

# Uncertainty in the World of Post Normal Science.



Jim Zidek<sup>1</sup>

<sup>1</sup>University of British Columbia

**Challenges in Statistical Modelling, July 2017**

# Outline

- Historical notes
- Uncertainty vs information
- Quantifying uncertainty
- Uncertainty in postnormal science
- The post-truth era

# Epochs in environmental statistics

- **1983—**: Acid rain
- **1990—**: Air pollution and health effects
- **2000—**: Climate change and mitigation

## Selected Grants from Peter's CV

- **1996–2001:** National Center for Environmental Statistics
- **2007–2009:** PIMS Research Group in Environmetrics
  - **2008:** One month workshop on water, Institute of Mathematical Statistics, National University of Singapore
- **2011–2016:** Statistical Methods for Atmospheric and Oceanic Sciences.

## Statistics in regulatory policy making

- **2005–2008:** I am appointed as a member of the US EPA Clean Air Scientific Advisory Committee for ozone

We had all become post-normal scientists!

“Post-normal science” e.g. climate change (Funtowicz and Ravetz 2003)

**Characterized by:** ”...**radical uncertainty**; plurality of legitimate perspectives....

uncertain facts; conflicting values; **high stakes; urgency of decisions**

the paradigm of **seeking “truth”** must be modified. “Such products may even be ...an irrelevance.”

## Grinell 2015, *Nature*:

*“In my view, a better way to assess and discuss risk is by using a method of inquiry called post-normal science (**PNS**)... to assist decision-making at the interface between environmental science & public policy.”*

## Key Elements of PNS:

- **QUALITY OF INFORMATION**
- **LARGE AMOUNTS OF UNCERTAINTY**

## But what is information?

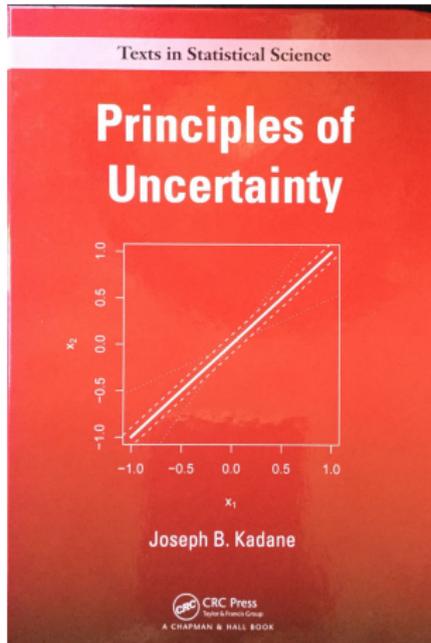
*“No other concept in statistics is more elusive in its meaning and less amenable to a generally agreed on definition” (Basu 1975)*

## And what is uncertainty?

- **BERNARDO AND SMITH 2001:** “incomplete knowledge in relation to a specified objective.”
- **HELTON 1997:** dichotomizes it:
  - “aleatory” (stochastic e.g fair coin toss)
  - “epistemic” (due to ignorance)
- **PARSONS 2001:** 16 different species of “uncertainty”

## Quantifying uncertainty

- **Lindley 2002; Kadane 2011:** “The language of uncertainty” is “Probability”
- **Frey & Rhodes 1996, O'Hagan 1988:** “Uncertainty” is “probability”
- **National institute of standards and technology:** “Uncertainty” is “variance”
- **Shannon 19??, Renyi 1961:** “Uncertainty” is “entropy”
- **Ebrahimi & Soofi 1999:** “Uncertainty” is “entropy” or “variance”



**Mostly about probability!**

**10**

Does more information reduce uncertainty?

**“DEMO”**

## Suppose we measure uncertainty by *Probability*

Let  $p = P(Y \in C)$  quantify uncertainty about outcome  $\{Y \in C\}$ .

- $p = 0$  and  $p = 1$  represent states of complete certainty
- $p = \frac{1}{2}$  represents state of maximal uncertainty

**But additional information  $\{Y \in A\}$  may not reduce our uncertainty about outcome by that measure.**

**Example:**  $Y \sim U[0, 1]$ ,  $C = (0, \frac{1}{8})$ ,  $A = (0, \frac{1}{4})$ . Then  $\frac{1}{8} = P(Y \in C) < P(Y \in C | Y \in A) = \frac{1}{2} = \mathbf{complete\ uncertainty!!}$

# What if we measure uncertainty by *Variance*

## Theorem 1 (van Eeden and Zidek 2003)

- $Y^{\text{real}}$  with density symmetric about 0
- $A = (-c, c)$

$\Rightarrow \text{Var}(Y|Y \in A) \uparrow$  in  $c$  in agreement with intuition.

**OPEN QUESTION** What if the density is not symmetric?

## Theorem 2 (van Eeden and Zidek 2003)

- $Y \sim N(\eta, 1)$
- $A = (-c, c)$

$\Rightarrow \text{Var}(Y|Y \in A) < V(Y)$ .

**REMARK:** Theorem 1  $\Rightarrow \text{Var}(Y|Y \in A) \uparrow$  in  $c$  when  $\eta = 0$ .

**CHALLENGING QUESTION:** If  $\eta \neq 0$  is

$$\text{Var}(Y | -c < Y < c) \uparrow$$

in  $c$ ? Prize offered for answer: **\$100**. Jiahua Chen collects: it is YES! (**Chen, van Eeden and Zidek 2013**).

**OPEN RESEARCH QUESTIONS:**

- What if  $A$  is not symmetric about 0?
- What happens when  $Y$  is not normally distributed?
- Other uncertainty metrics? [Some work on entropy **van Eeden and Zidek 2003**]

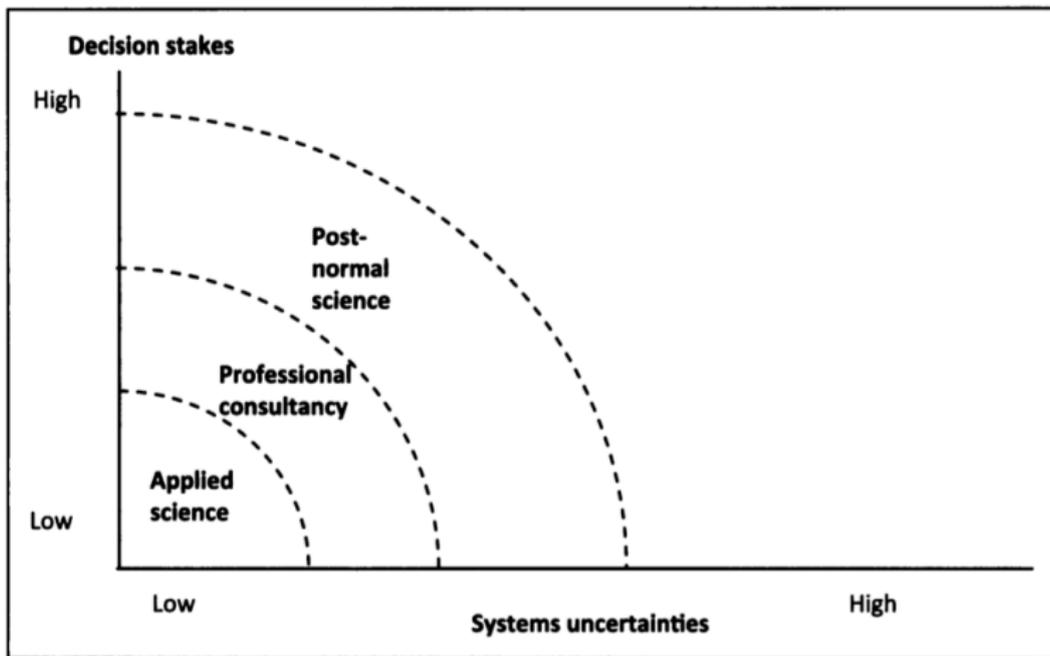
# But how does uncertainty affect information?

## Welcome to the murky world of PNS

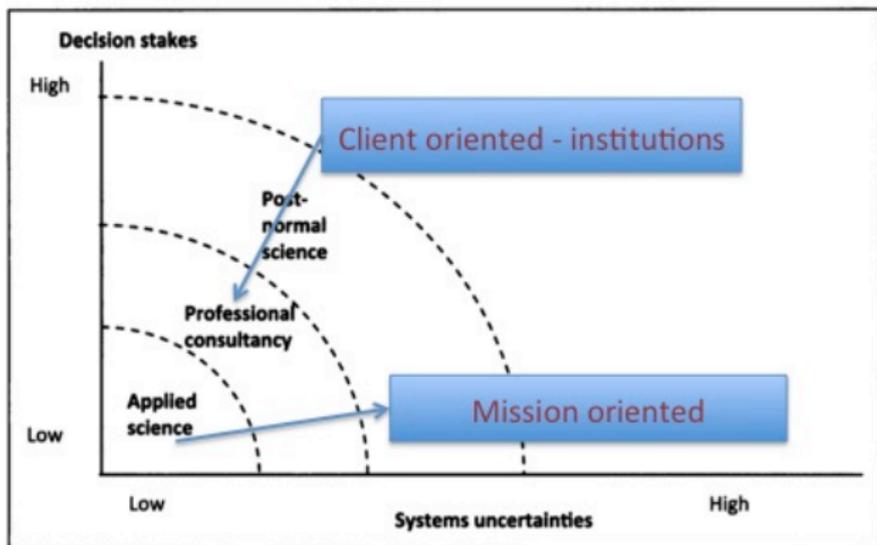
- A world of **big science**
- Driven by **values**; determines research funding & types of data collected
- Relies on **extended peer review** systems e.g. CASAC Ozone Committee
- **Information** of variable and uncertain quality
- **Uncertainty** quantitative & qualitative. About data quality; experts' qualifications; published research;.....

- **Facts** are replaced by “**systems**” about which uncertainty varies
- **High stakes** attach to decisions (e.g. policies)

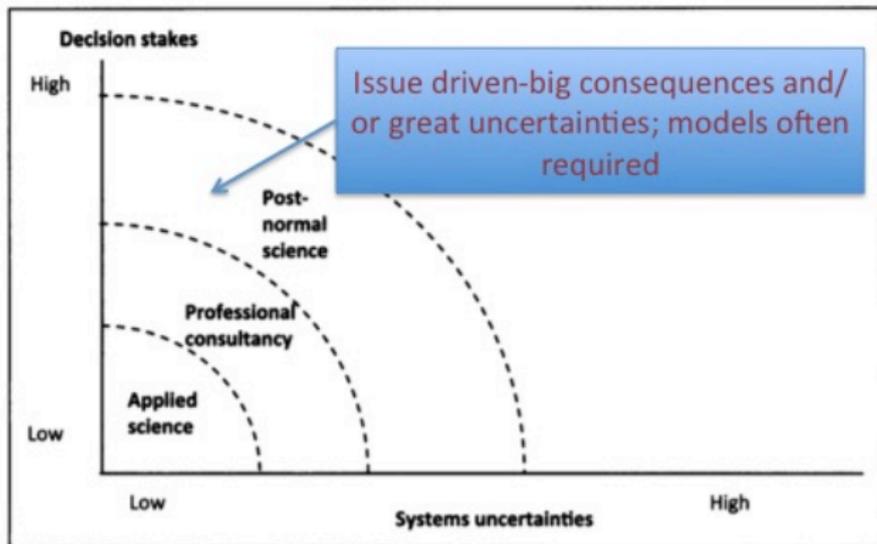
# Iconic representation of PNS



**Figure 1.** Modes of inquiry for different levels of uncertainty and decision stakes (Funtowicz and Ravetz 1991, 145).



**Figure 1.** Modes of inquiry for different levels of uncertainty and decision stakes (Funtowicz and Ravetz 1991, 145).



**Figure 1.** Modes of inquiry for different levels of uncertainty and decision stakes (Funtowicz and Ravetz 1991, 145).

## But what about those models?

*Oreskes, Schrader-Frechette & Belitz (1994) Science, 263, 641-646*

- highly influential attack on **models**
  - physical models cannot be shown to represent reality – validation meaningless/pointless
  - cited over 95 times so far in 2017
  - used to justify not validating!

Oreskes et al attack common model assessment practices:

- verification
- validation
- verifying numerical solutions
- calibration
- confirmation

\*\*\*\*\*

E.g. Argument against value of **Confirmation**:

*Agreement between model data & real data  $\Rightarrow$  truth*

**A logical fallacy** called “*affirming the consequence*”

*EXAMPLE: Assumption H says: “It is raining.”*

*Model says: “If H, Jim will work at home .”*

*You visit & find me at home. You conclude H valid since model prediction agrees with observation perfectly!*

## **NOTES:**

- Poor predictions would imply bad model!
- But good predictions don't imply good model!
  - many “good models” possible
  - wrong assumptions can cancel each other

## Oreskes conclusions:

*“The primary purpose of models is heuristic...useful for guiding further study but not susceptible to proof... [Any model is] a work of fiction. ... A model, like a novel may resonate with nature, but is not the ‘real thing’.”*

## Doing post normal science

- Collect relevant data
- Obtain assessments of panel of experts
- Convene “extended panel of reviewers” representing groups with legitimate perspectives e.g. American Lung Association
- Assess quality of data, experts, reports & associated uncertainties
- Form conclusions

## Dealing with ALL the uncertainty:

\*\*\*\*\*

Use Numerical–Units–Spread–Assessment–Pedigree (NUSAP) matrix.

- “*Numerical*” could be data average or relative risk
- *Units* of measurement
- “*Spread*” could be a standard error
- “*Assessment*” could be “significance level” or something qualitative
- “*Pedigree*” characterized by Pedigree matrix to assess quality of data; experts; scientific reports; etc.

**Example (van der Sluijs, Kloprogge, Risby , & Ravetz):**  
 Pedigree matrix for analysis of data re VOC in paint

<i>Code</i>	<i>Proxy</i>	<i>Empirical</i>	<i>Method</i>	<i>Validation</i>
4	Exact measure	Large sample direct measurements	Best available practice	Compared with indep. mmts of same variable
3	Good fit or measure	Small sample direct measurements	Reliable method commonly accepted	Compared with indep. mmts of closely related variable
2	Well correlated	Modeled/ derived data	Acceptable method limited consensus on reliability	Compared with mmts not independent
1	Weak correlation	Educated guesses / rule of thumb estimate	Preliminary methods unknown reliability	Weak / indirect validation
0	Not clearly related	Crude speculation	No discernible rigor	No validation

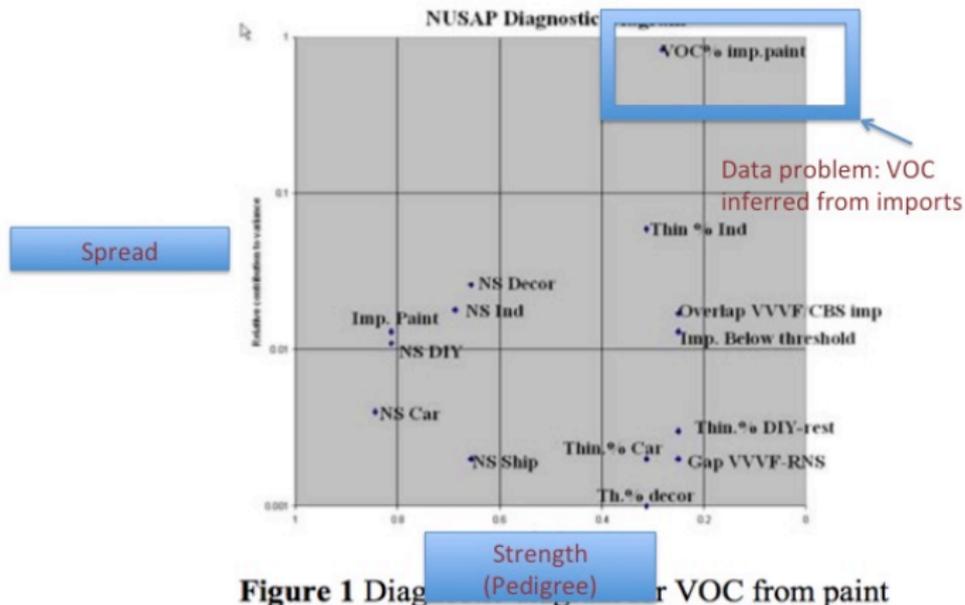
**Table 1.** Pedigree matrix for emission monitoring.  
 Note that the columns are independent.

## After consulting the experts on the data sources:

	<i>Proxy</i>	<i>Empirical</i>	<i>Method</i>	<i>Validation</i>	<i>Strength</i>
NS-SHI	3	3.5	4	0	0.7
NS-B&S	3	3.5	4	0	0.7
NS-DIY	2.5	3.5	4	3	0.8
NS-CAR	3	3.5	4	3	0.8
NS-IND	3	3.5	4	0.5	0.7
Th%-SHI	2	1	2	0	0.3
Th%-B&S	2	1	2	0	0.3
Th%-DIY	1	1	2	0	0.25
Th%-CAR	2	1	2	0	0.3
Th%-IND	2	1	2	0	0.3
Imported	3	4	4	2	0.8
VOC%	1	2	1.5	0	0.3

**Table 2.** Pedigree scores for input parameters. The strength-column, averages and normalizes the scores on a scale from 0 to 1.

# NUSAP Diagnostic Plot

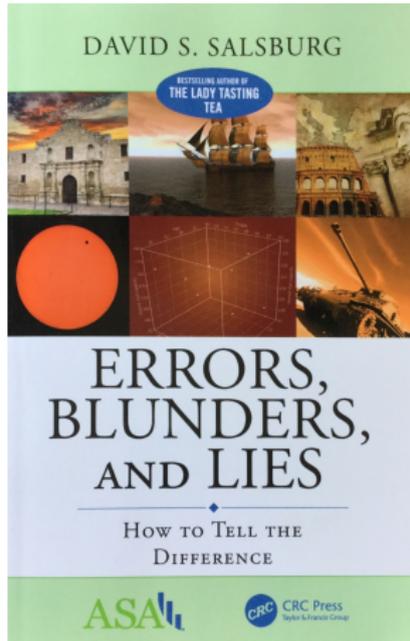


## Concluding comments

- **“Brussels Declaration on Ethics and Principles for Science and Society Policy-Making.”:**
  - 20 recommendations about science in regulatory policy
  - *“The application of science is not without risks and uncertainties, and these factors should be openly acknowledged and identified. ”*

- **Baltimore JSM 2017 panel: What role should statisticians play in environmental policy and regulation?**
  - Organized by Megan Higgs (Neptune and Company)
  - Will explore uncertainty in this context.

- Post normal science enters era of “**post-truth**”; See Royal Statistical Society Panel 2017.



2017 Chapman & Hall/CRC Press Publication

- Simplest questions about relationship between measures of uncertain and quality of information are difficult to answer and the issue has not been much explored.
- The world of post-normal-science presents new statistical challenges owing to the way in which the work is done e.g. by extended peer review groups.
- Characterizing qualitative uncertainty needs to be explored by statistical scientists. Is it susceptible to analytical theory?
- New issues about uncertainty arising in the new era of post-truth

**CONGRATULATIONS PETER!!!!**

Contact information Email: [jimstat.ubc.ca](mailto:jimstat.ubc.ca)

Webpage: <http://www.stat.ubc.ca/~jim/>