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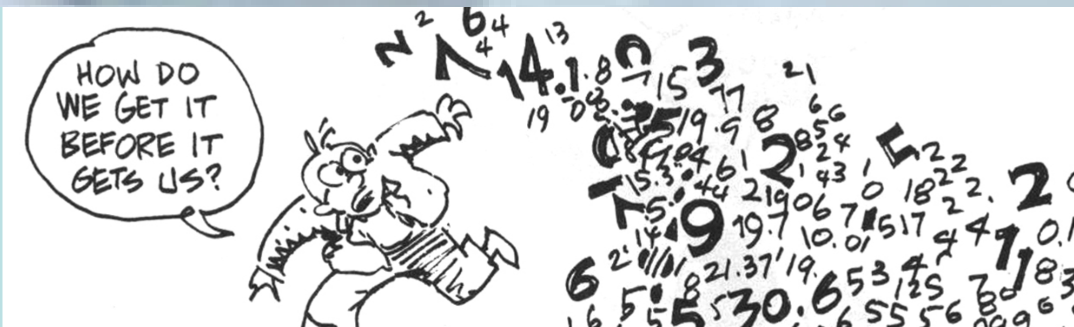
Potential Impact Of Uncertainty on Surge Prediction



Two Major Types of Data Needs

Current forecast systems focus on this problem

Forecasts:

- **Go/No-Go Evacuation Decision**
  - long lead time (3-5 days)
  - must be conservative
  - uncertainty "factored in"
- **Storm-Approach Operations**
  - time-phased information
  - late evacuation routing
  - gate/spillway decisions
  - uncertainty quantified
- **Post-Storm Operations**
  - time-phased information
  - accurate damage assessment
  - accurate systems assessment
  - critical recovery decisions

Planning/Risk Mitigation:

- **Accurate Hazard Climatology**
  - consistent data set
  - long period of record
  - uncertainty quantified
  - climatic variability
- **Accurate Response Specification**
  - human response
  - system response
- **Quantified Risk/Alternatives**
  - time-phased options
  - climatic variability
  - uncertainty quantified
  - Objective "cost" estimates

Net Change: We need more accurate information and uncertainty estimates

Risk is often strongly related to exceeding some threshold

So what does it mean when we say 5m ± 0.8m in this situation??

Uncertainty is usually either neglected or used primarily as a reason to neglect something

Let's use a block-by-block forecast tool!!

EMA:I need my forecast 4 days before landfall!!

Let's use this "super-accurate" 10-year weather record to estimate the 1,000,000-yr surge!!!

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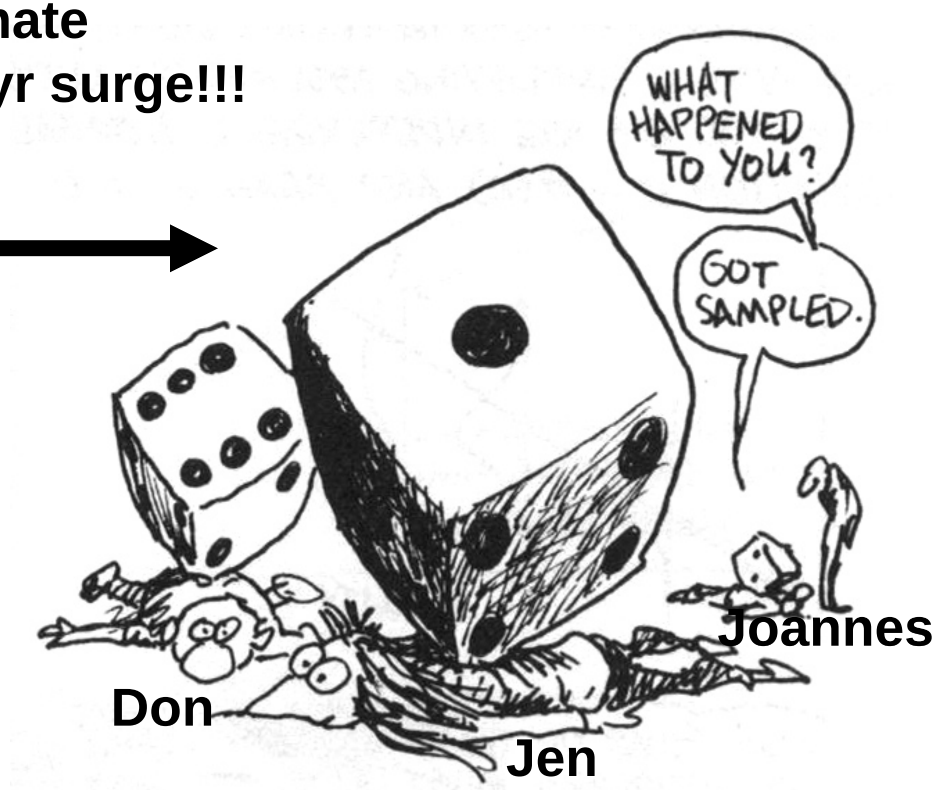
Forecast

Planning

Forecasting and Planning typically have different needs and will be affected differently by uncertainty



Conclusions - Forecast

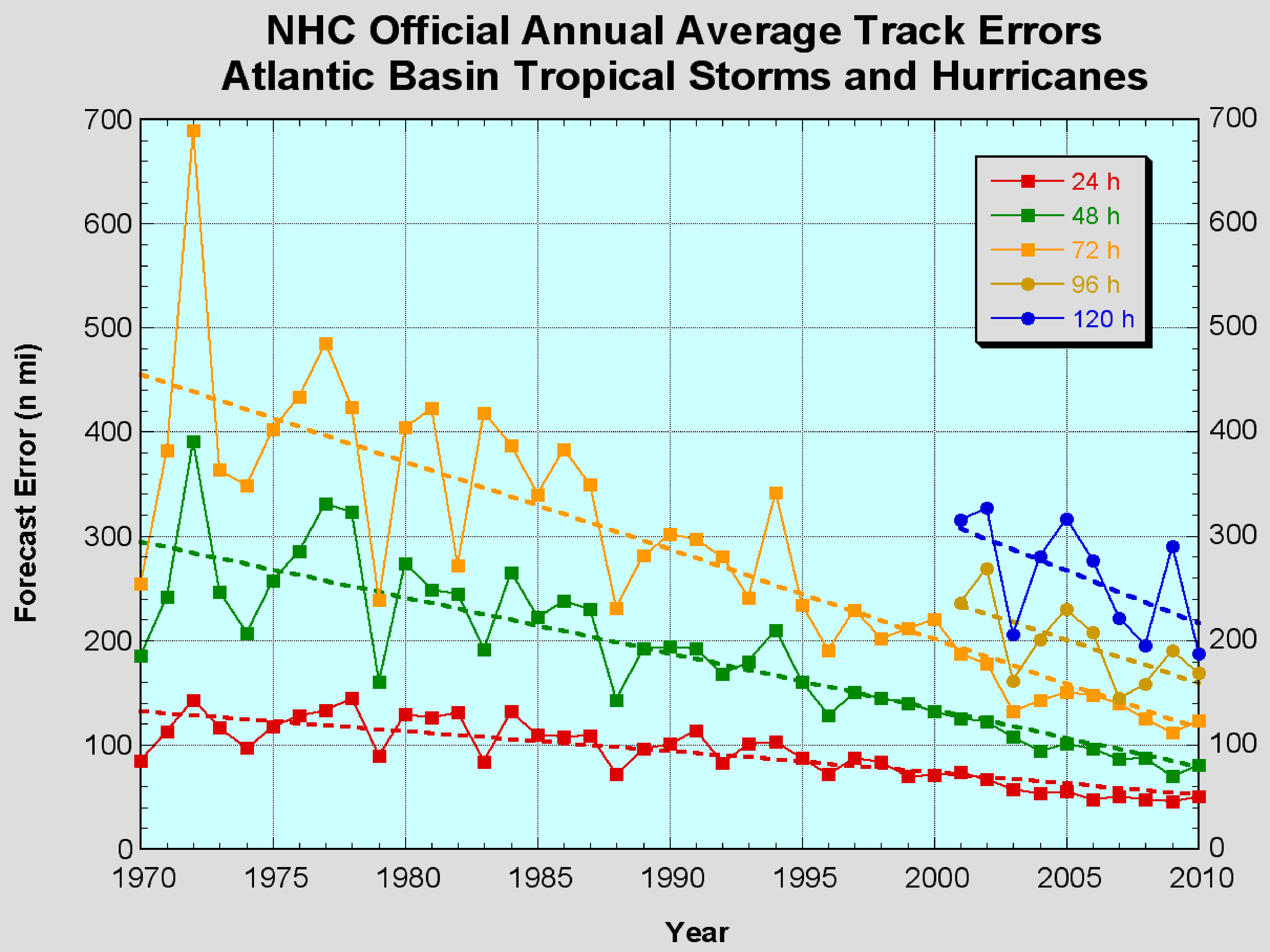
- **Forecast uncertainty is dominated by errors in storm track, intensity and size – but random errors and bias in the surge model are also significant**
- **Problems with high ratios of false positives and/or false negatives are very storm and site dependent not a generalized property**
- **False positives can be reduced by 70-90% by making a surge-based decision at t-24 vs. t-72.**
- The use of arbitrary MEOWS and MOMS does not have a well-defined statistical interpretation and leads to difficult-to-quantify and potentially unnecessary factors of conservatism which can detract from public trust in the forecast

Conclusions – 100-yr to 1000-yr

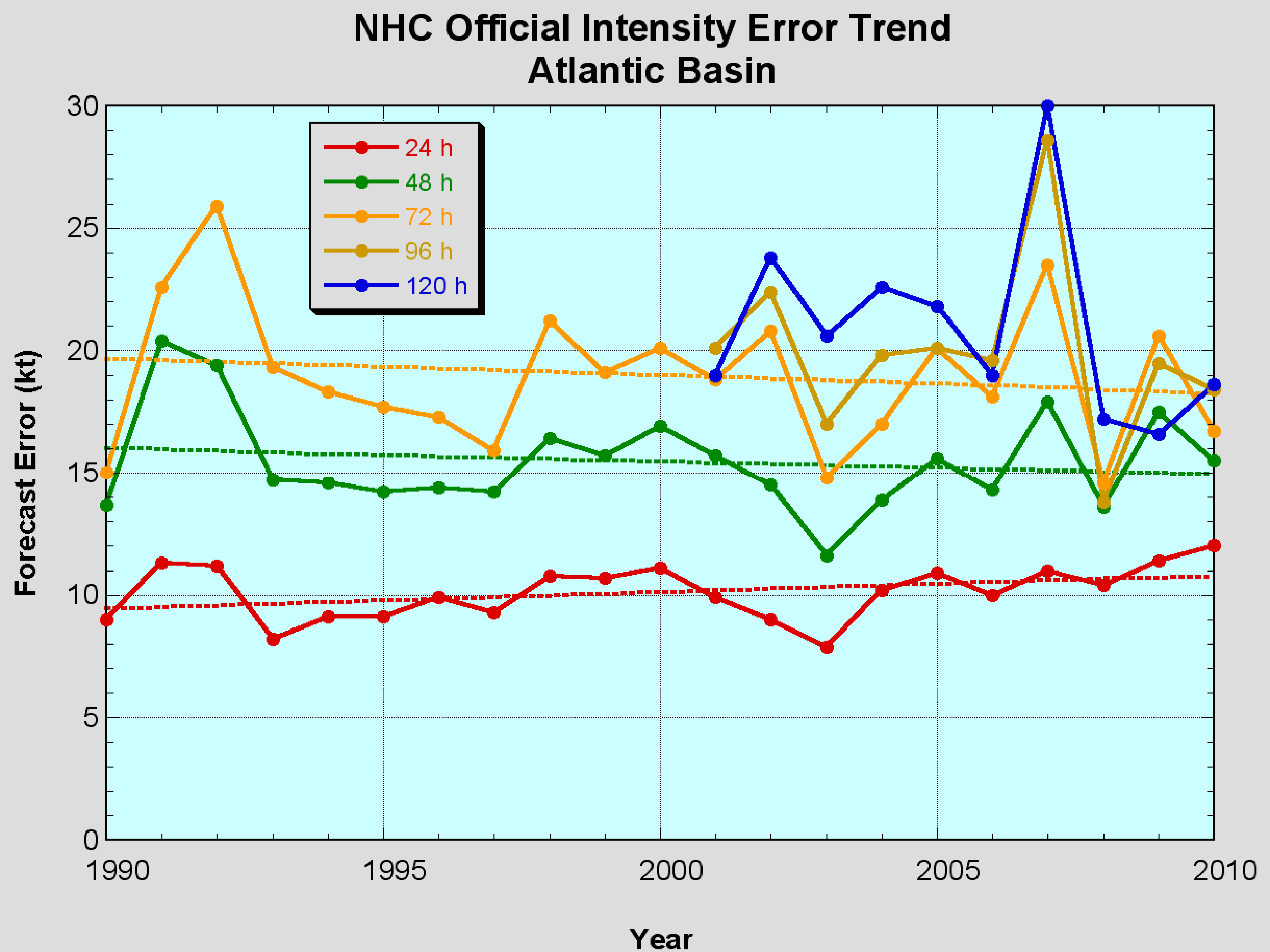
- **We should abandon the annual exceedance probability (1/return period) frequency approach to design and consider “design-life” within our design framework**
- **The determination of design values in the 100-yr to 1000-yr range are significantly affected by uncertainty in both the model capabilities and in the sampling of the basic forcing characteristics**
- **Resampling does not represent all uncertainty in estimates**
- The impact of uncertainty on design estimates in the Gulf of Mexico are typically in the 10 - 20% range for a (0.01 chance of flooding over 50 years)

Conclusions – Extreme Extremes

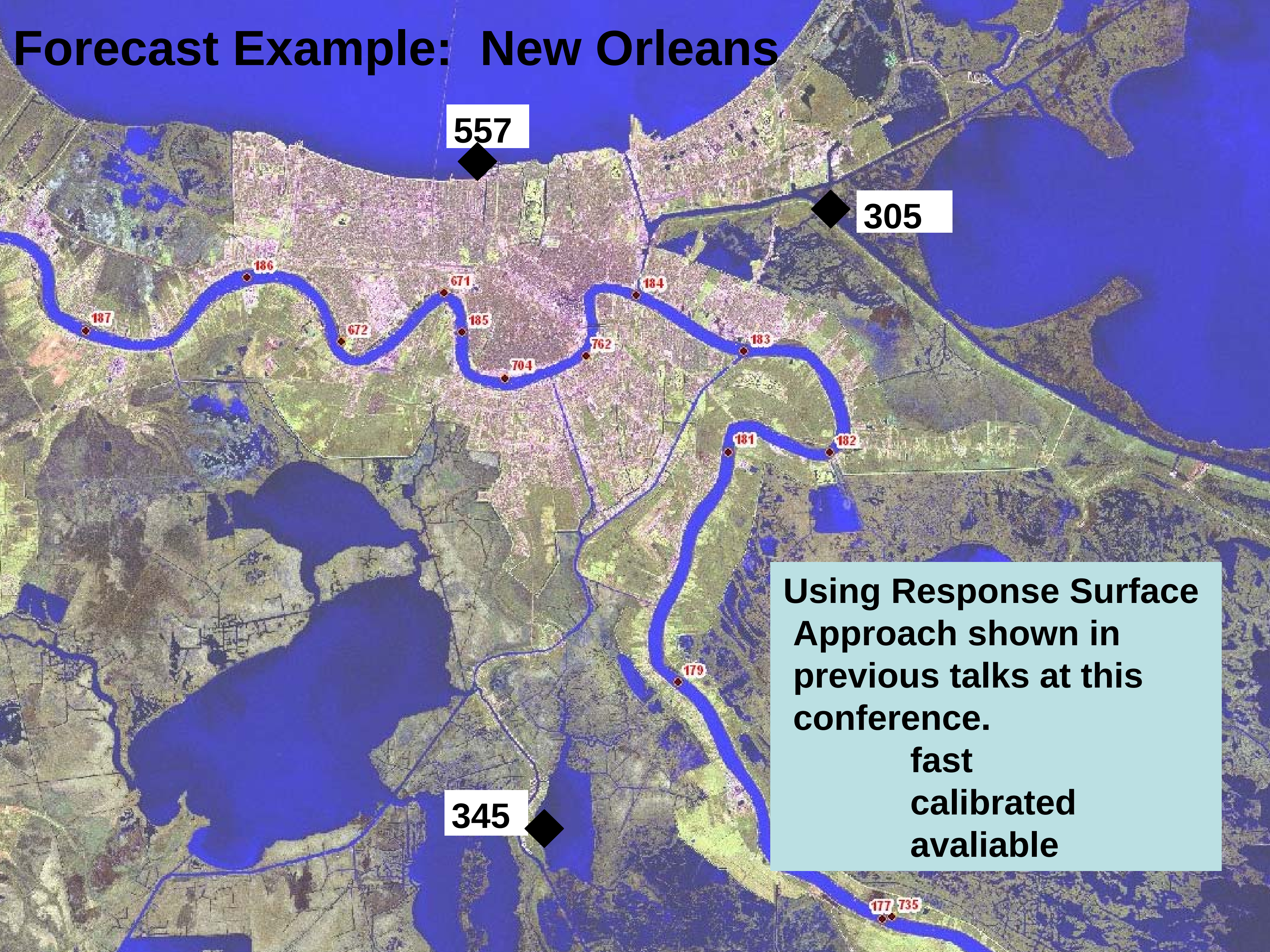
- **Uncertainty due to sampling variability creates a larger and larger risk as the record length becomes larger**
- **The practice of using the mean estimate for the very-long-term estimates leads to a large underestimate in the risk**
- **The Estimated Maximum Possible Surge (EMPS) is very much affected by uncertainty created by epistemic (lack of knowledge) factors as well as by aleatory (sampling uncertainty) factors**



NHC Official Annual Average Track Errors
Atlantic Basin Tropical Storms and Hurricanes
Forecast Error (n mi)
Year
24 h
48 h
72 h
96 h
120 h
0
100
200
300
400
500
600
700
1970
1975
1980
1985
1990
1995
2000
2005
2010


NHC Official Intensity Error Trend
Atlantic Basin
24 h
48 h
72 h
96 h
120 h
Forecast Error (kt)
0
5
10
15
20
25
30
1990
1995
2000
2005
2010
Year

Forecast Example: New Orleans



Using Response Surface Approach shown in previous talks at this conference.

- fast
- calibrated
- avaliable

If we let x_i be the probability of a parameter value given the deterministic forecast value, i.e.

Using pre-calculated surges from Response function approach

$$x_i = \hat{x} + \varepsilon_i$$

and it is understood that

$$p(x_i) = p(x_i \mid \hat{x}_i)$$

(Here assuming "no-bias," Gaussian errors)

Then:

$$p(\eta) = \int\int\int\int\int p(x_1, x_2, x_3, x_4, x_5)\delta[\eta - \Lambda(x_1, x_2, x_3, x_4, x_5)]dx_1 dx_2 dx_3 dx_4 dx_5$$

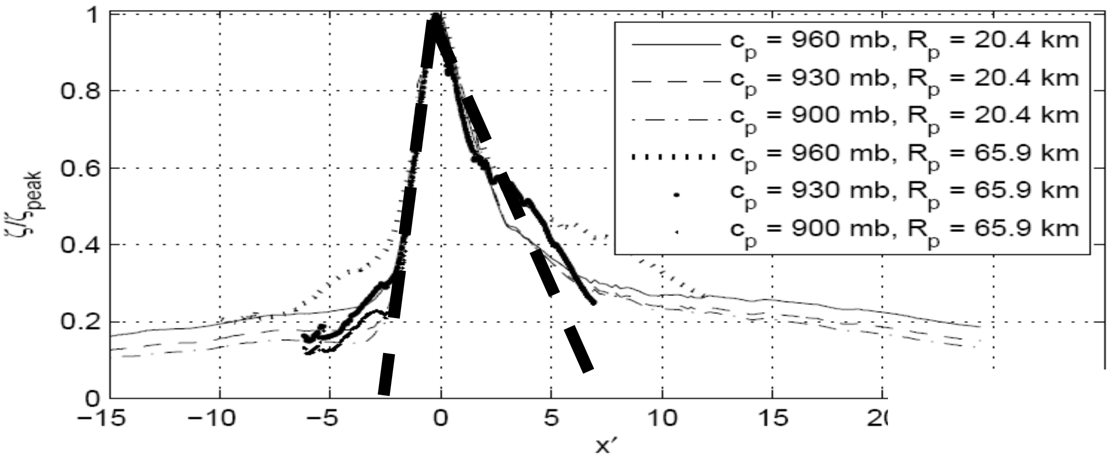
$$F(\eta) = \int\int\int\int\int p(x_1, x_2, x_3, x_4, x_5)H[\eta - \Lambda(x_1, x_2, x_3, x_4, x_5)]dx_1 dx_2 dx_3 dx_4 dx_5$$

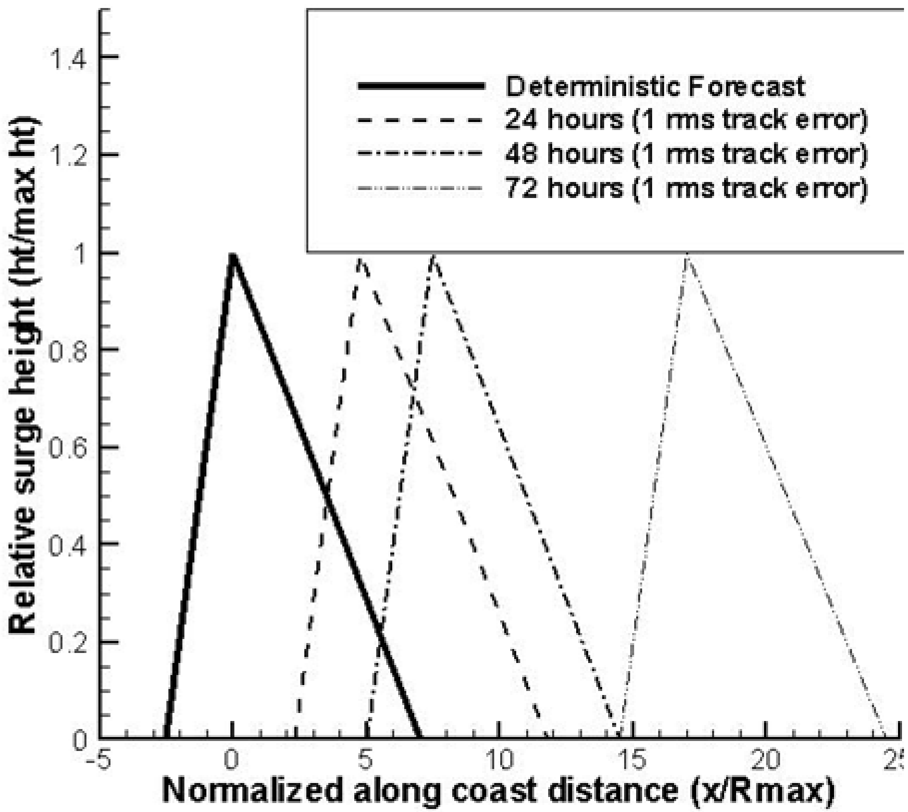
yields a good estimate of the statistical forecast characteristics

Errors (needed to define $p(x_i)$)

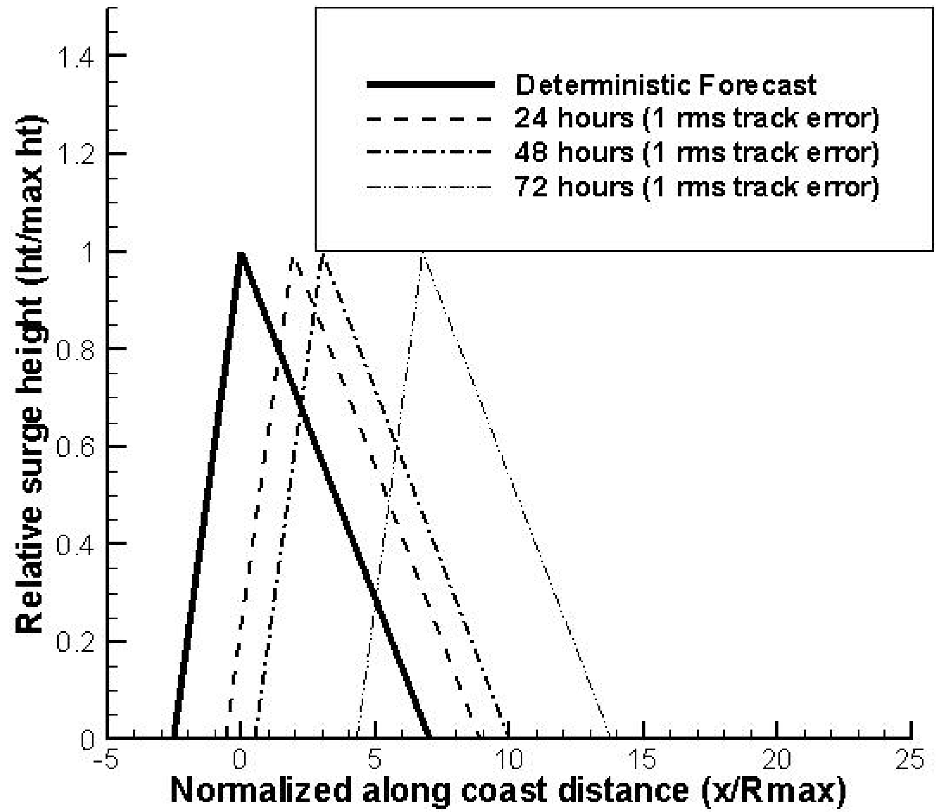
- Use NHC along-track error estimates – and convert from wind to Cp
- Use NHC intensity error estimates
- Estimate size errors by variation over time
- Estimate forward speed error from NHC along-track error estimates
- Estimate angle error at coast from straight line geometry

Simple interpretation of error in surges due to error in landfall location



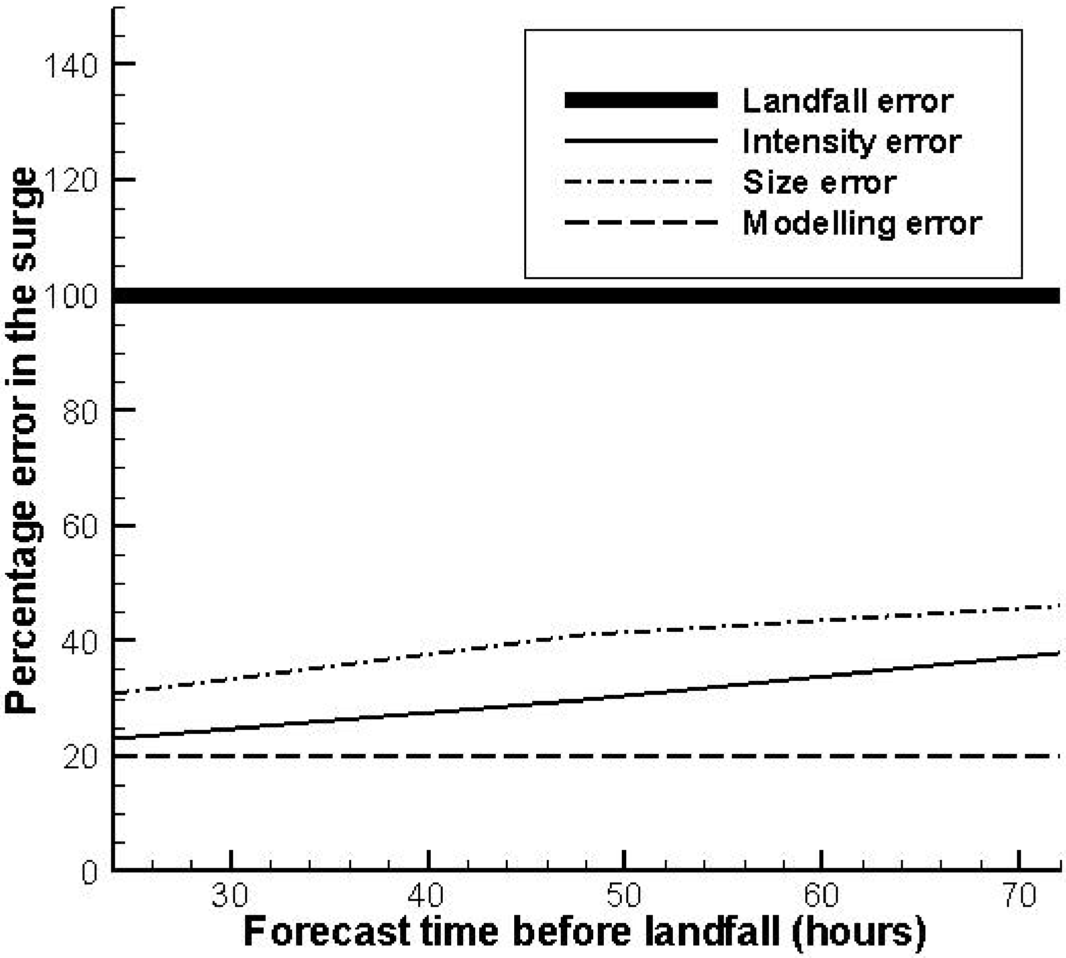


SMALL Storm Rmax = 10nm



LARGE Storm Rmax = 25nm

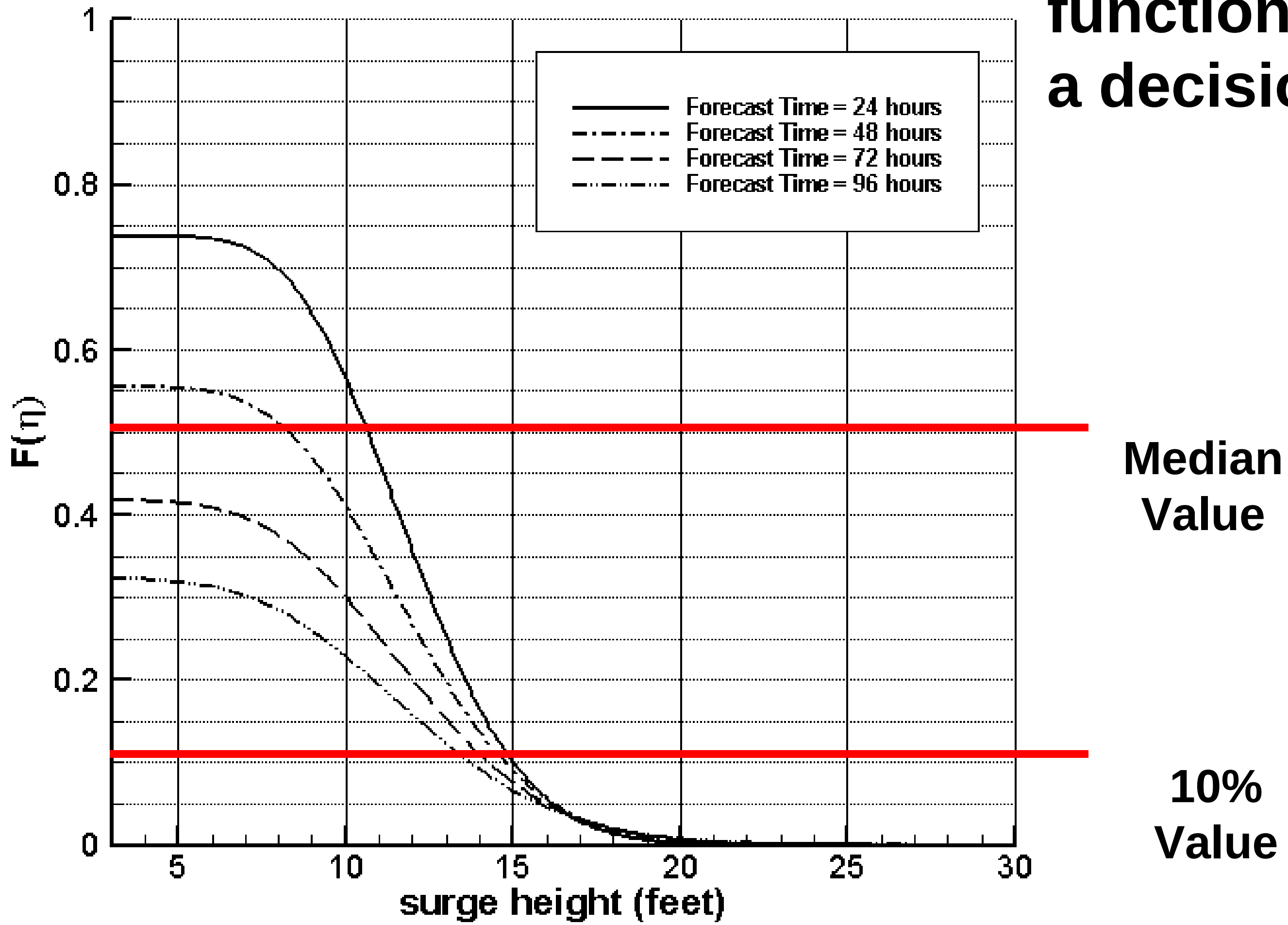
Using scaling analyses from the Response Surface, we can estimate the percentage impacts that each of the different types of error might have on forecast surges



And the winner is (as expected) landfall location

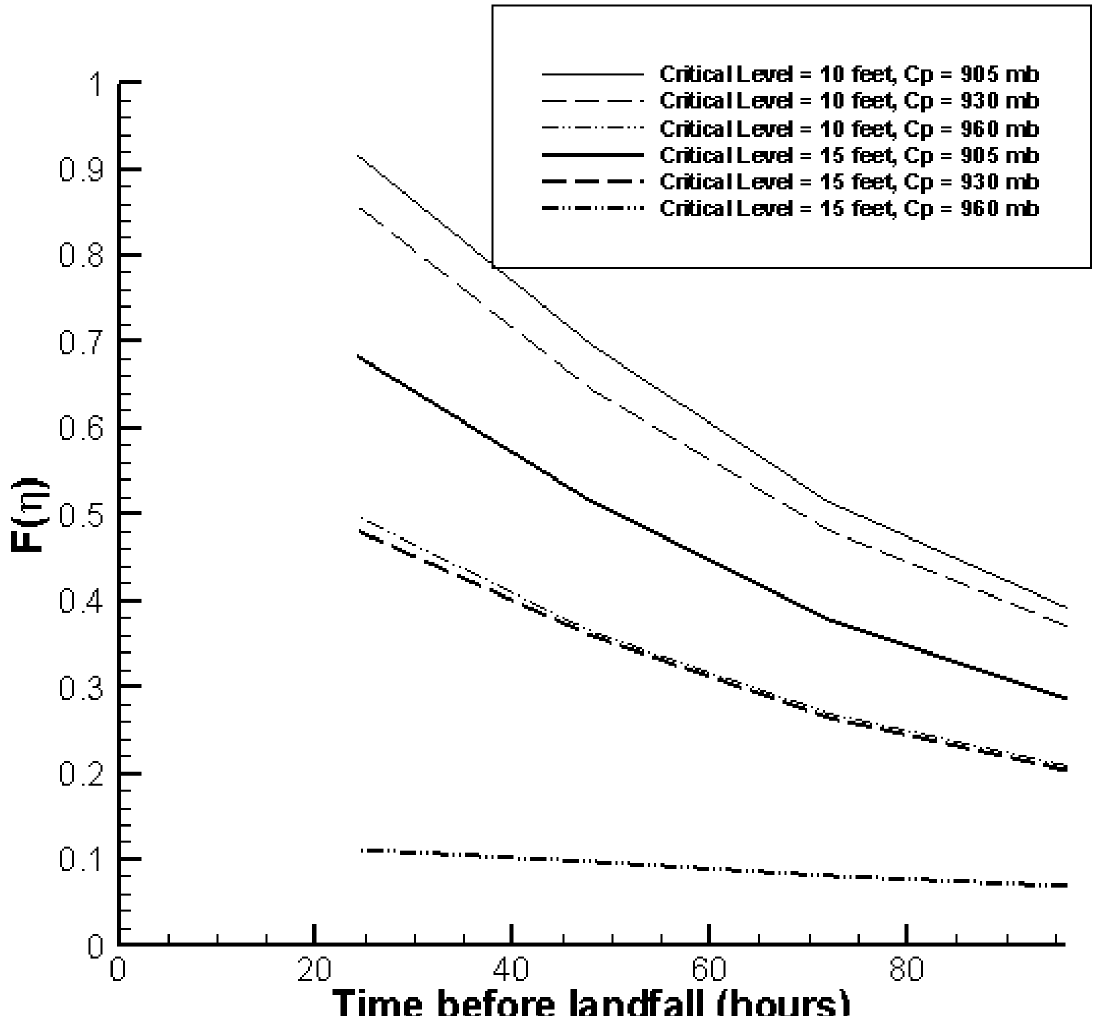
IHNC 1 (Q305)

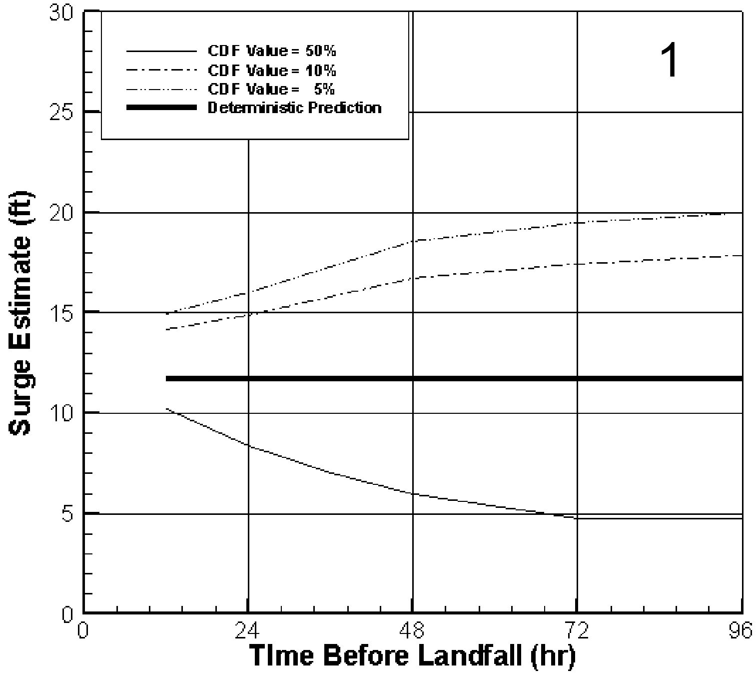
Could use this directly with a loss function to optimize a decision.

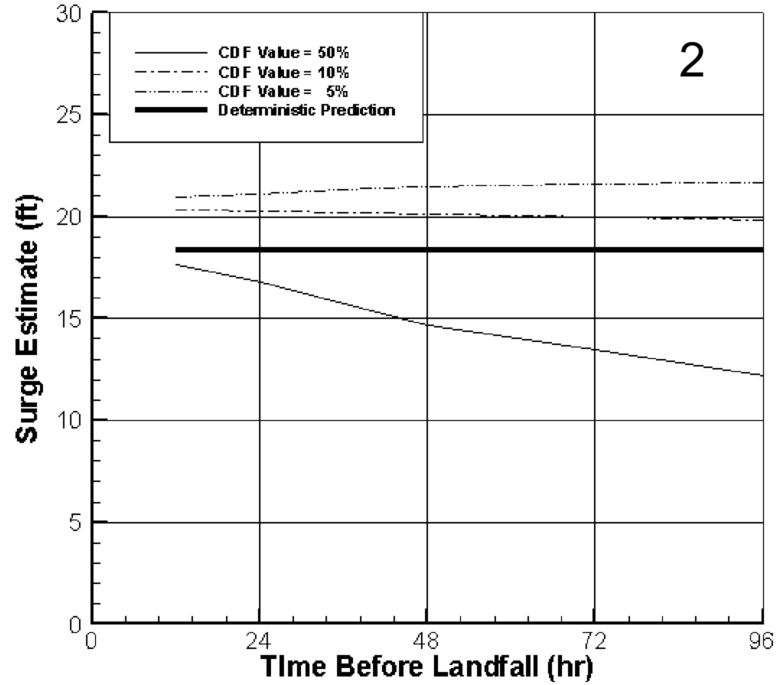


Central Pressure = 955 mb
Reference Longitude = 90 degrees

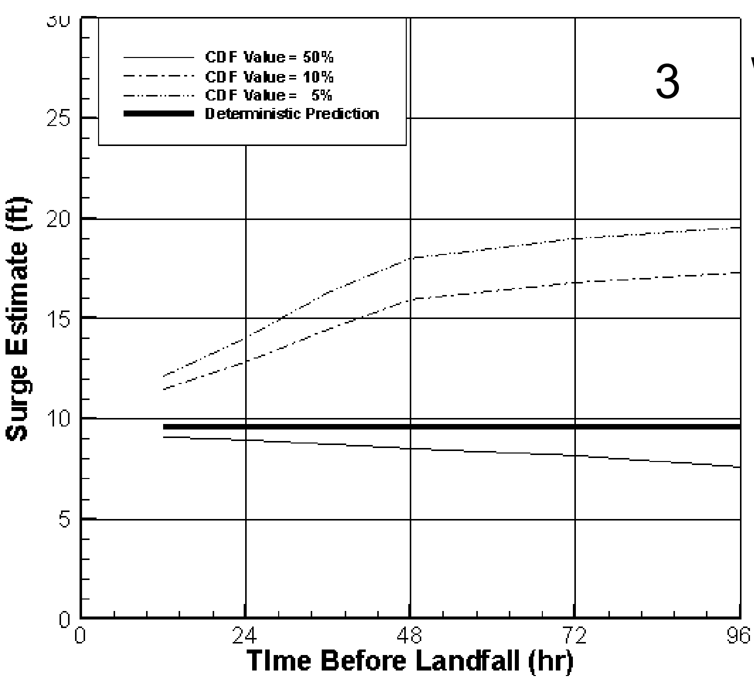
Probability of exceeding 2 selected thresholds given 3 central pressures and a perfect forecast at Site 305

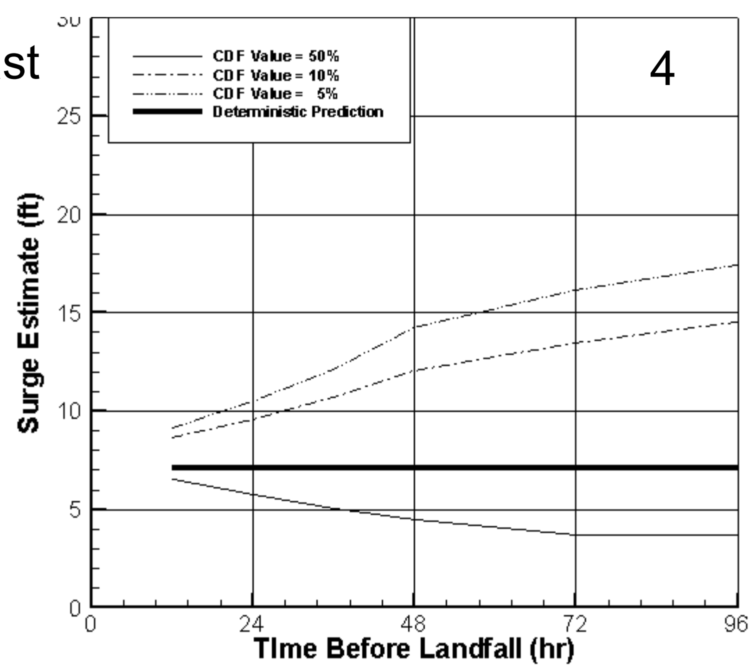


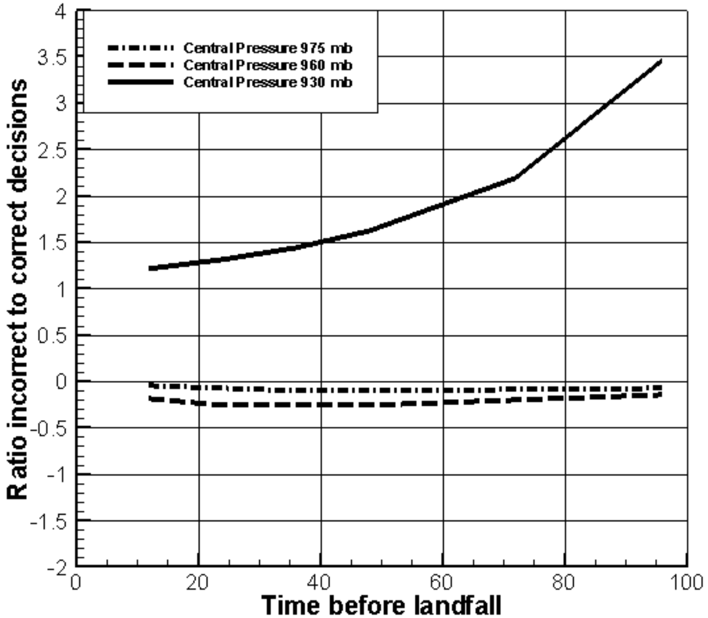


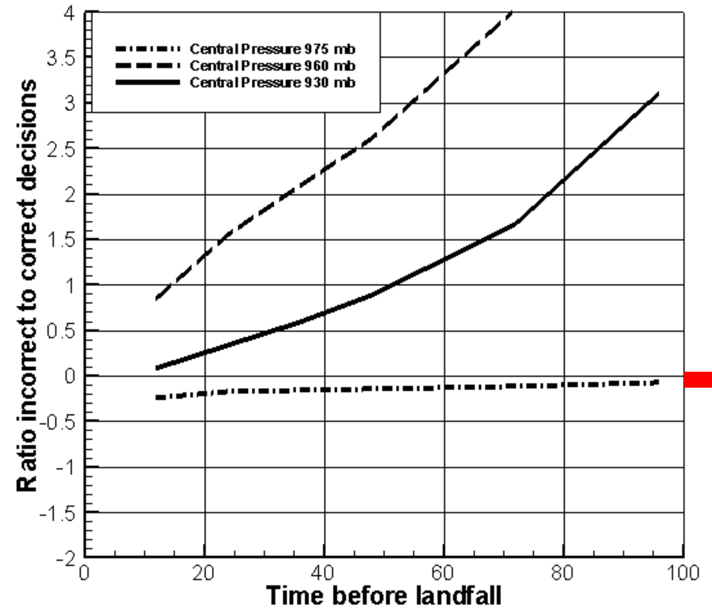


Tracks
West-East
1-4





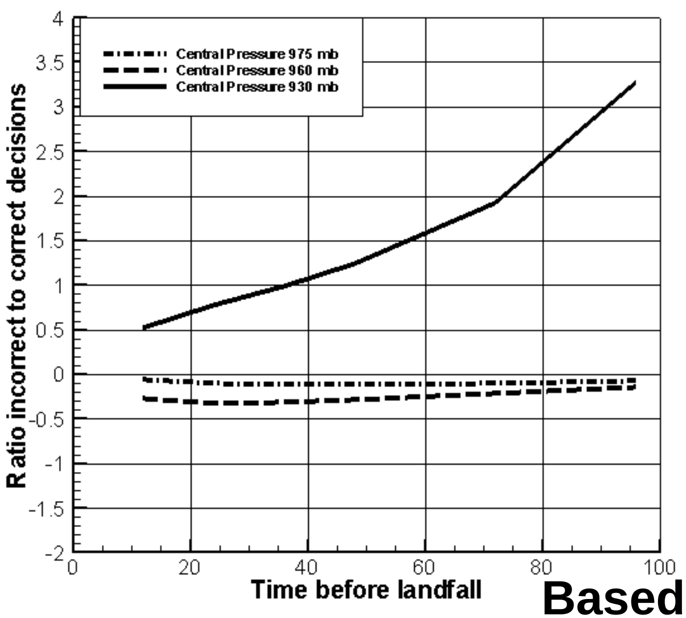


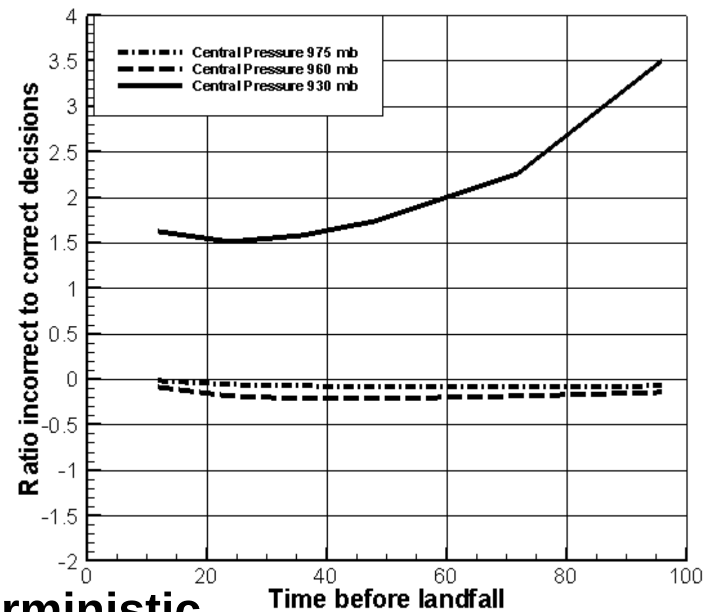


False positives

False negatives

Consequences of false negatives can be much larger than false positives





Based on deterministic estimate

Additional Results

- A bias in the models had the same effect on the statistics as (artificially) changing the decision threshold
- The ratio of false positives can be very high if either
  - The deterministic surge is close to the decision threshold (4-8), or
  - The decision threshold is chosen to be very conservative (10-20)

- Some projects have very long lifetimes (dams, ports, nuclear power plants, levees around urban areas, etc.)
- The likelihood of a failure over an m-year lifetime is $1-(1-F(\eta))^m$ which strongly depends on m!
- For very long return periods the relationship asymptotically approaches the limit such that the actual design return period is effectively divided by m
- These should not be treated as equivalent in terms of the annual probability for design needed to achieve a given level of protection

Designs in the 100 – 1000 year range

$$F(\eta) = \iiint \ldots \iiint H[\eta + \sum_j \varepsilon_j - \Theta(z_1, \ldots, z_n)] p(z_1, \ldots, z_n) dz_1 \ldots dz_n$$

These terms are a combination of aleatory and epistemic uncertainty

where

η is the surge height

Θ is a numerical operator (model)

z_i is a parameter affecting the surges

ε_j is a random deviation characterized by an associated standard deviation σ_j^2 (i.e. no biased included)

One can experiment numerically with the impact that the magnitude of different terms has on the surge probabilities

Resampling does not capture the epistemic errors in the models nor the aleatory errors in the parameter probabilities! These tend to be as large or larger than the resampling variability

An Estimate of the Upper Limit for Storm Surges (PMSS or EMPS?)

- In designs and safety analyses of large, long-term structures we are asked to supply estimates of annual exceedance probabilities in the range of 10^{-6}
- This sounds like a very rare event unless one assumes there are 100 such facilities and that each facility is expected to last for 100 years.
- **A logical question then relates to the relative error in an error estimate and the possible existence on an upper limit.**

Uncertainty in an estimate is very difficult to estimate without some assumptions regarding parent distributions and the "effective" number of samples (which depends on the autocorrelation attributes of the phenomenon). For extremes, the overall characteristics tend to vary as a function of the return period and the number of samples.

$S_x \sim \phi\left(\frac{T}{\sqrt{N}}\right)$, where S_x is the rms of the Gaussian uncertainty band

For a Gumbel Distribution, with a distributional rms of S

$S_x \sim S\sqrt{\frac{1.100y^2 + 1.1396y + 1}{N}}$, for large T $y \approx \ln(T) - \frac{T}{2}$

Unfortunately, this makes the estimation of very-low-probability events very uncertain. For hurricane surges the typical rms value of the uncertainty is in the 10% range for the 100-year return period (assuming a Gumbel Distribution).

For very low frequencies (very large T), the confidence limits become much larger than the predicted surge values.

Functional dependence of the surge on forcing parameters as they become large-valued.

Irish and Resio (2010)

Becomes Asymptotic

Storm Intensity

$$\zeta = \left(\frac{\rho_a}{\rho_w}\right)\frac{c_d V^2}{g}\int_0^L \frac{dx}{h(x)} = \left(\frac{\rho_a}{\rho_w}\right)\frac{c_d V^2}{g\langle h\rangle}L \qquad \zeta = \left(\frac{\rho_a}{\rho_w}\right)\frac{c_d}{\langle h\rangle}\frac{\lambda \Delta p}{\rho_a g}L$$

NO

But, what is the 1 in 1,000,000 value of this??

Storm Size

$$\zeta = \chi_1 \Delta p \frac{L_*}{h_* \phi_*}\psi_x\left(\frac{R}{L_*}\right) \qquad \psi_x\left(\frac{R}{L_*}\right) = \left(\frac{R}{L_*}\right) \quad when \left(\frac{R}{L_*}\right) \le 1$$

$$= 1 \quad when \left(\frac{R}{L_*}\right) > 1$$

YES

Storm Forward Speed

$$\zeta = \chi_1 \Delta p \frac{L_*}{h_* \phi_*}\psi_x\left(\frac{R}{L_*}\right)\psi_t\left(\frac{t_*}{t_\infty}\right) \qquad \psi_t\left(\frac{t_*}{t_\infty}\right) = \left(\frac{t_*}{t_\infty}\right) \quad when \left(\frac{t_*}{t_\infty}\right) \le 1$$

$$= 1 \quad when \left(\frac{t_*}{t_\infty}\right) > 1$$

YES

If we focus on the “tail” of the distribution, we see that some physical limits appear.

Incorporation of Uncertainty into Extreme Extremes

- NRC-related work

$$p(x) = \int_{0}^{\infty} \int_{-\infty}^{\infty} p[\hat{x}(T_r) + \varepsilon \mid \hat{x}] p(\hat{x}) p(\varepsilon) \delta(\hat{x} + \varepsilon - x) d\varepsilon d\hat{x}(T_r)$$

where

$\hat{x}(T_r)$ denotes the deterministic estimate of x for a given return period and

ε denotes the deviation from the the "best-fit" surge estimate.

$$T_r(x) = \frac{1}{1 - F(x)}$$

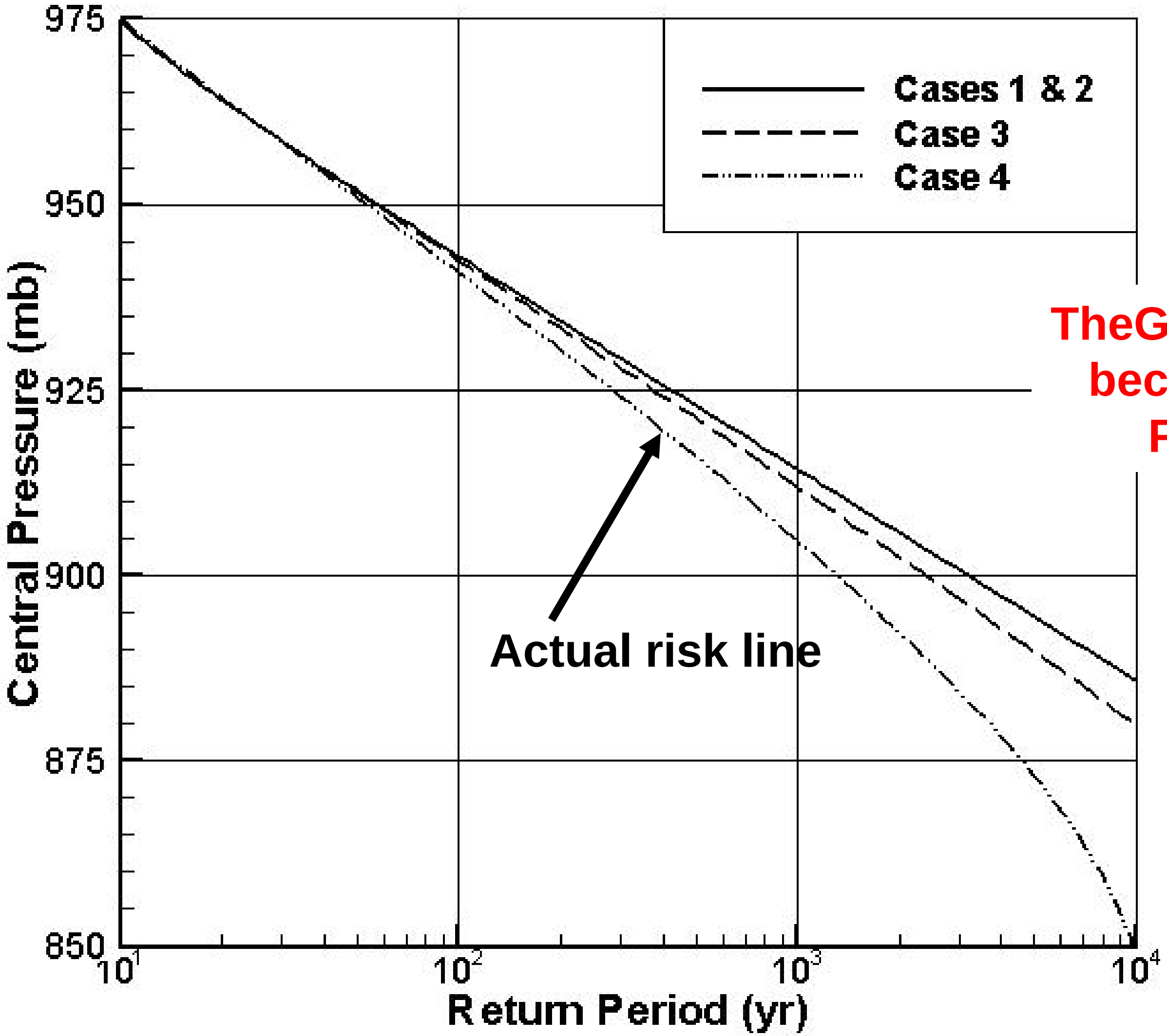
with

$$F(x) = \int_{0}^{\infty} \int_{-\infty}^{\infty} p[\hat{x}(T_r) + \varepsilon \mid \hat{x}] p(\hat{x}) p(\varepsilon) H(\hat{x} + \varepsilon - x) d\varepsilon d\hat{x}(T_r)$$

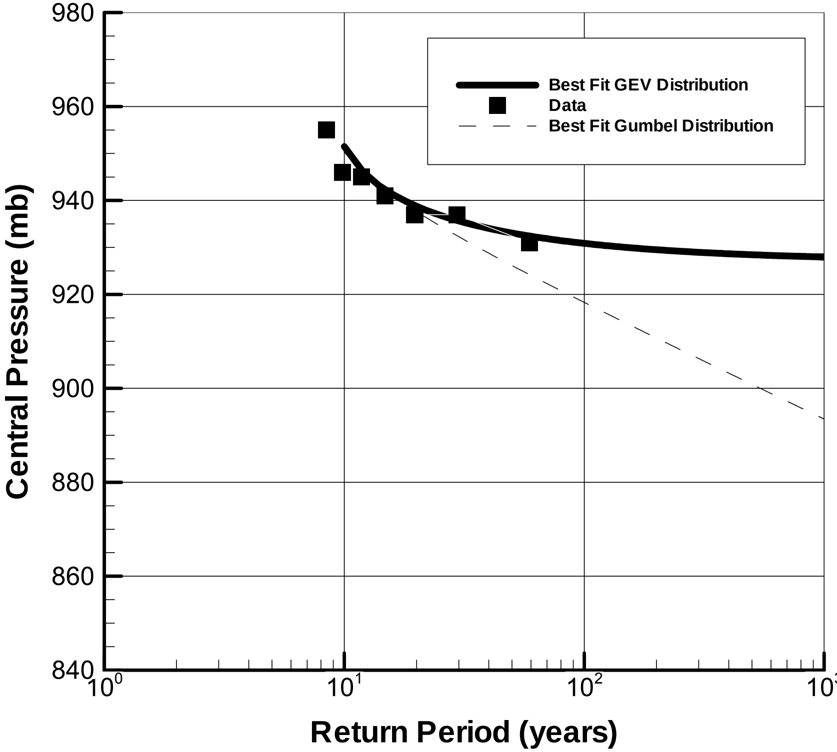
where

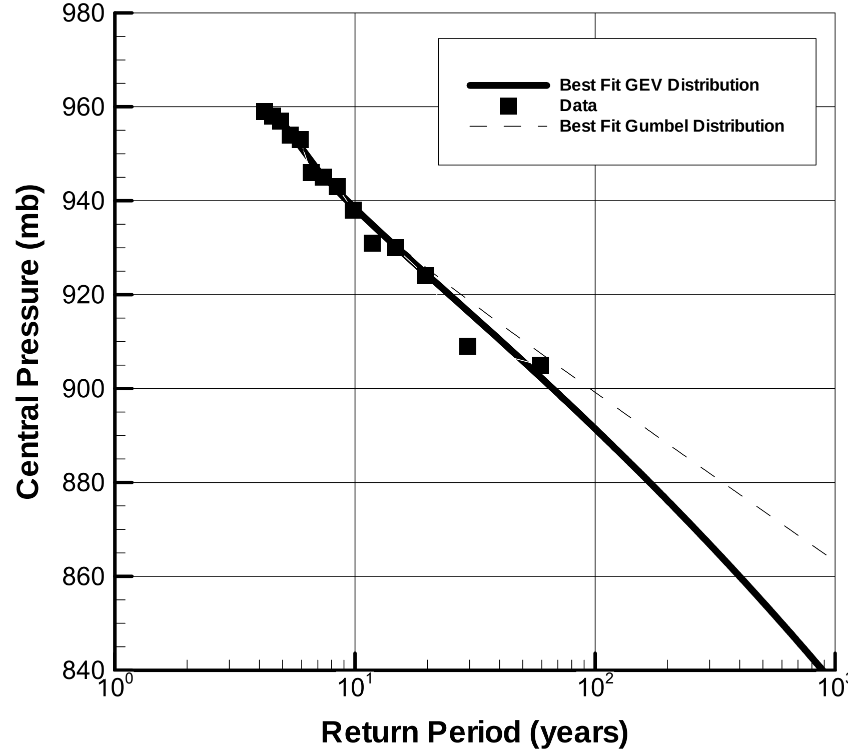
H(□) is the Heaviside Function, equal to 1 if □ ≥ 0 and equal to 0 if □ < 0 .

Comparison of Estimated Central Pressures with and without Uncertainty



TheGumbel Distribution become a Frechet or Fisher-Tippett II





Other surprises still await us!

Best-fit GEV and Gumbel distributions for GOM central pressures along with the data plotted with a simple

$$T_r = \frac{n+1}{m}$$

plotting position, where n= number of years in the sample and m=rank, for all storms in years with 4 or less storms occurring in that year in left panel and all storms in years with more than 4 storms.

NOTE: Over a 30 mb difference (>5 ft surge for New Orleans area) at 100-yr return period!

Questions?

"Imagination is more important than knowledge" A. Einstein

Artist - Carl Lundgren