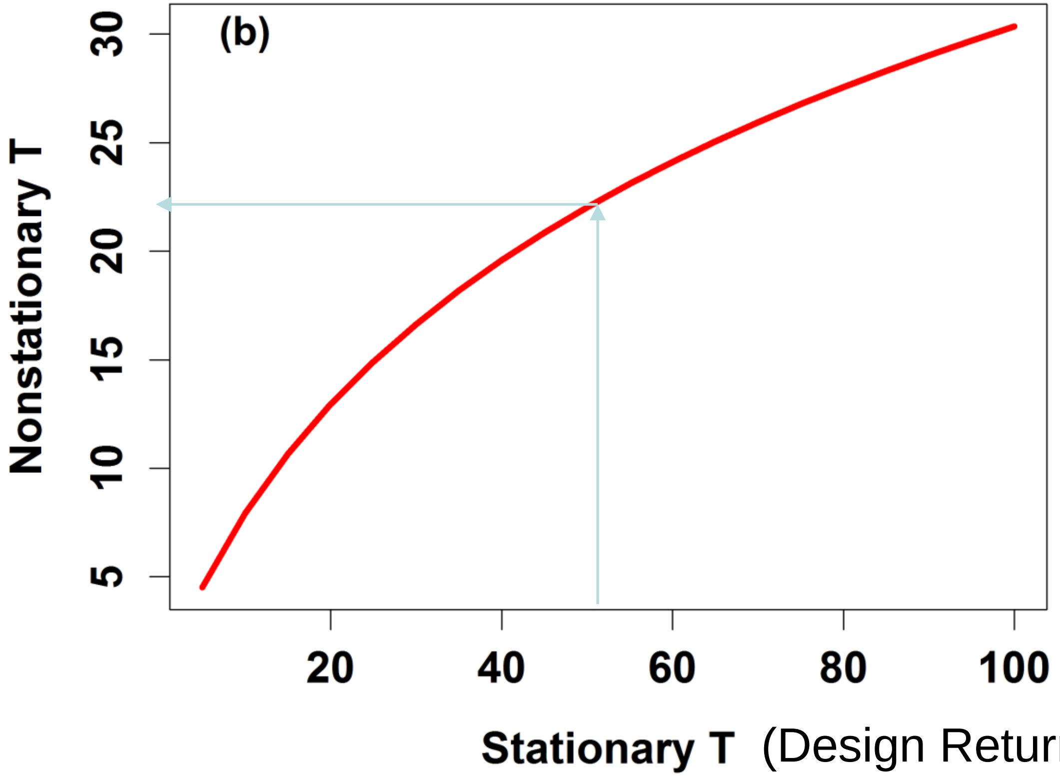
$$\mu(t) = \beta_0 + \beta_1 t + \beta_2 t^2;\ \sigma(t) = \sigma; \xi(t) = \xi$$

$$\mu(t) = \beta_0 + \beta_1 NINO3(t);\ \sigma(t) = \sigma; \xi(t) = \xi$$

$$\mu(t) = \beta_0 + \beta_1 . MSL(t);\ \sigma(t) = \sigma; \xi(t) = \xi$$

Return Period Curve (Floods)

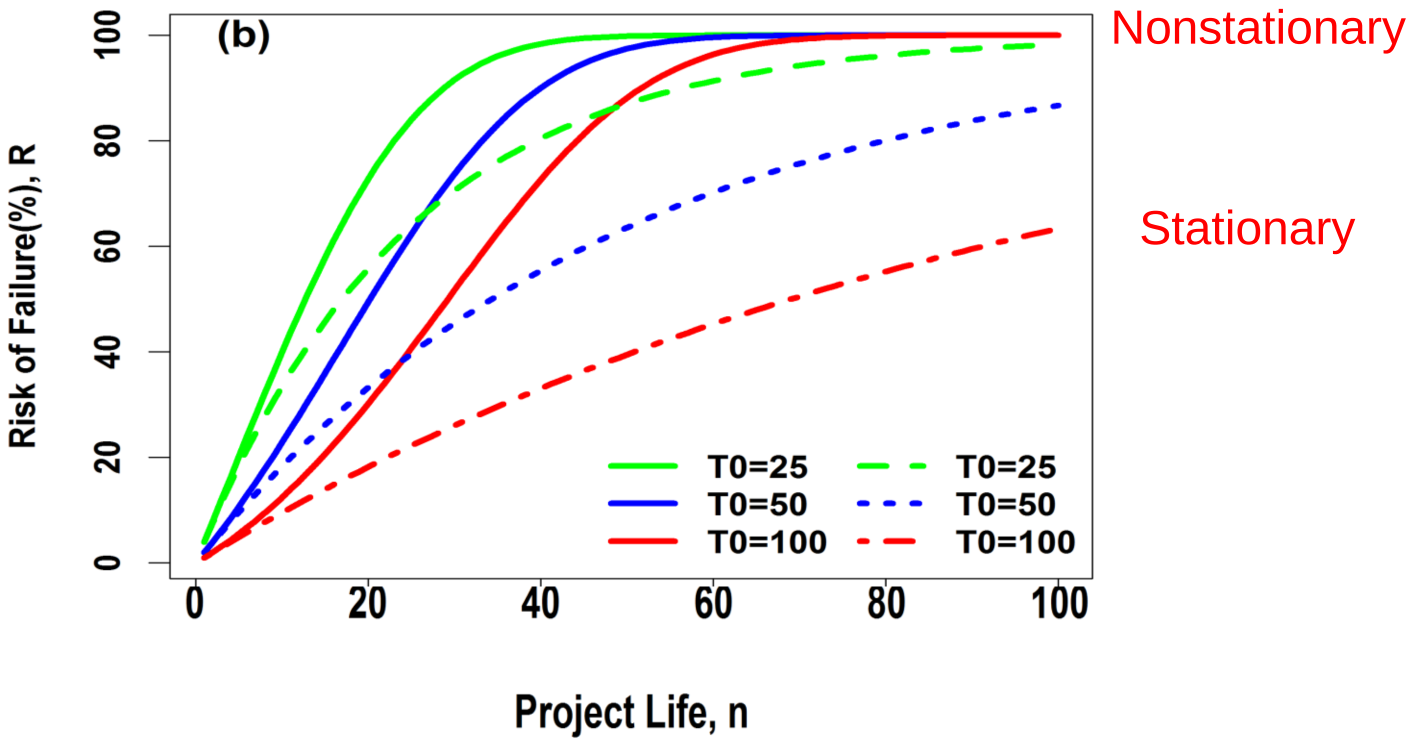
Should we call this:
- Nonstationary return period (NRP)
- Nonstationary Expected Waiting Time (NEWT)
- 1/Percent Chance Exceedance



(Design Return Period)

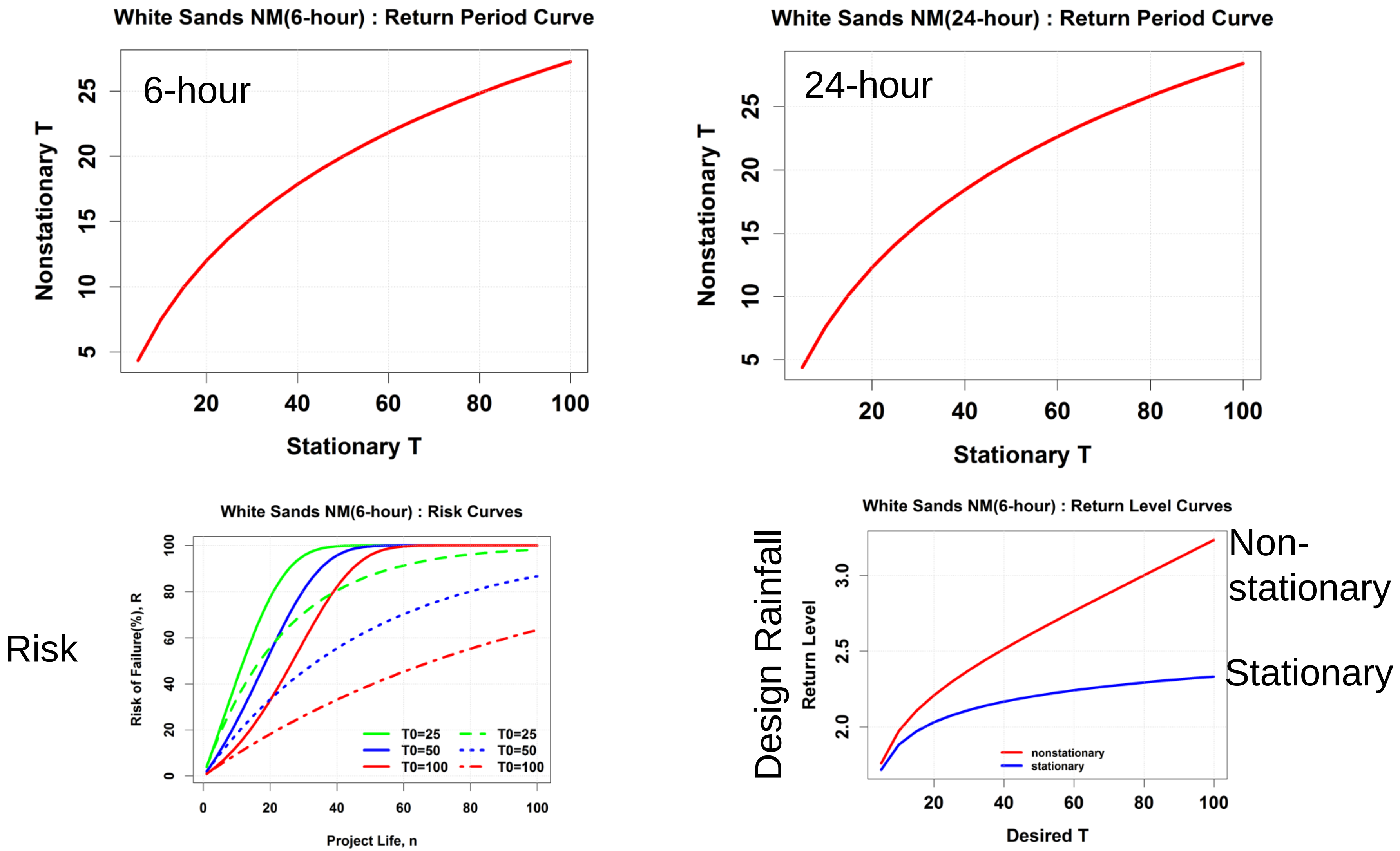
Variation of the non-stationary return period *T* as a function of the initial return period T_0 (referred to as stationary *T* in the horizontal) for Little Sugar Creek (Salas and Obeysekera, 2014)

Risk: Stationary versus Nonstationary

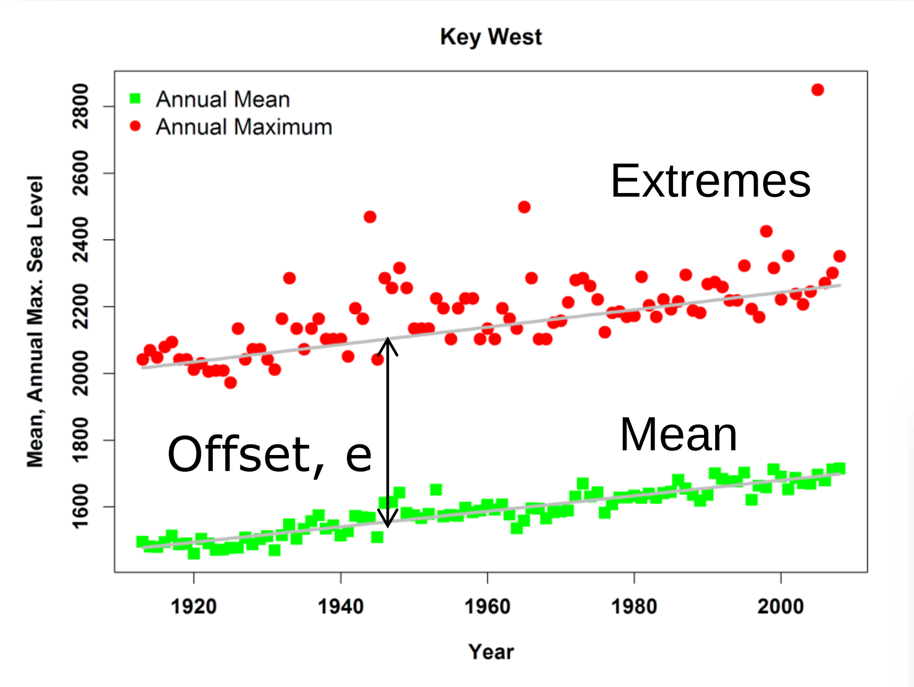


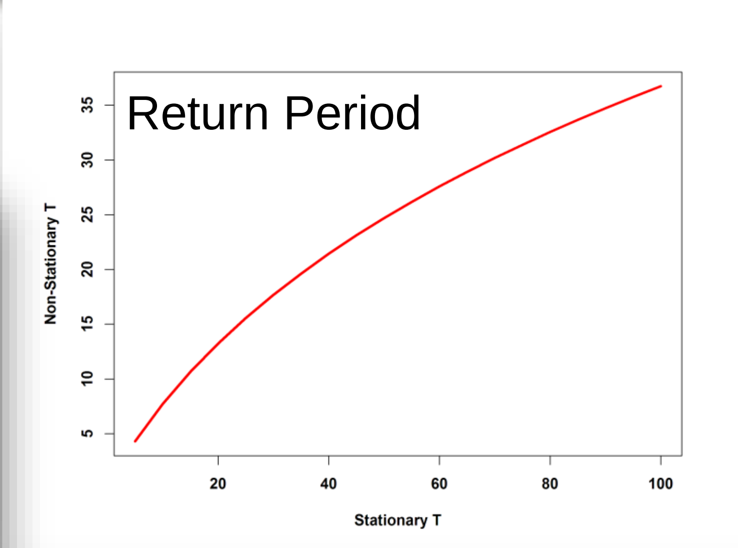
Non-stationary risk as a function of *n* for Little Sugar Creek assuming Gumbel models & initial designs T_0 = 25, 50, & 100 years. Risk for the stationary condition (dashed lines) and risk for non-stationary conditions (solid lines) (Salas and Obeysekera, 2013).

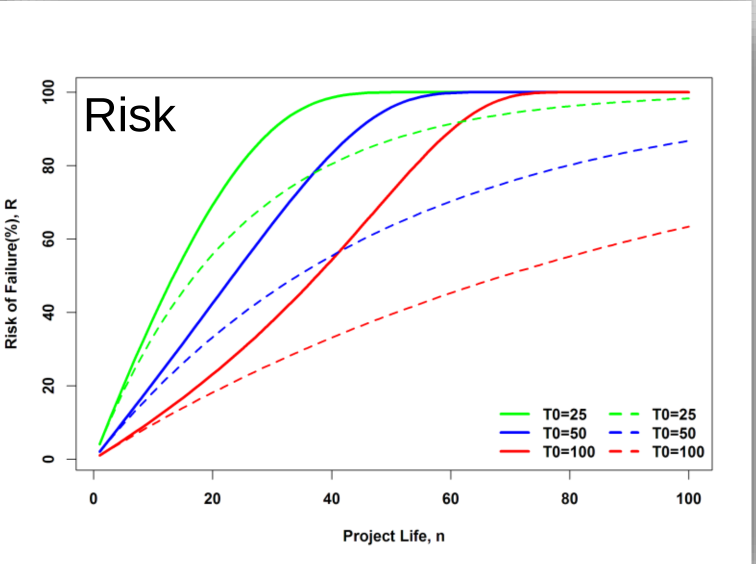
Return Period Curve (Precipitation)



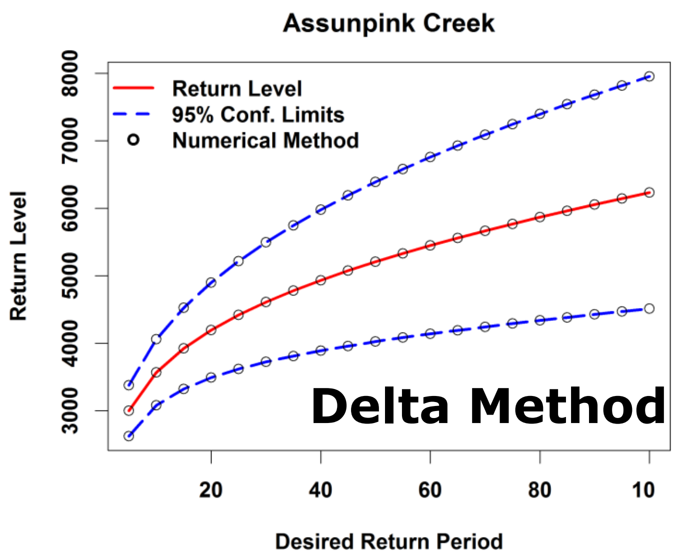
Sea Level Trends in Key West, Florida

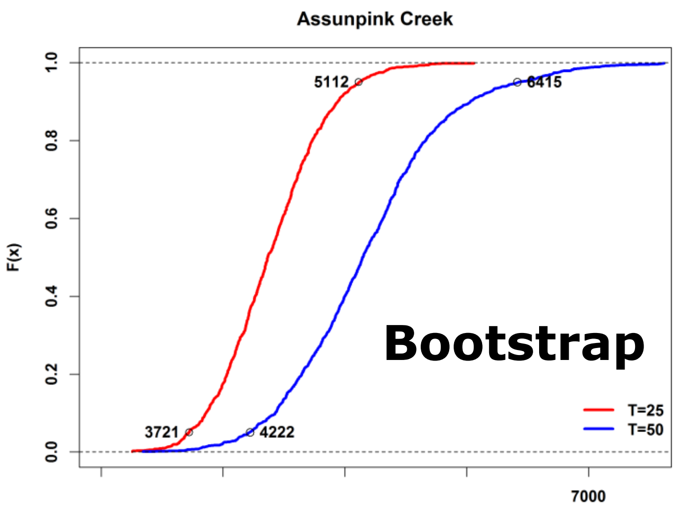


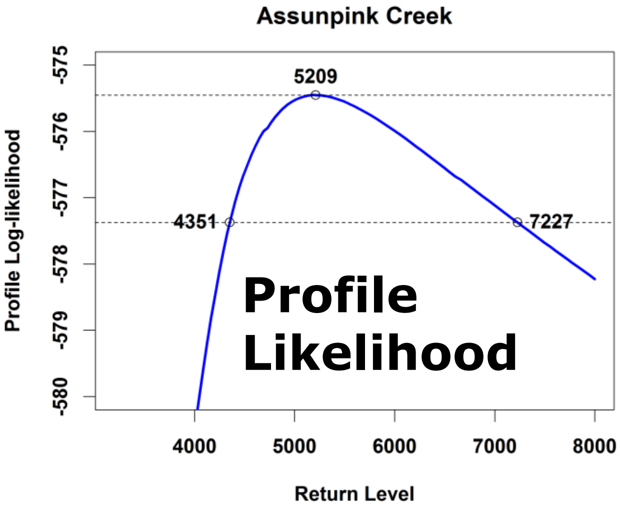




Confidence Intervals of Design Quantiles Nonstationary Case (Obeysekera & Salas 2015)

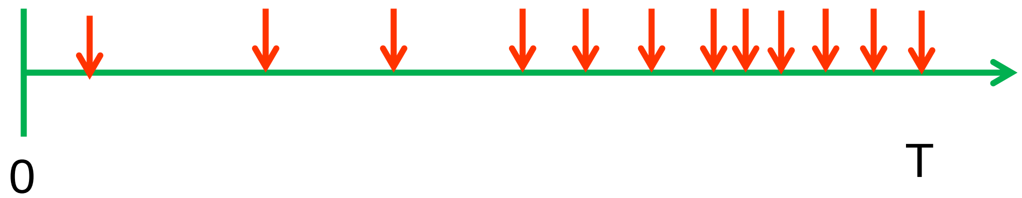






Frequency of Flooding under Non-Stationarity (Obeysekera & Salas 2016)

- Frequency of flooding increases with time



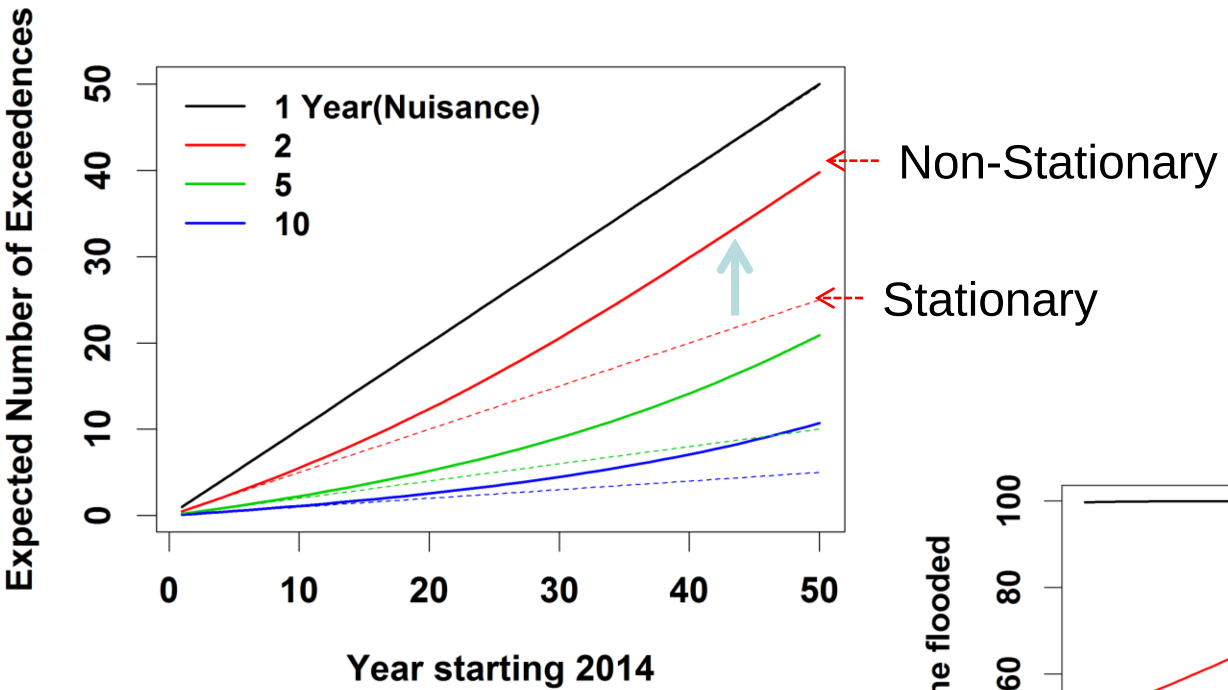
- Number of floods, N_T, has **Poisson Binomial Distribution** (Hong 2013) with the following properties:

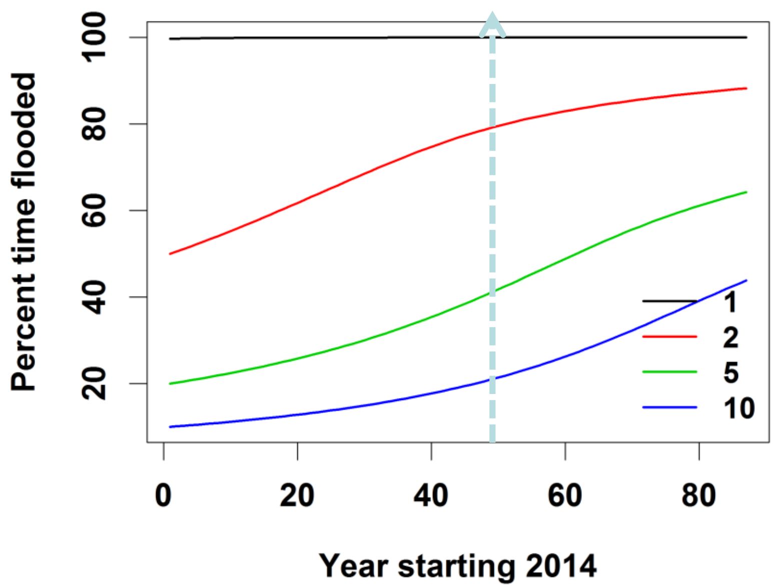
$$PMF: \sum_{A \epsilon F_k} \prod_{i \epsilon A} p_i \prod_{j \epsilon A^c} (1 - p_j)$$

F_k = subset of k integers From (1,2,..T)

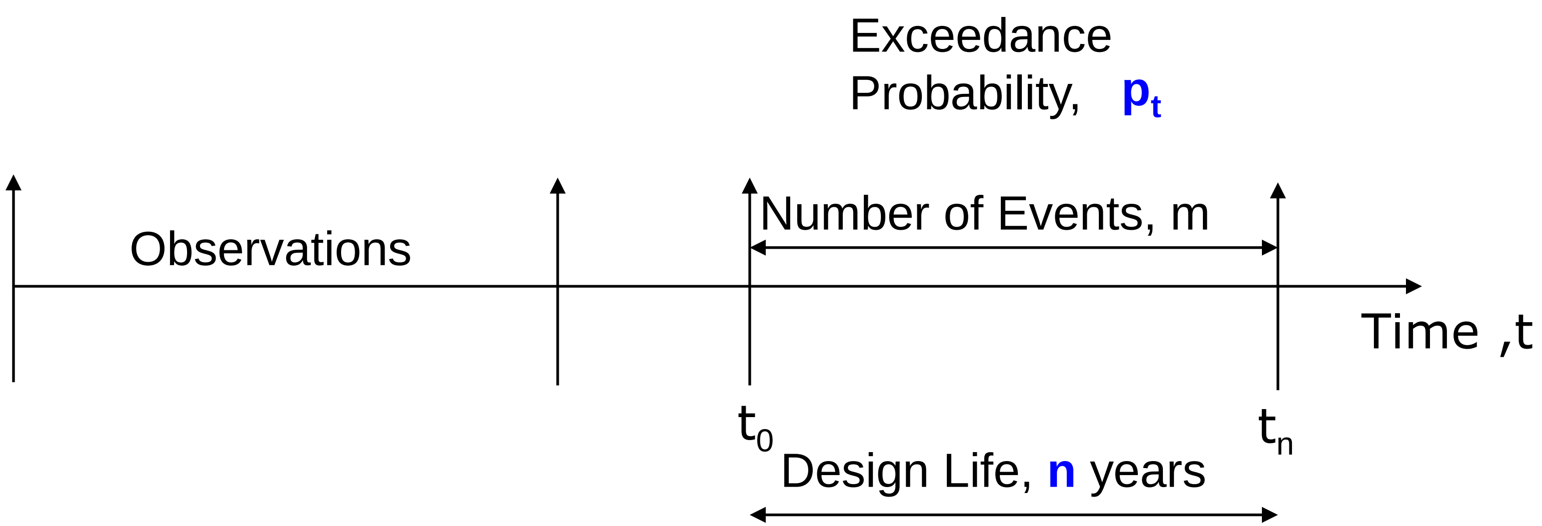
$$E[N_T] = \sum_{i=1}^{n} p_i \qquad Var(N_T) = \sum_{i=1}^{n} (1 - p_i) p_i$$

Frequency of Flooding: Sea Level extremes at Sewell Point





Hydrologic Design Problem



X = Waiting Time, or First Arrival Time of an event exceeding design starting from t_0 (X=1,2,3,…..)

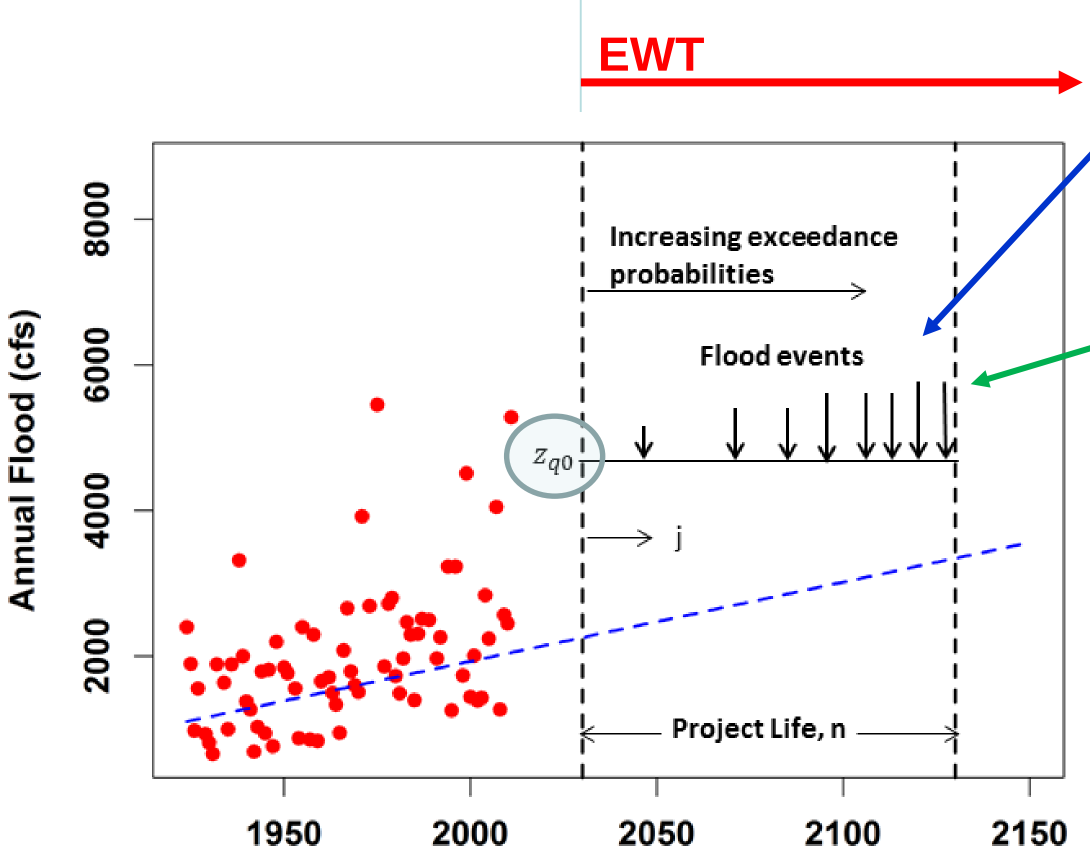
z_{q0} = Design Return Level (quantile)

R = Risk of one or more events

T = Design Return Period

Criteria: EWT, ENE, DLL, AAR

Hydrologic Design considering Nonstationarity



AAR: Design for average p_t

DLL: What level should we design to maintain a specified risk (e.g. 5%)

ENE: What level should we design for if we can tolerate, say m events over the life

Design methods under stationarity (Salas , Obeysekera & Vogel, 2017)

Design Method	**Primary Parameters**	**Return Period T**	**Design Quantile z_q (Return Level)**	**Risk of Failure R Over Design Life n**	**Probability Distribution**
EWT[1]	T	T (specified)	Solve for z_q in	$R = 1-(1-1/T)^n$	Geometric
ENE = 1	n	$n\,p = 1$, $p = 1/n$ $T = n$	Solve for z_q in	$R = 1-(1-1/n)^n$	Binomial
ENE = m ($m > 1$)	n, m	$n\,p = m$, $p = m/n$ $T = n/m$	Solve for z_q in	$R = 1-(1-m/n)^n$	Binomial
DLL	R, n	$p = 1 - (1-R)^{1/n}$ $T = 1/p$	Solve for z_q in	R (specified)	Geometric or Binomial

[1]Note that specifying average waiting time T as the design parameter is equivalent to specifying the exceedance probability p since p=1/T (refer to Section 2). Then, the expressions in the columns for design quantile and risk of failure R, are written as and $R = 1-(1-p)^n$, respectively. EWT, ENE and DLL denote, expected waiting time, expected number of events, and design life level, respectively.

Design methods under nonstationarity (Salas, Obeysekera & Vogel, 2017)

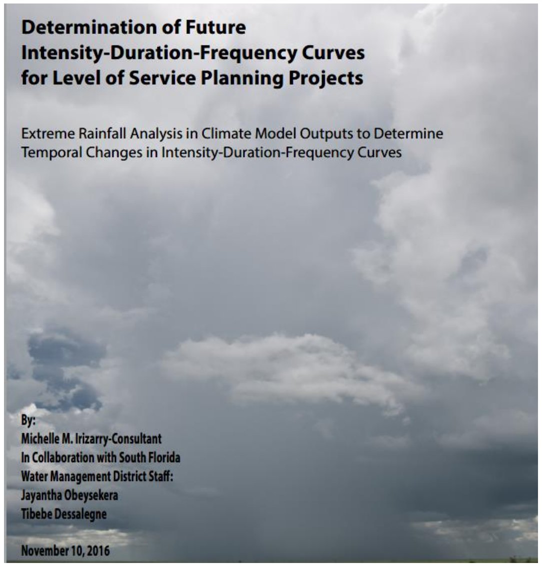
Design Method	Primary Parameters	Return Period T	Design Quantile z_{q0} (Return Level)	Risk of Failure R Over Design Life n	Probability Distribution
EWT	T	T (specified)	Given T, find z_{q0} in Eq.(12)$^{(1)}$ (12)	(14)$^{(1)}$	Nonhomogeneous Geometric Distribution
ENE = 1	n	Based on z_{q0} from Eq.(19a) find p_0 from Then from p_0 find T_0	Solve for z_{q0} in (19a)$^{(1)}$	(14)$^{(1)}$	Poisson-Binomial Distribution
ENE = m ($m > 1$)	n, m	Based on z_{q0} from Eq.(19b) find p_0 from Then from p_0 find T_0	Solve for z_{q0} in (19b)$^{(1)}$	(14)$^{(1)}$	Poisson-Binomial Distribution
DLL	R, n	Find z_{q0} from Eq. (14) find p_0 from Then from p_0 find T_0	Given R find z_{q0} in Eq. (14) (14)$^{(1)}$	R (specified)	NHGD or Poisson-Binomial Distribution
AAR(n)	n	(27)	Solve for z_{q0} in Eq. (27)		Binomial

(1) Note that (refer to Section 6.1)
In addition, note that if the EWT method is used for assessing a previously designed project where the design quantile z_{q0} is known (and the corresponding exceedance probability p_0 and return period T_0), then T can be determined from Equation (12) and R from Equation (14) without any numerical or trial and error calculations (refer to Section 6.1)

Other approaches (Salas, Obeysekera and Vogel 2017)

- Regression: Conditional Moments
- Magnification Factors
  - Examples: LN2, LN3, GEV, and LP3
- Risk Based Decision Making (combine trend detection with hypothesis testing)
- Time series modeling

DDF Curves using climate model data (bias corrected downscaled data from USBR)

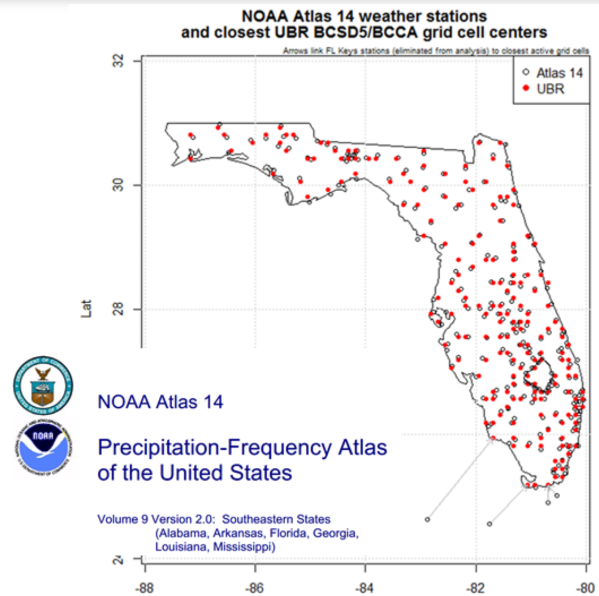


Determination of Future Intensity-Duration-Frequency Curves for Level of Service Planning Projects

Extreme Rainfall Analysis in Climate Model Outputs to Determine Temporal Changes in Intensity-Duration-Frequency Curves

By:
Michelle M. Irizarry-Consultant
In Collaboration with South Florida Water Management District Staff:
Jayantha Obeysekera
Tibebe Dessalegne

November 10, 2016



Methods:

- Completely Parametric Method
- Regional Frequency Analysis, RFA (similar to Atlas 14)
- At-Site RFA
- Unified GEV
- Constrained Scaling

Perc	24-hr_2-year	24-hr_5-year	24-hr_10-year	24-hr_25-year	24-hr_50-year	24-hr_100-year
5%	-2.35 (-57.4%)	-3.28 (-59.6%)	-3.99 (-60.8%)	-5 (-62.3%)	-5.86 (-63.3%)	-6.82 (-64.2%)
10%	-2.33 (-57%)	-3.25 (-59%)	-3.96 (-60.4%)	-4.94 (-61.4%)	-5.76 (-62.1%)	-6.71 (-62.9%)
50%	-2.25 (-54.9%)	-3.1 (-56.3%)	-3.76 (-57.3%)	-4.67 (-58.1%)	-5.45 (-58.7%)	-6.34 (-59.2%)
90%	-2.19 (-53.5%)	-3.05 (-55.3%)	-3.66 (-55.9%)	-4.53 (-56.3%)	-5.24 (-56.3%)	-6.01 (-55.8%)
95%	-2.16 (-52.9%)	-3.03 (-54.7%)	-3.64 (-55.3%)	-4.43 (-54.7%)	-5.11 (-54.5%)	-5.84 (-54.1%)

- ➢ Bias is very large!
- ➢ Larger than delta change

Where we are and challenges ahead

- The methods outlined here may form the basis for hydrologic designs considering nonstationarity
- Detection of nonstationarity. Perceived nonstationarity may actually be natural variability
- Projections into the future:
  - Climate Change. How do we use climate models for predicting future extremes? Are the ready?
  - Land use changes and other anthropogenic changes
- How do we incorporate the new techniques into standard practice? How do we deal with uncertainty? Adaptive Designs?

References

Revisiting the Concepts of Return Period and Risk for Nonstationary Hydrologic Extreme Events

Jose D. Salas, M.ASCE[1]; and Jayantha Obeysekera, M.ASCE[2]

J. Hydrol. Eng. 2014.19:554-568.

Quantifying the Uncertainty of Design Floods under Nonstationary Conditions

Jayantha Obeysekera, M.ASCE[1]; and Jose D. Salas, M.ASCE[2]

J. Hydrol. Eng. 2014.19:1438-1446.

Frequency of Recurrent Extremes under Nonstationarity

Jayantha Obeysekera, M.ASCE[1]; and Jose D. Salas, M.ASCE[2]

(paper published online: J. Hydrologic Engineering)

Techniques for assessing water infrastructure for nonstationary extreme events: a review

J.D. Salas[a], J. Obeysekera[b], and R.M. Vogel[c] (paper in review)

Questions

"Nonstationary" Stochastic Models
ARMA

Consider say annual floods x_t LN distributed, and

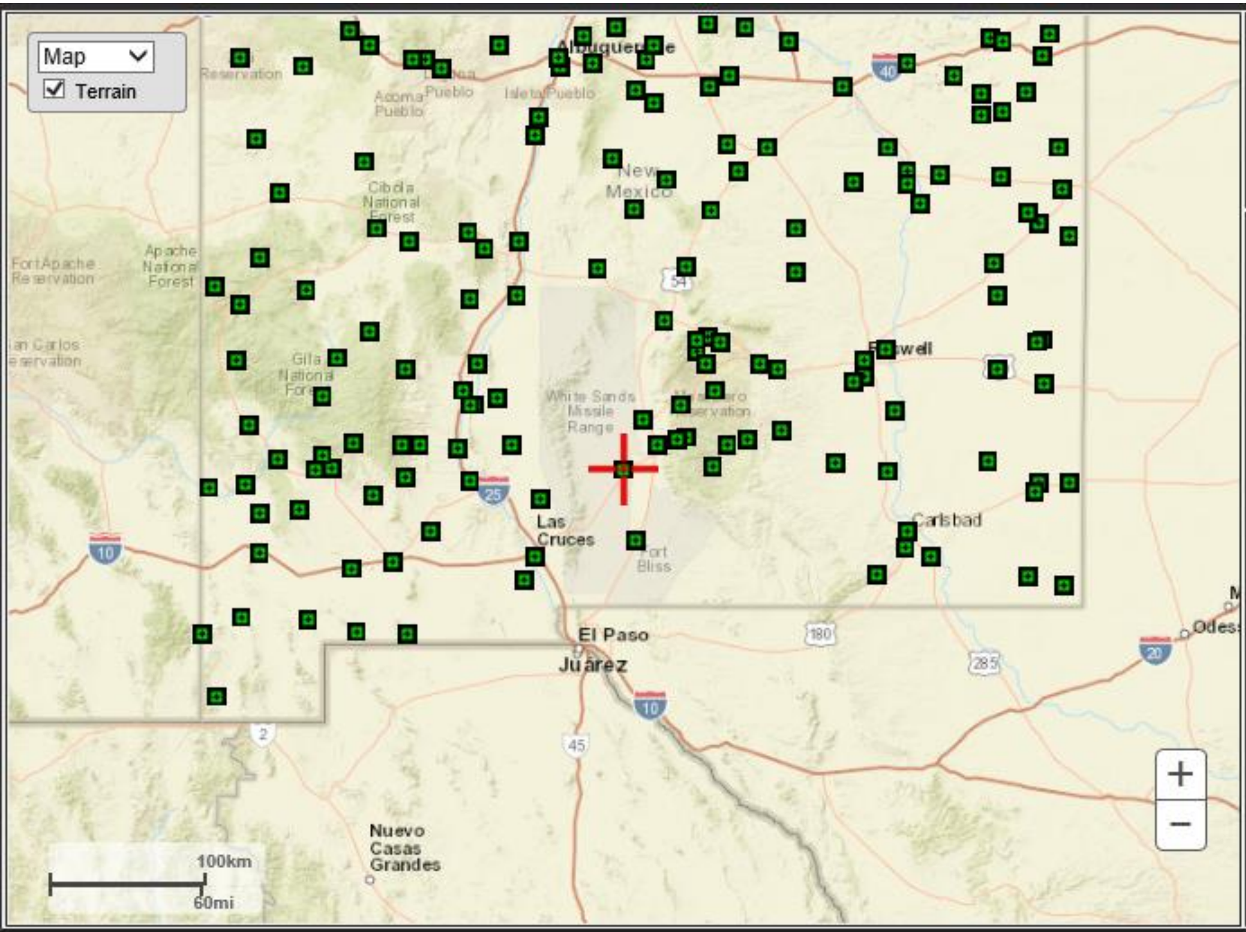
$y_t = \log(x_t)$ where $y_t \sim N(\mu, \sigma_y^2)$.

Let $z_t = y_t - \mu = \log(x_t) - \mu$ where $z_t \sim N(0, \sigma_y^2)$. Then

$$z_t = \mu + \phi_1(z_{t-1} - \mu) + \phi_2(z_{t-2} - \mu) + \varepsilon_t - \theta\,\varepsilon_{t-1}$$

where $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$ (Note that σ_ε^2 is related to σ_y^2)

Stedinger and Griffis (2011) followed this procedure for the Mississippi annual floods at Hannibal.



a) Select location
Move crosshair or double click

b) Click on station icon
Show stations on map

Location information:

Name: Alamogordo, New Mexico, USA*

Station name: WHITE SANDS NATL MON

Site ID: 29-9686

Latitude: 32.7817°

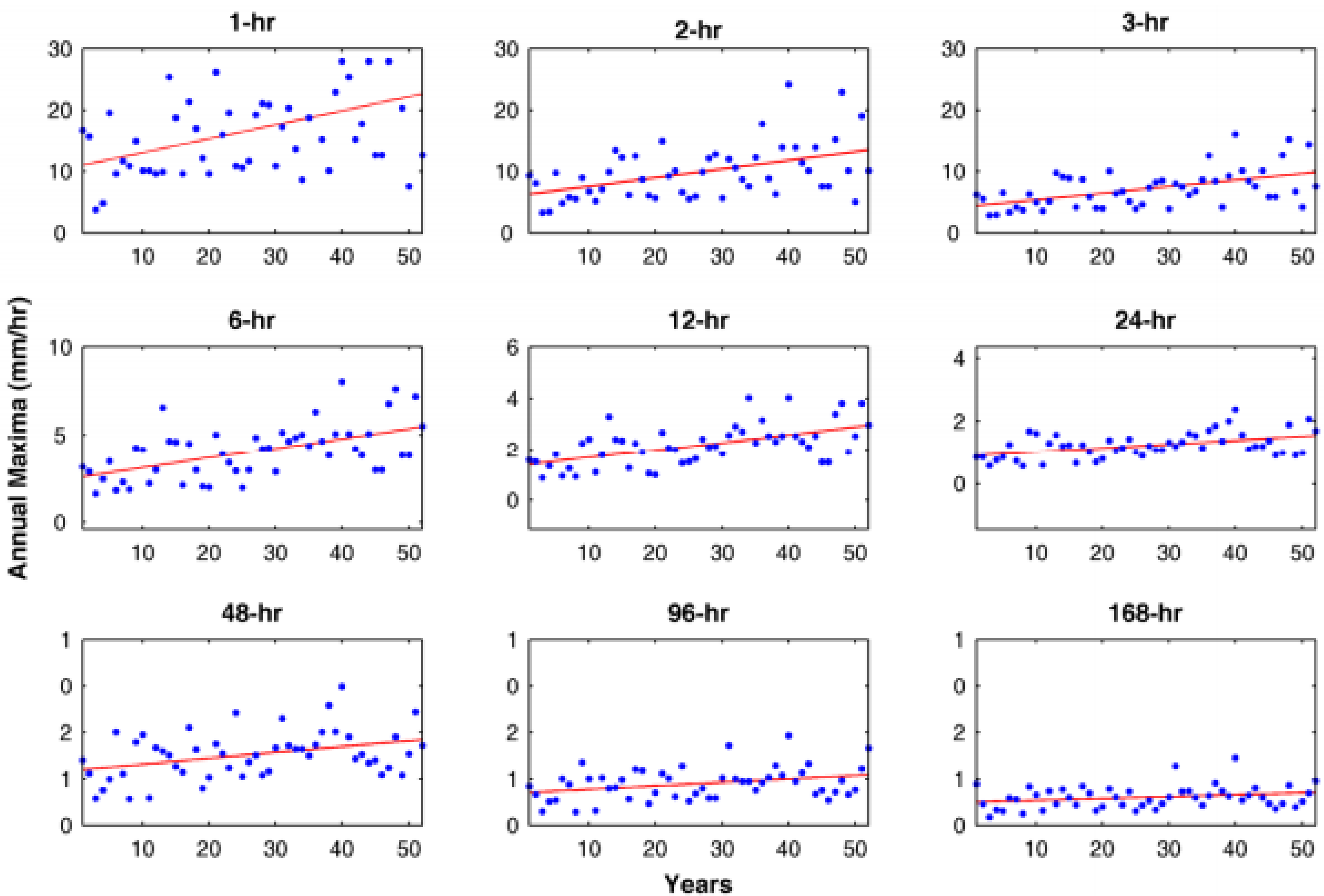
Longitude: -106.1747°

Elevation: 3995 ft

* Source: ESRI Maps

** Source: USGS

Extreme Precipitation (Cheng & AghaKouchak)



Risk Analysis, Vol. 18, No. 4, 1998

Risk of Extreme Events Under Nonstationary Conditions

J. Rolf Olsen,[1] James H. Lambert,[1] and Yacov Y. Haimes[1,2]

Climatic Change (2009) 97:67–76
DOI 10.1007/s10584-009-9654-7

The effect of changing climate on the frequency of absolute extreme events

T. M. L. Wigley

Stedinger & others; Singh & collaborators; Salas and Obeysekera, Ouarda et al; Katz; Rootzen & Katz; Villarini & others; Parey; Cooley; Vogel & collaborators; Frances & collaborators; Serinaldi & Kilsby; Cancellieri & collaborators; Volpi: Aghakouchak; and many many others