Uncertainty Sources, Types and Quantification Models for Risk Studies

Bilal M. Ayyub, PhD, PE
Professor and Director
Center for Technology and Systems Management
University of Maryland, College Park



Workshop on Risk Assessment and Safety Decision Making Under Uncertainty
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CTSM
Technology for Intelligent Decisions

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Outline

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- Risk quantification and management
- Uncertainty in prediction and validation
- Knowledge and ignorance terminology
- Formalized languages
  - Generalized information theory
  - Generalized theory of uncertainty
- Uncertainty at the system level
- Open questions

Risk Terminology

Risk: The potential for loss or harm to systems due to the likelihood of an unwanted event and its adverse consequences.

Risk is an aggregate of (Hazard and scenarios, Consequences, Vulnerability, Threat rate)

Risk Assessment and Management

1. What could happen?
2. How likely is it to happen?
3. What are the consequences if it happens?

Risk Assessment

4. What can be done?
5. What are the costs and benefits?
6. What effect will these actions have on future options?

Risk Management

Need for *REAL* Data

Data Sources for Quantitative Risk Analysis

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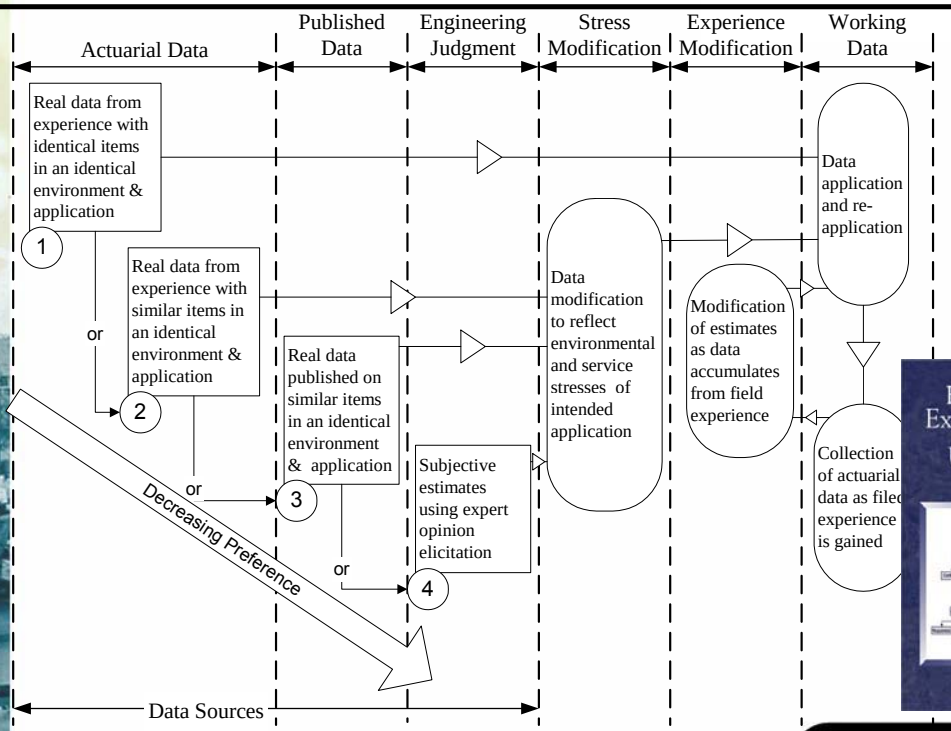
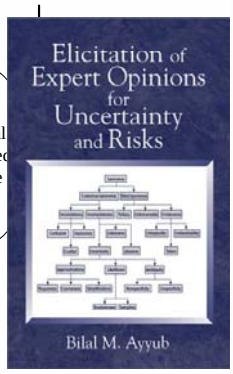


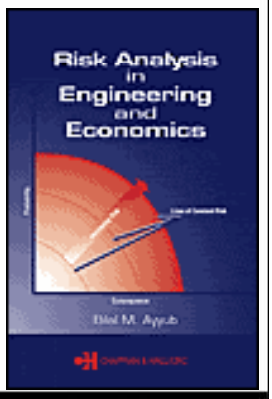


Risk Management

- Identify alternative risk mitigation strategies
- Assess benefits and costs of each
- Assess impact of strategy on future options

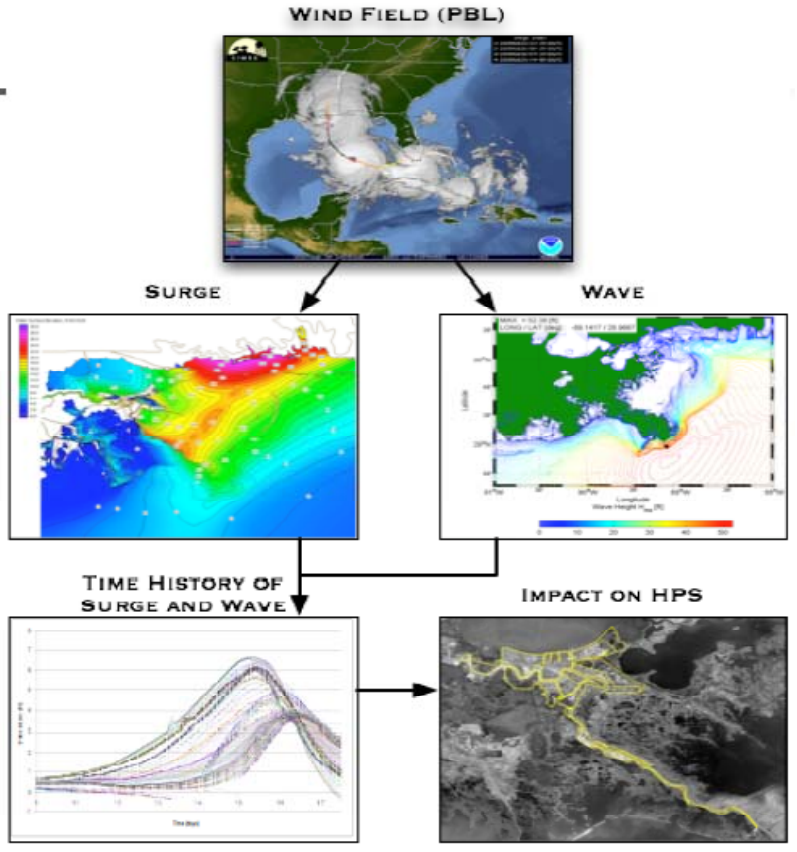
Benefit = (Risk Before) – (Risk After)

$$\text{B/C Ratio} = \frac{\text{Benefit}}{\text{Cost}}$$



Hurricane Katrina: Risk Methodology

Hurricanes



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Hurricane Katrina: Methodology

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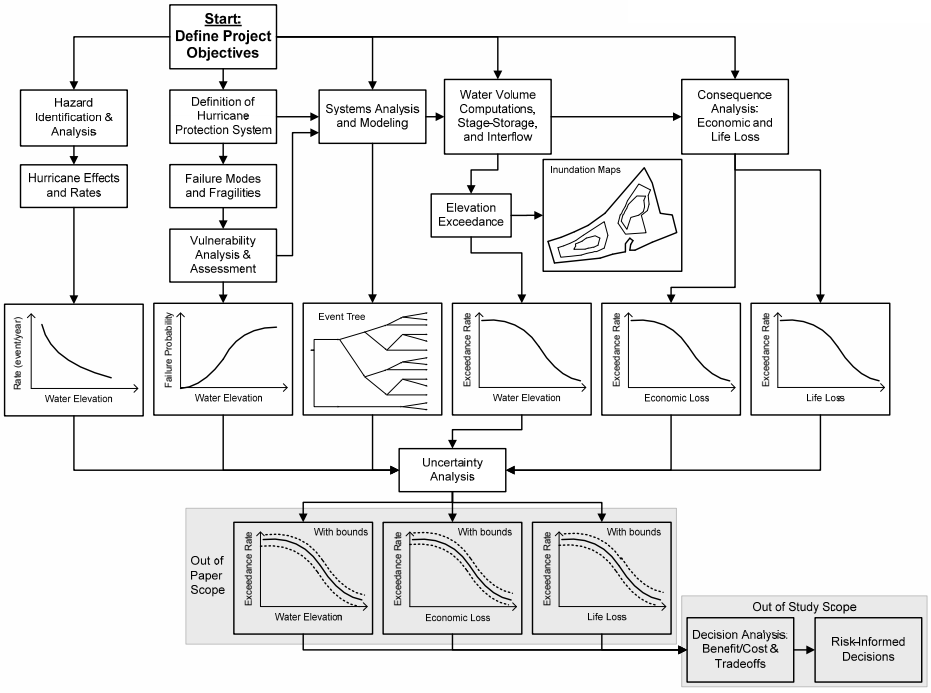

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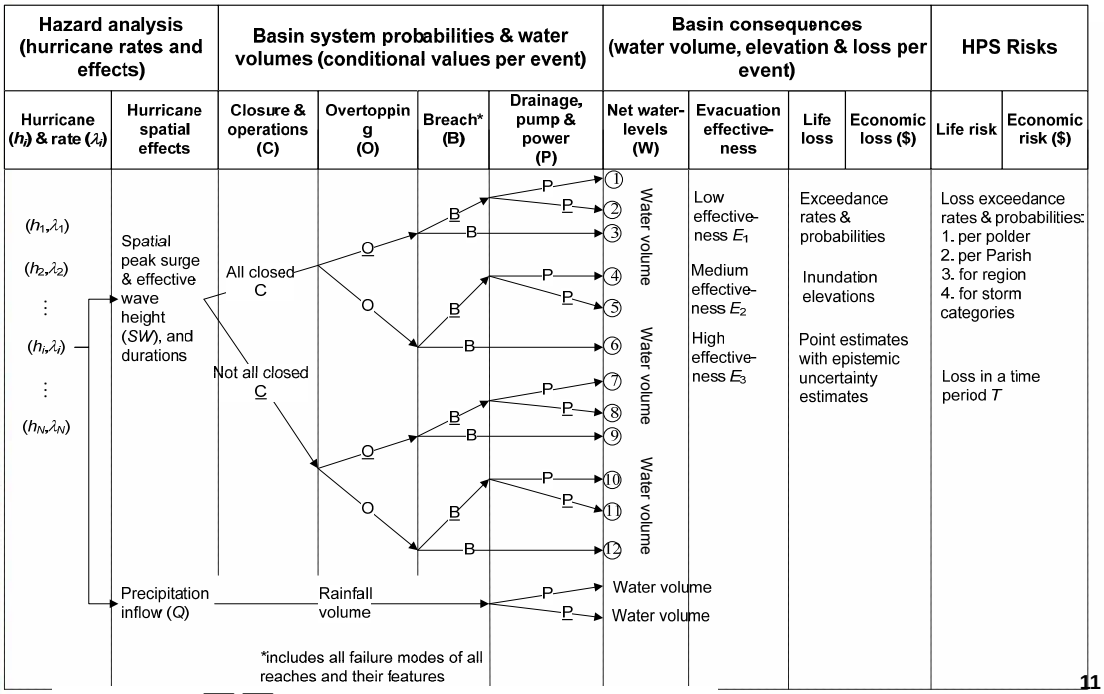
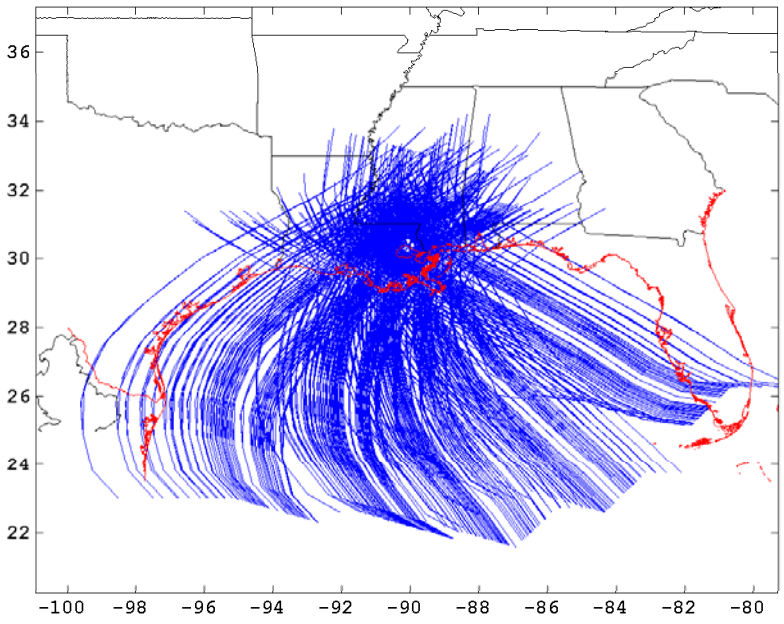
Event Tree



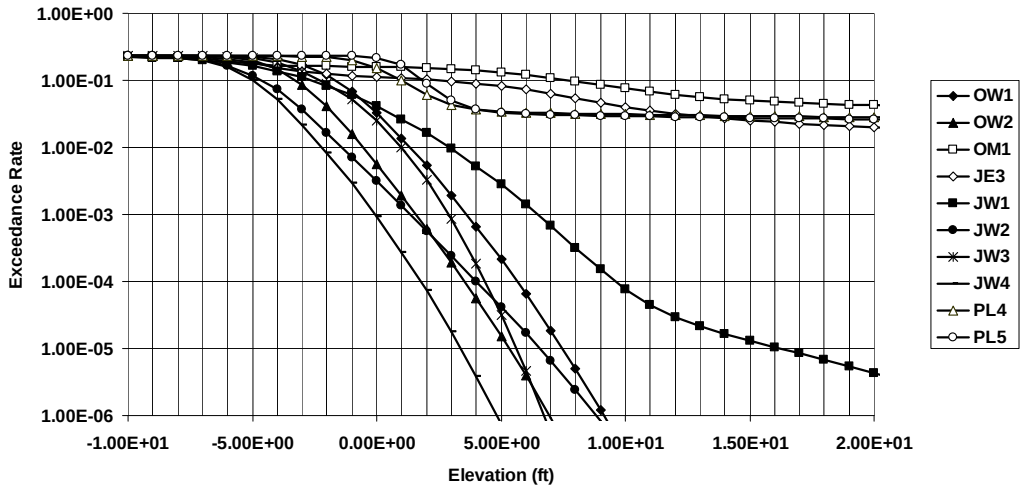
$$\lambda(C > c) = \sum_i \sum_j \lambda P(h_i) P(S_j \mid h_i) \times P(C > c \mid h_i, S_j)$$

Simulated Hurricane Tracks



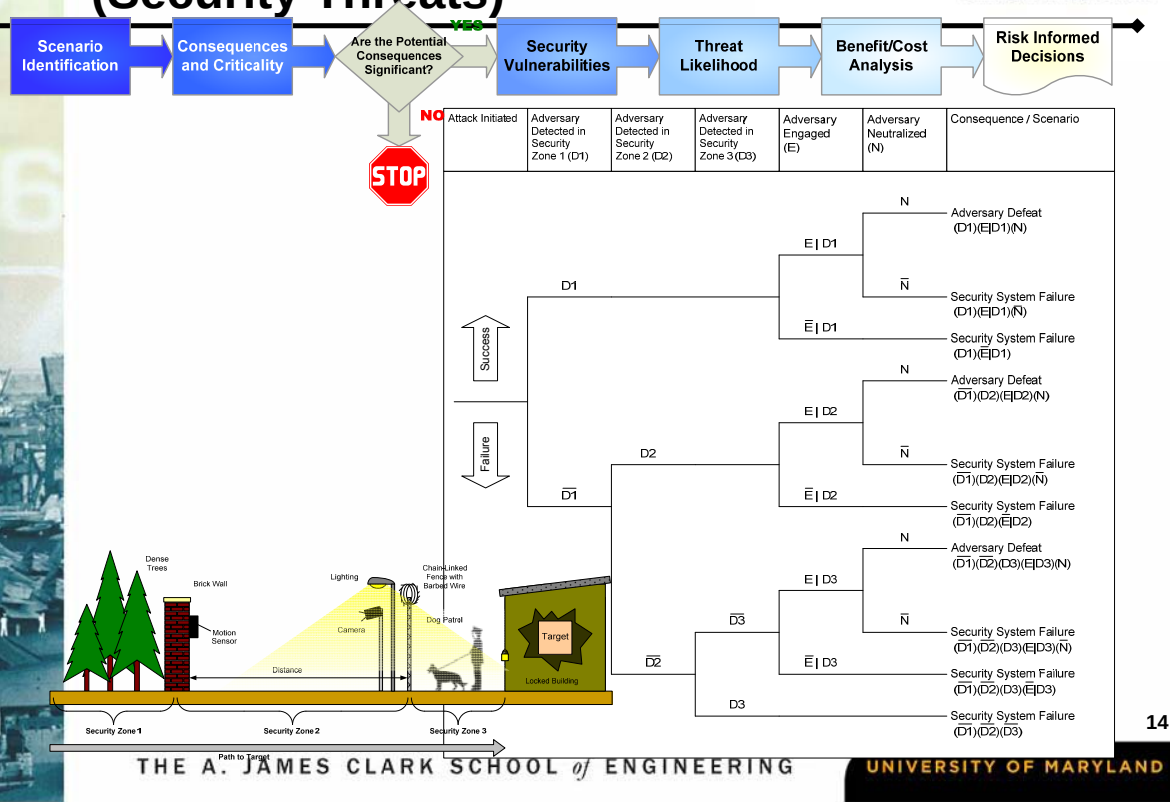
Hazard/Elevation Profiles

$$\lambda(E > e) = \sum_{\text{All storms \& branches}} \lambda P(h) P(S \mid h) P(E > e \mid h, S)$$



Results provided are for illustration purposes.

Security Vulnerability Assessment (Security Threats)



Rail Safety and Security

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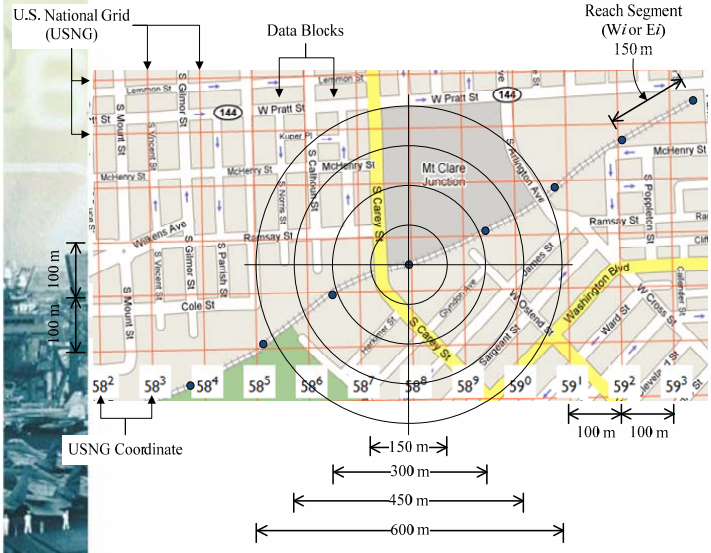
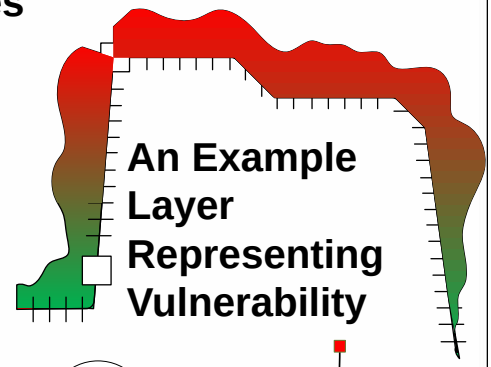
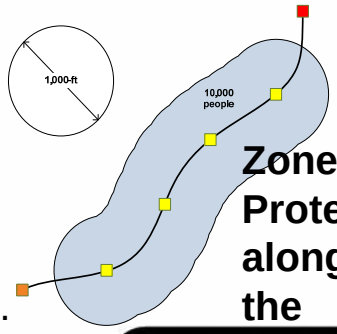
4 Different Influence Circles





An Example Layer Representing Vulnerability



Zone to Protect along the

Inventory: people, structures, schools, utilities, police resources, fire stations, hospitals, …

Requirements for risk methods

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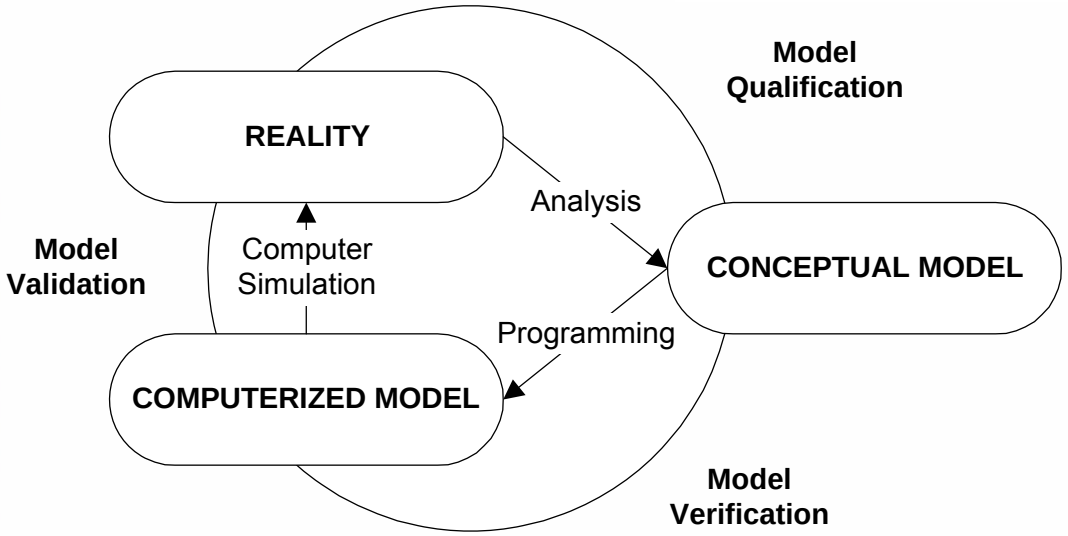
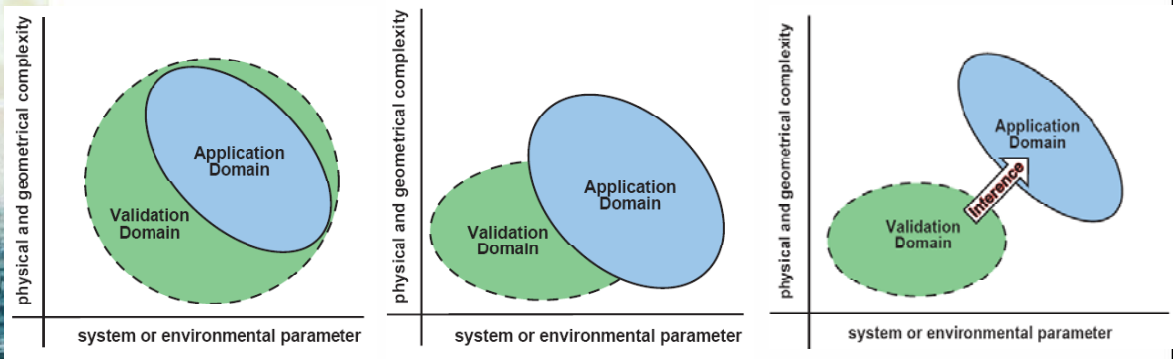
- A multi-hazard quantitative risk framework for informing decisions:
  - Analytic
  - Quantitative
  - Probabilistic
  - Consistent
  - Transparent
  - Defensible
- Reliability of knowledge

Verification, Validation and Accreditation



Model Validation

Validation and application domains (Sandia report)



Model Validation

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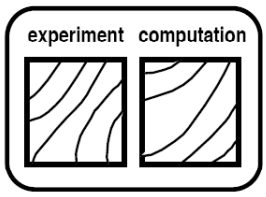
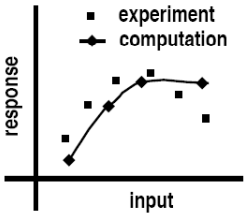
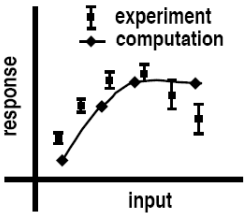
Validation methods (Sandia report)



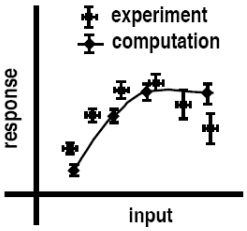
(a) Viewgraph Norm



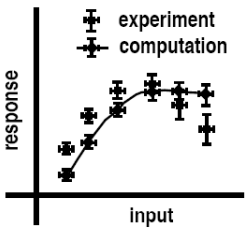
(b) Deterministic



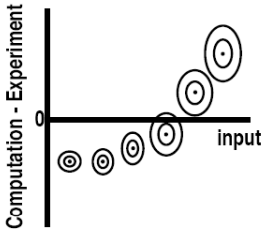
(c) Experimental Uncertainty



(d) Numerical Error



(e) Nondeterministic Computation



(f) Quantitative Comparison

Validation: Capsize Risk

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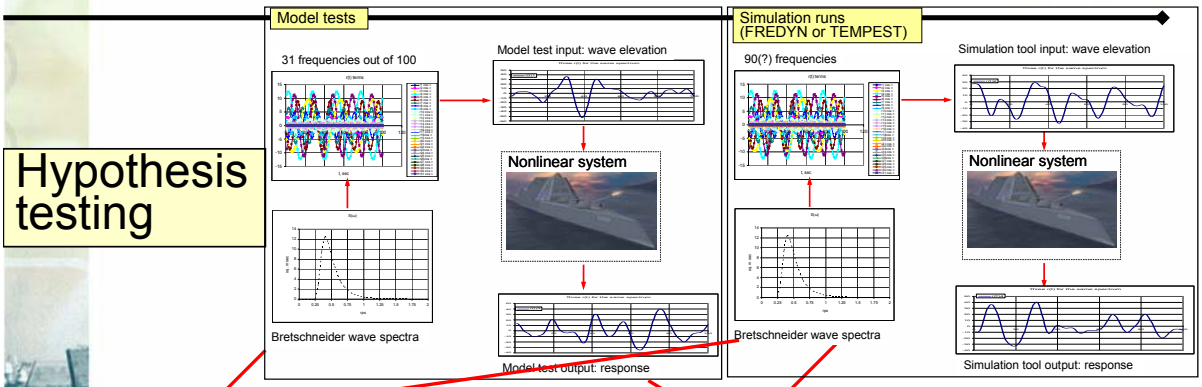
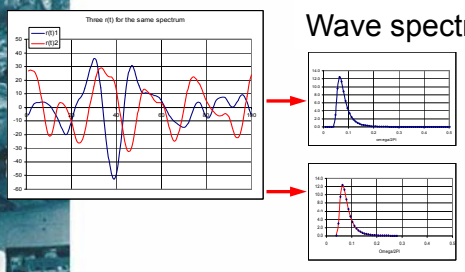
Hypothesis testing

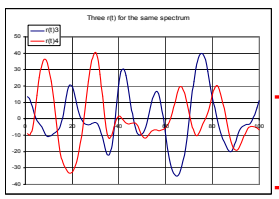


Input Hypothesis testing

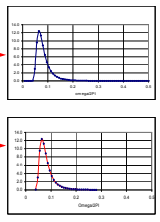


Wave spectra

Output Hypothesis testing



Response spectra



Definition of Validation

- Validation

  The process of determining the degree to which a model is an accurate representation of the real-world from the perspective of the intended uses of the model

Knowledge & Ignorance

- Notions, representations and measures
  - Knowledge and ignorance
  - Information and uncertainty
  - Other considerations
    - Opinion
    - Language
    - Cognitive processes

Knowledge & Ignorance

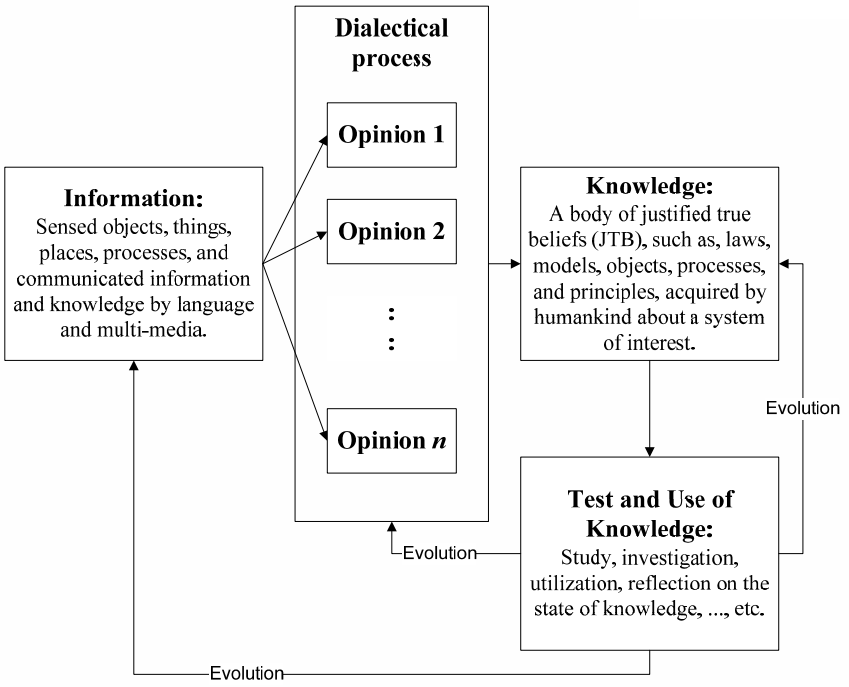
- *The greatest enemy of knowledge is not Ignorance, it is the Illusion of knowledge*

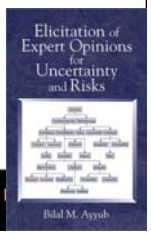
  Stephen Hawking

Knowledge & Ignorance

- Knowledge can be defined as *justified true beliefs* (JTBs)
- Knowledge is *subjective* or *relative*, and cannot be separated from the human experience (model-dependent reality)
- Knowledge can be *fallible*
- *Reliability* of knowledge
- Evolutionary epistemology

Evolutionary Epistemology





Knowledge & Ignorance

- *The object of reasoning is to find out, from the consideration of what we already know, something else which we do not know.*

  C. S. Peirce

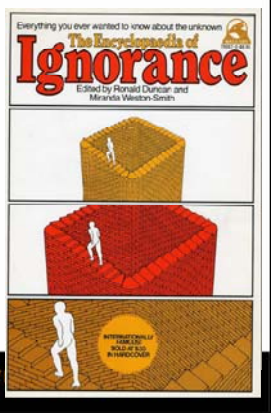
- *It takes considerable knowledge to realize the extent of self ignorance.*

  Thomas Sowell

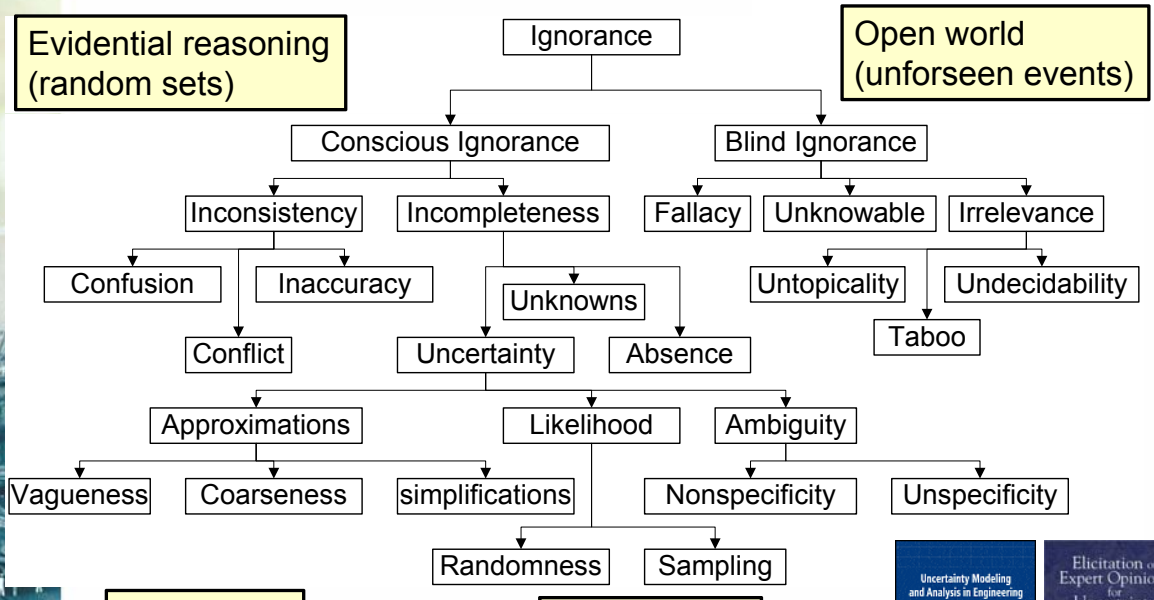
Knowledge & Ignorance

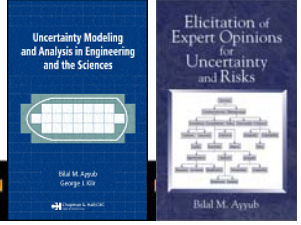
- *Compared to our pond of knowledge, our ignorance remains Atlantic*
- *Invited scientists to state what they would like to know in their respective fields, and noted that the more eminent they were the more readily and generously they described their ignorance*

Duncan and Weston-Smith

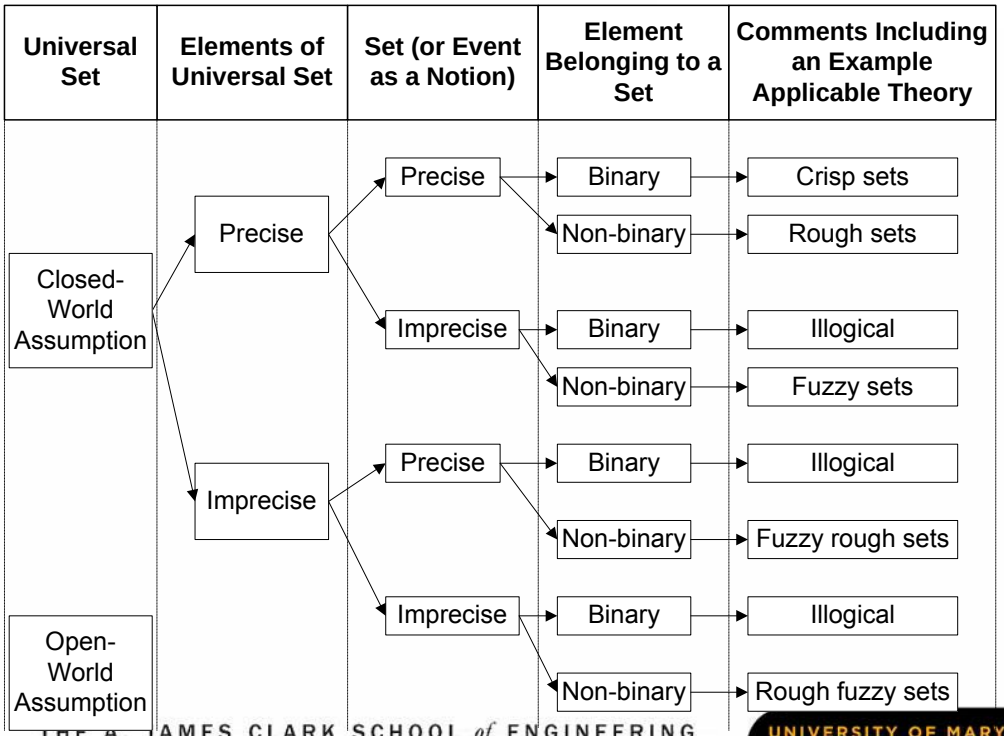


Classification of Ignorance





Identification and Classification of Theories



Aleatory and Epistemic Uncertainties

Inherit randomness (i.e., *aleatory uncertainty*)

- It cannot be reduced or eliminated by enhancing the underlying knowledge base.
- Examples: wave loads on an offshore platform, strength properties of materials

$\overline{P}$

Subjective (or *epistemic*) *uncertainty*

- Uncertainty is also present as a result of a lack of complete knowledge. It can be reduced as a result of enhancing the state of knowledge by expending resources
- Example: Consequences

$\hat{P}$

Aleatory and Epistemic Uncertainties

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Combined uncertainty

$$P = \overline{P}\,\hat{P}$$

$$\hat{P} = LN[1.0, COV(\hat{P})]$$

$$COV(P) = \sqrt{[COV(\overline{P})]^2 + [COV(\hat{P})]^2}$$

Classifying Monotone Measures

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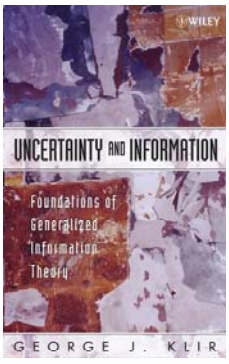
Boolean Algebras:
Classical sets and propositions

Generalizations →

Weaker algebras:
Fuzzy sets or propositions of various types

Classical probability theory



Classical measures:
Additive

Generalizations →

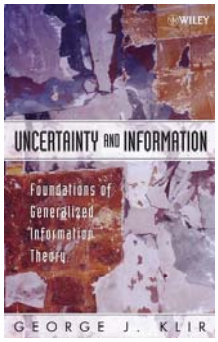
Weaker measures:
Monotone with various special properties

Classifying Monotone Measures

- **Classical probability theory:** classical probability (additive) functions defined on classical (crisp) sets.
- **Probability theory based on fuzzy events:** classical probability (additive) functions defined on fuzzy sets.
- **Dempster-Shafer Theory (DST) of evidence:** a pair of special semicontinuous monotone measures, called *belief and plausibility measures*, which are defined on classical sets and which conveniently represent lower and upper probabilities, respectively.
- **Theory based on feasible interval-valued probability distributions (FIPD):** according to the FIPD, lower and upper probabilities are determined for all sets $A \in PX$ by intervals of probabilities on singletons ($x \in X$).

Generalized Information Theory

- Generalized Information Theory (G. Klir):
  - Level 1. Find an appropriate mathematical representation of the conceived type of uncertainty
  - Level 2. Develop a calculus by which this type of uncertainty attributes can be properly quantified and manipulated
  - Level 3. Find a meaningful way of measuring relevant uncertainty in any formalized in the theory
  - Level 4. Develop methodological aspects of the theory, including procedures for making the various uncertainty principles operational within the theory



Generalized Theory of Uncertainty — Lotfi A. Zadeh

- Uncertainty is an *attribute of information*
- Information is *conveyed by constraining* the values of a variable
- Proposition is a *carrier of information*
- Proposition = generalized constraint

- Example:
  Critical pressure is 500 ksi
  - constrains pressure

Closed-World Versus Open-World Assumption

- Mathematical definitions based on the universal (Ω) and null (ϕ) sets
  - Closed world

    $m(\phi) = 0$

    $Bel(\Omega) = 1$
  - Open world

    $m(\phi) \geq 0$

    $Bel(\Omega) \leq 1$
- Inconsistency based on a body of evidence
  - A high level of inconsistency → unseen events or nonempty "null set"

Closed-World Versus Open-World Assumption

- Patterns:
  - Computational linguistics, Cryptography

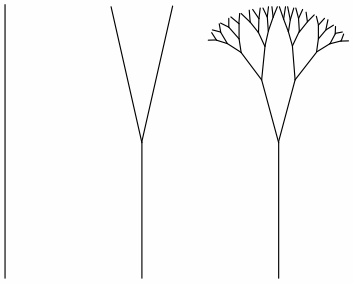
S = *C, C, P, C, B, B, P, C*
where
C = cyber attack (1)
P = perimeter breach (2)
B = bomb attack (3)

Pattern S = 11213321

What is the probability of an unseen event (U)?

Closed-World Versus Open-World Assumption

- Patterns
  - Witten-Bell Model
  - Does not account for the sequence order and trends
  - Does not account for pattern of the non-sequence type (such as self similarity)

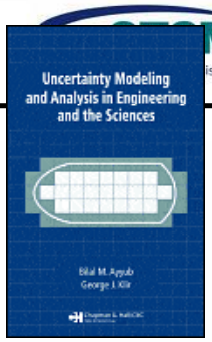


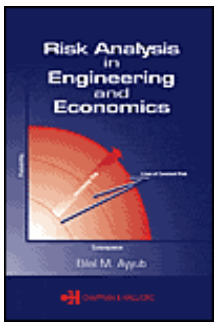
Open Questions

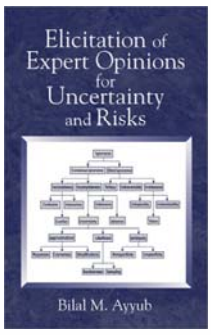
- A unified theory:
  - Knowledge and ignorance
  - Information and uncertainty
- Foundational bases:
  - Generalized Information Theory
  - Generalized Theory of Uncertainty
- Uncertainty types and quantification methods
- Open world and pattern analysis

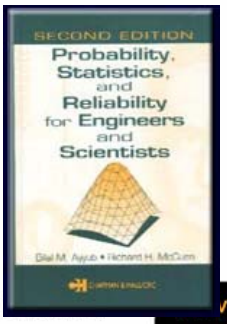
Selected Publications

- Ayyub, B.M., and Klir, G.J., Uncertainty Analysis in Engineering and the Sciences, Chapman & Hall/CRC Press, 2006.
- Ayyub, B.M., Risk Analysis in Engineering and Economics, Chapman & Hall/CRC Press, 2003.
- Ayyub, B. M. , Elicitation of Expert Opinions for Uncertainty and Risks, CRC Press, FL, 2001.
- Ayyub, B.M., and McCuen, R., Probability, Statistics and Reliability for Engineers and Scientists, Chapman & Hall/CRC Press, 2003.









Contact Information

Bilal M. Ayyub, PhD, PE
Professor and Director
Center for Technology and Systems Management
University of Maryland, College Park

301-405-1956 (Tel)
ba@umd.edu

301-405-2585 (Fax)
http://www.ctsm.umd.edu