Uncertainty and Decision Making: Probability and Beyond

George Kuczera

on behalf of Decision Science group

30 May 2012

THE UNIVERSITY OF NEWCASTLE AUSTRALIA

Types of Uncertainty

“There are known knowns; there are things we know we know.

We also know there are known unknowns; that is to say we know there are some things we do not know.

But there are also unknown unknowns – the ones we don't know we don't know.”

Donald Rumsfeld

US Defence Secretary

Types of Uncertainty

More judgment, less reliance on data

Quantitative uncertainty (known unknowns)

- All outcomes known
- Probabilities can be inferred from observations and prior knowledge
- Probability theory can deal with:
  - Intrinsic (natural, inherent)
  - Epistemic (limited information, parameter uncertainty)

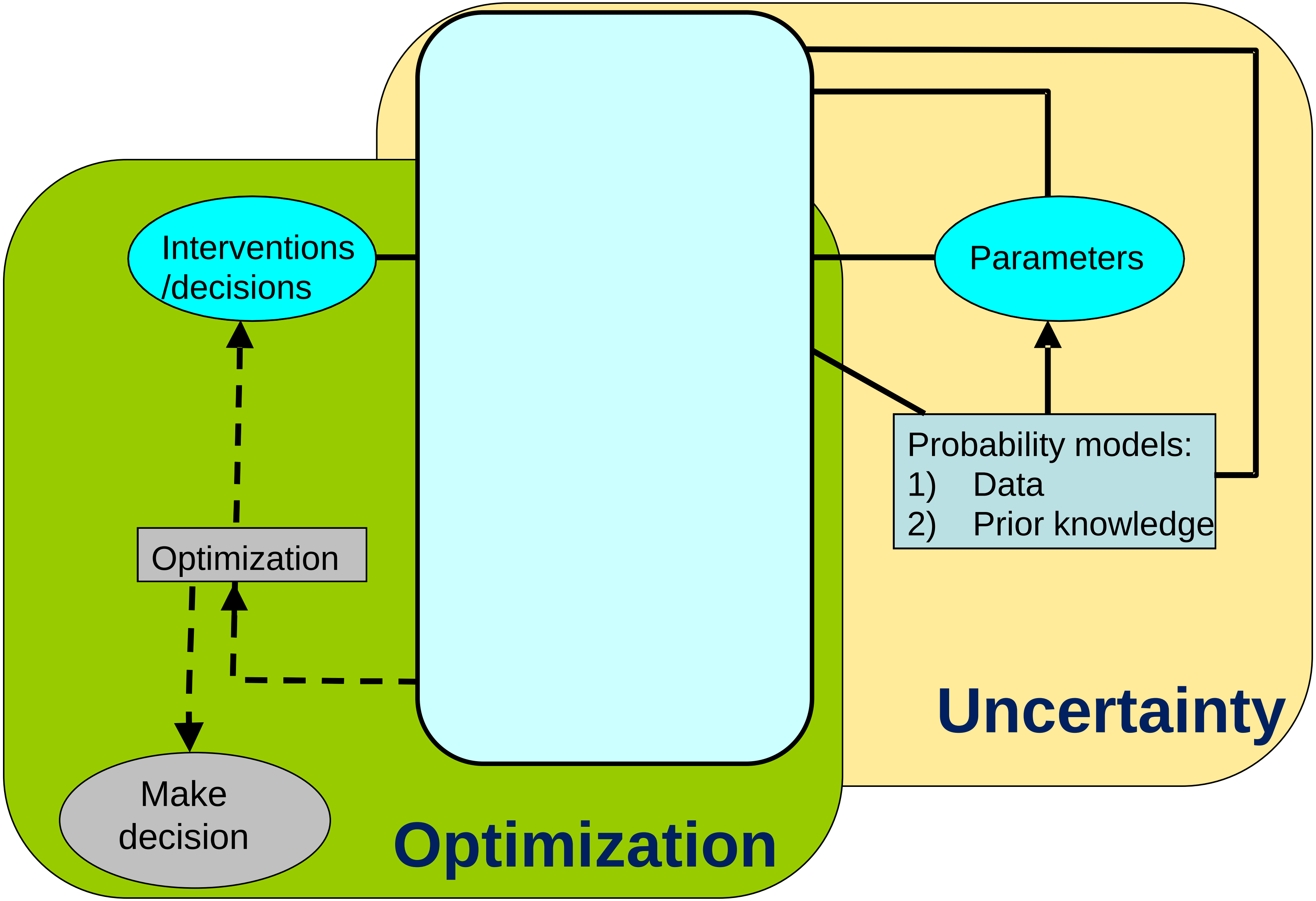
Scenario (or assumption) uncertainty

- Scenarios represent assumptions on which the whole analysis is conditioned
- Plausible outcomes usually known
- Few, if any, observations to validate assumptions
- Greater reliance on judgment

Ignorance (unknown unknowns)

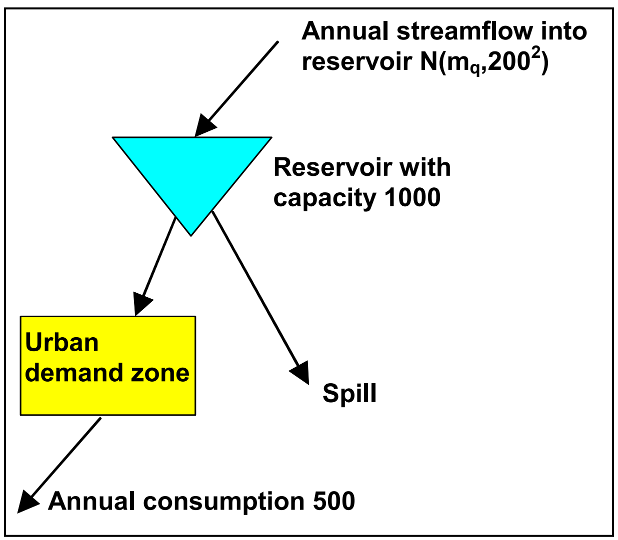
- Not all outcomes known

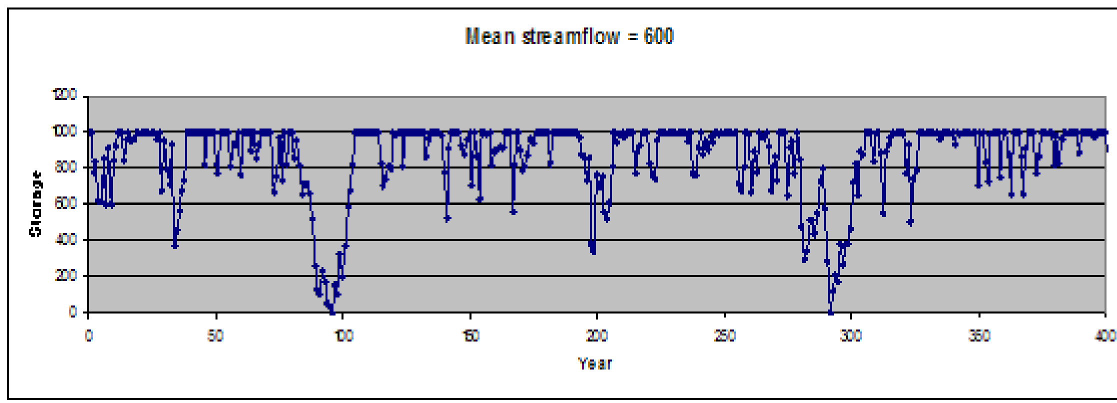
“Insight” Decision-Making Framework



Intrinsic Uncertainty

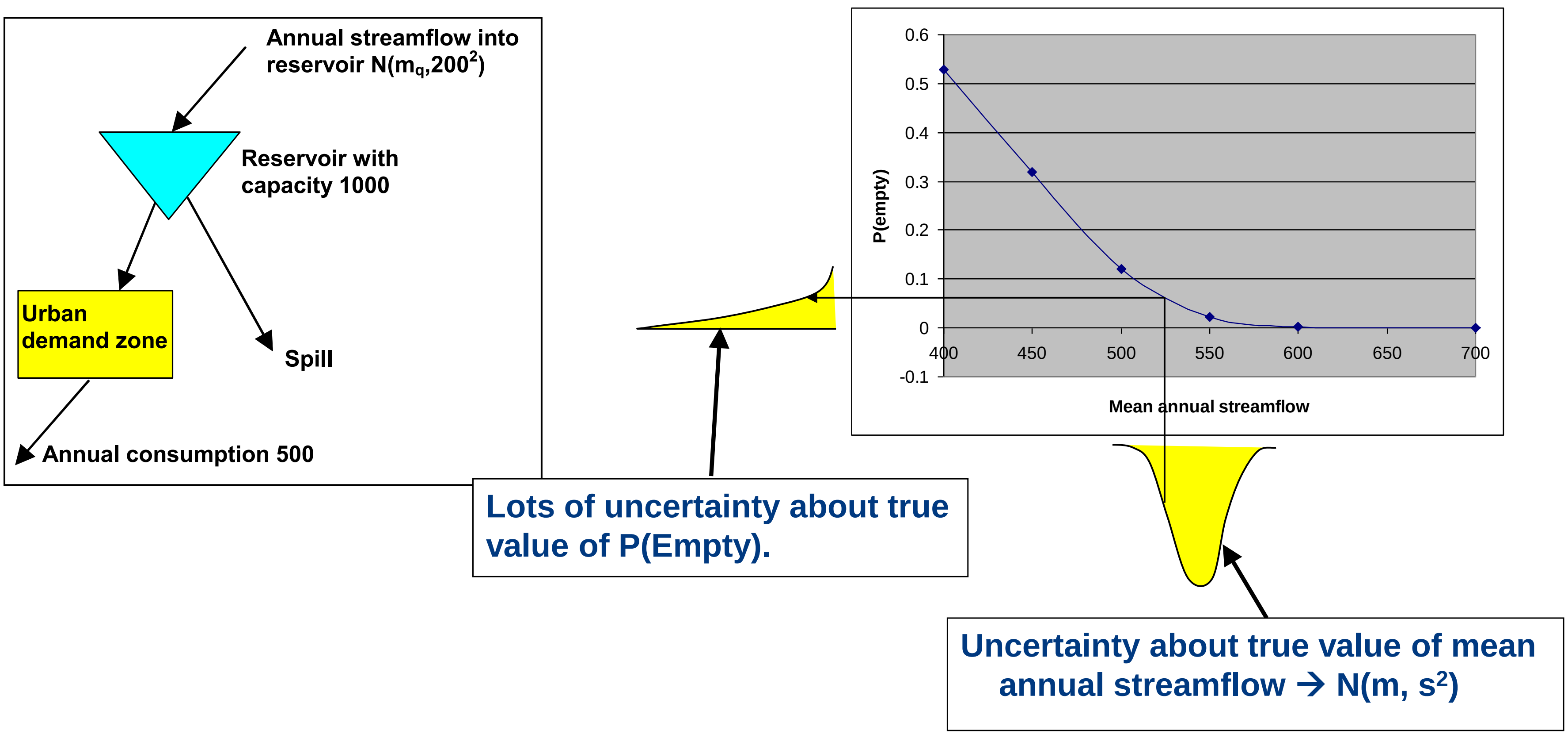
- Use Monte Carlo simulation to sample intrinsic or natural variability
- For example, simulate water resource system using long historic or synthetically generated climate series to estimate probability of running out P(empty)



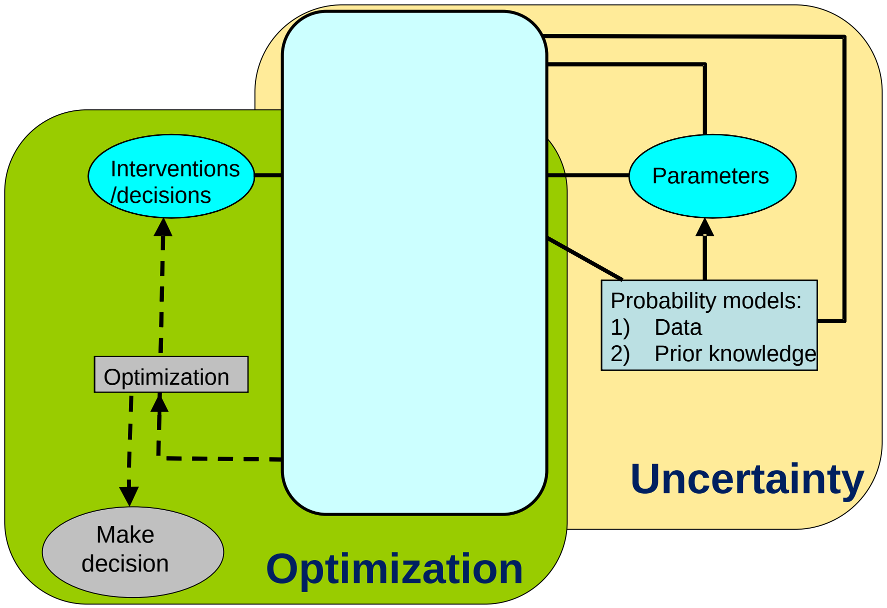


Epistemic (or Parameter) Uncertainty

- Sample parameter uncertainty and then replicate Monte Carlo simulation
- For example, uncertainty about average streamflow parameter introduces uncertainty about P(empty)

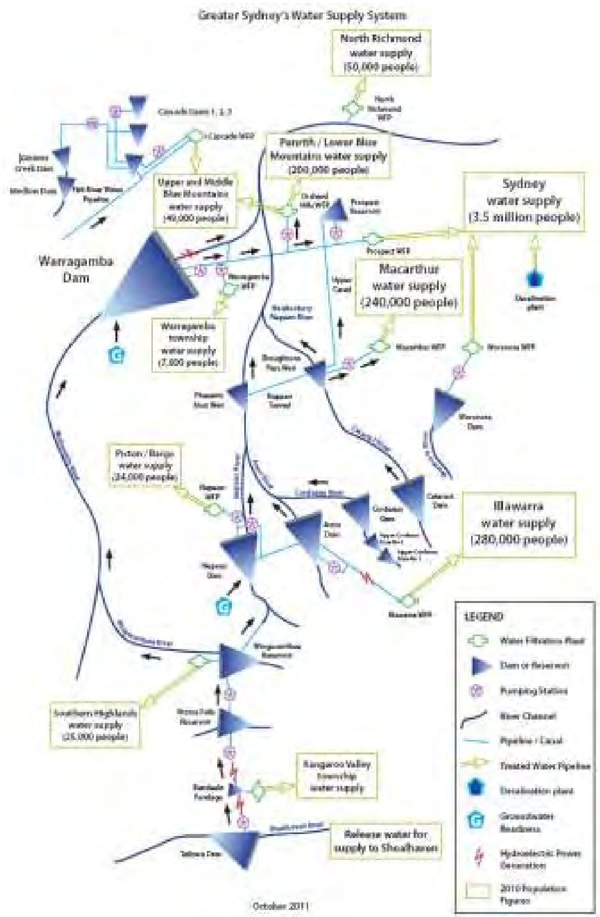


Incorporating "Known Unknowns" in Decision Making



- Use of multi-replicate Monte Carlo simulation samples variability due to intrinsic and parameter uncertainty
- This means outputs from model simulation will be random, which, in turn, means performance measures will be random
- Decision makers select statistics of output that summarize performance e.g. expected cost, expected chance of violating environmental flow constraint, expected chance of running out of water,…
- Use multi-criterion optimization to identify best decisions

Example

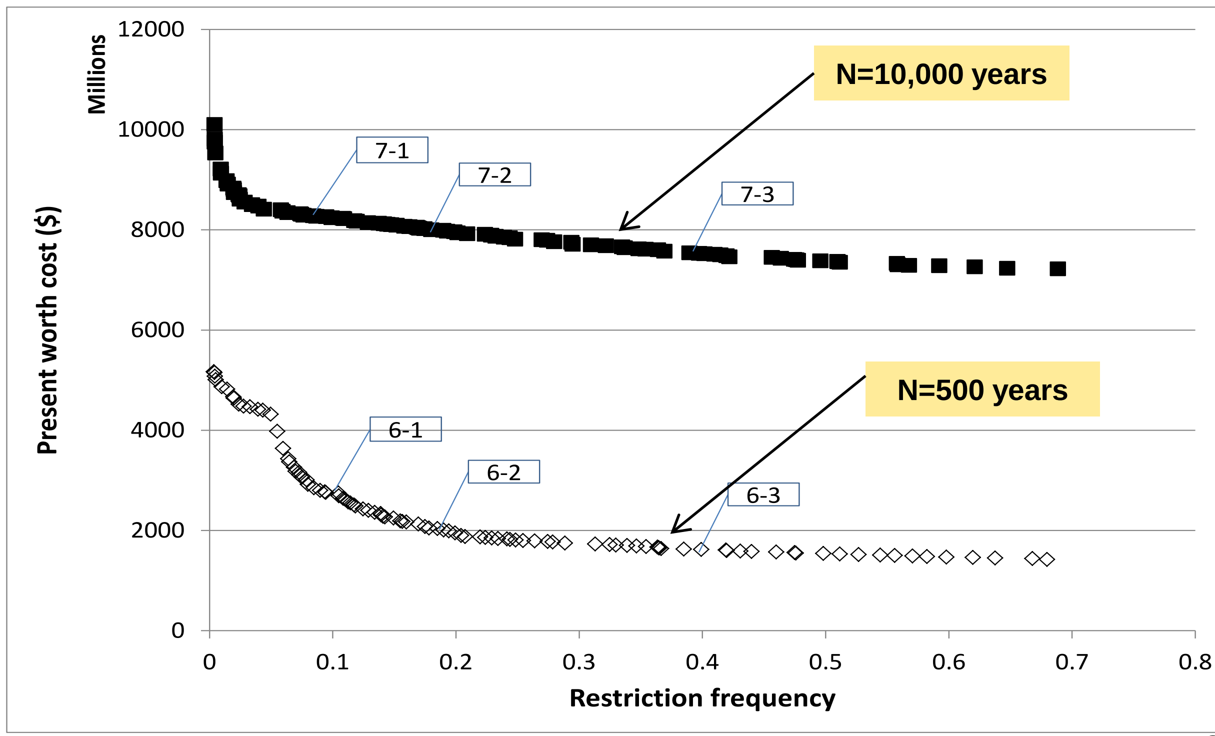


A future Sydney with 7 million population

Find solutions that minimize

1. Expected total present worth cost
2. Frequency of restrictions

while not running out of water in severe drought



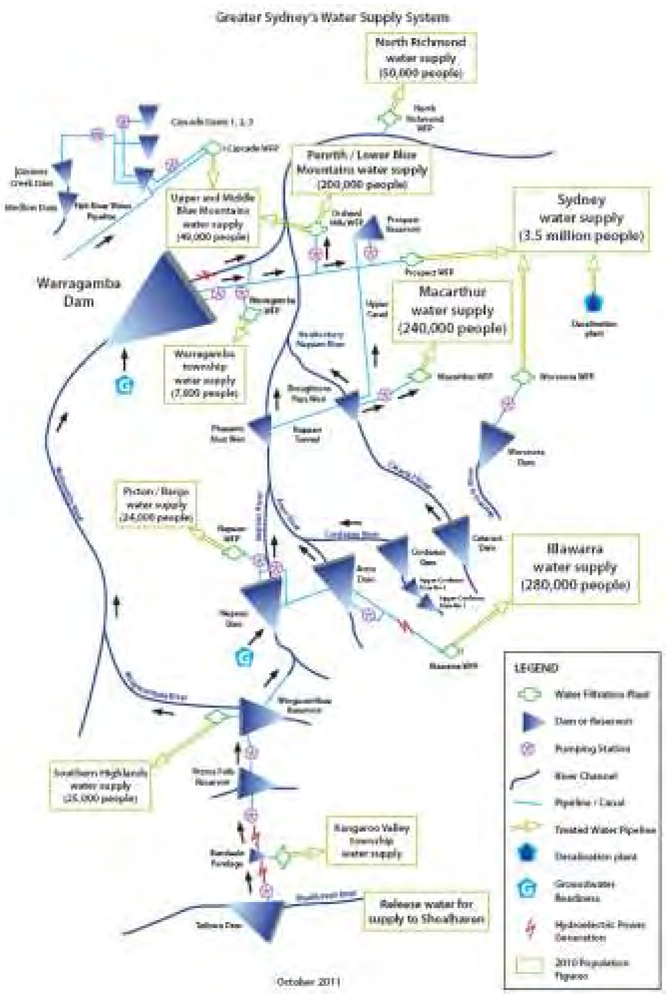
Towards “Unknown Unknowns”

- Good capability dealing with intrinsic and parameter uncertainty when probability models can be constructed with satisfactory accuracy
- Incorporating other forms of uncertainty into decision making remains a challenge
- Consider two cases:
  - Scenario uncertainty
  - Characterizing uncertainty in complex models

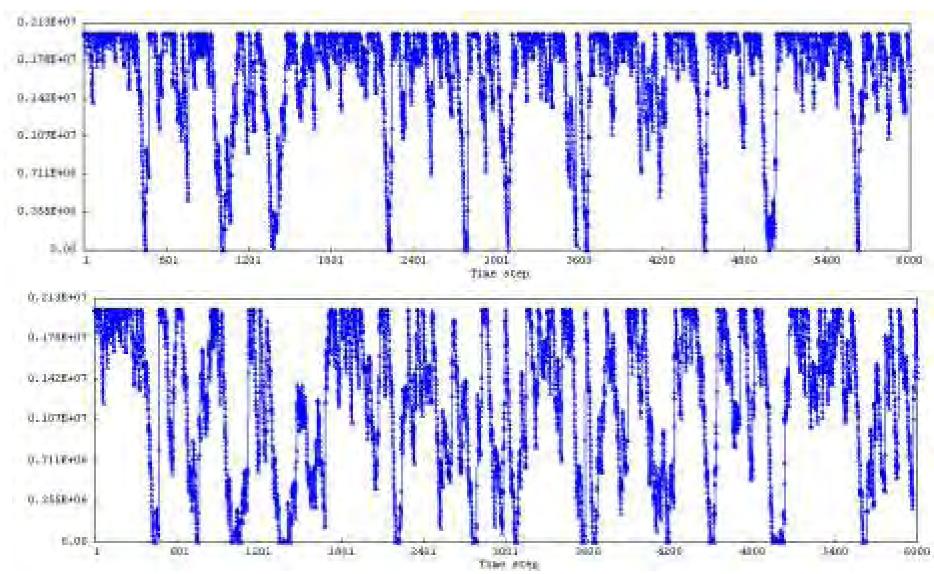
Scenario (Assumption) Uncertainty

- Scenario uncertainty affects many decision making problems
- For example, future climate change uncertainty:
  - GCM model uncertainty
  - Emission scenario uncertainty
  - Cannot assign probabilities in a meaningful manner
- One approach is to adopt a conservative strategy
  - optimize the system for the worst-case climate scenario.
  - may be unduly “expensive” with other strategies offering similar robustness at far lower “costs”.
- Better to use multi-criterion optimization to explore trade-off between efficiency and robustness

Cilmate Change Uncertainty: Example



Storage time series for two climate change scenarios with different change factors:



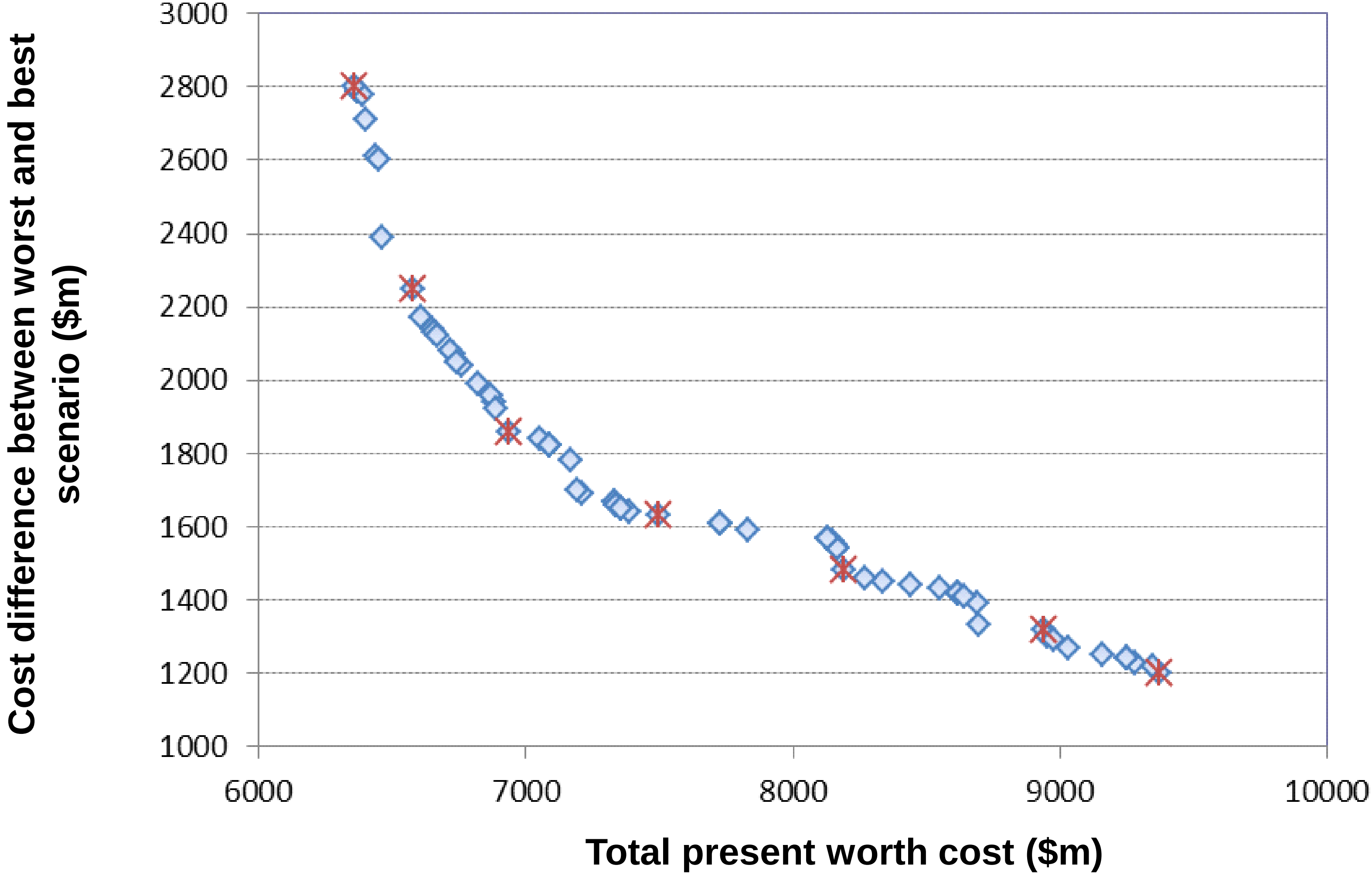
100%

70%

Consider 5 plausible future climate change scenarios

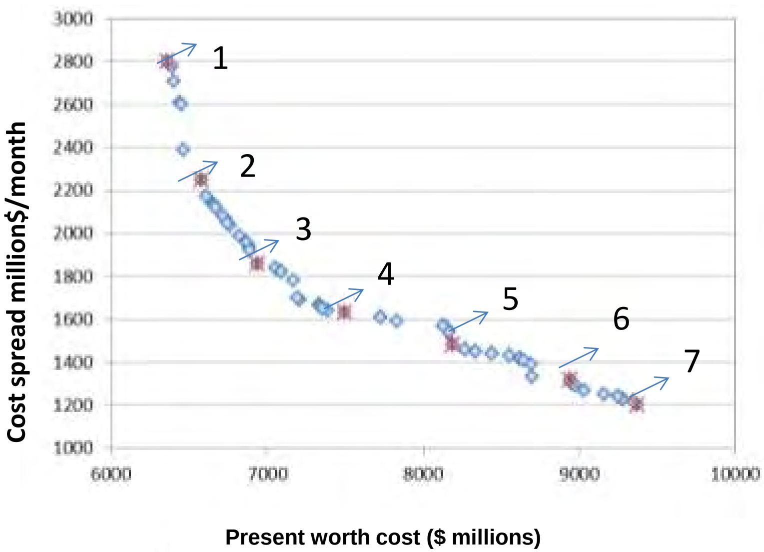
Pareto Optimal Efficiency vs Robustness Trade-off

Minimize: 1) Expected cost across scenarios; and
2) Cost difference between worst and best scenario



Efficiency vs Robustness Trade-Off Solutions

Variable	Solution on Pareto front						
	1	2	3	4	5	6	7
Expected present worth cost, $ millions	6360	6580	6940	7500	8190	8940	9370
Cost spread, $ millions	2800	2250	1860	1630	1480	1320	1200
Warragamba pump trigger	0.933	0.978	1	1	1	1	1
Avon pump trigger	0.304	0.300	0.306	0.305	0.311	0.963	0.865
Restriction storage trigger	0.579	0.447	0.387	0.233	0.247	0.246	0.215
Desalination capacity, ML/day	185	259	298	455	688	701	701
Desalination storage trigger	0.611	0.608	0.569	0.556	0.365	0.357	0.340
Shoalhaven storage capacity ML	998206	996851	999194	990021	975647	884788	924999



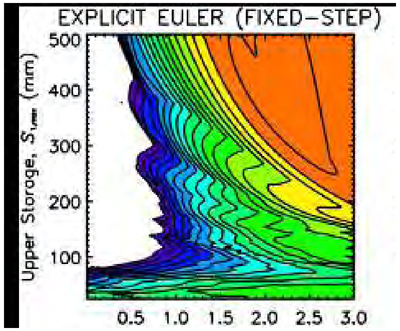
Future climate scenario	% Restrictions						
	1	2	3	4	5	6	7
1	2.38	0.55	0.23	0.00	0.05	0.03	0.00
2	4.13	0.80	0.48	0.03	0.15	0.13	0.05
3	7.10	2.00	1.07	0.17	0.37	0.23	0.18
4	12.5	5.38	3.23	0.38	1.07	1.05	0.70
5	19.4	11.4	8.35	2.85	4.28	3.68	2.38

More robust solutions:

- More expensive
- Favour harvesting additional sources
- Less reliant on rationing/restrictions

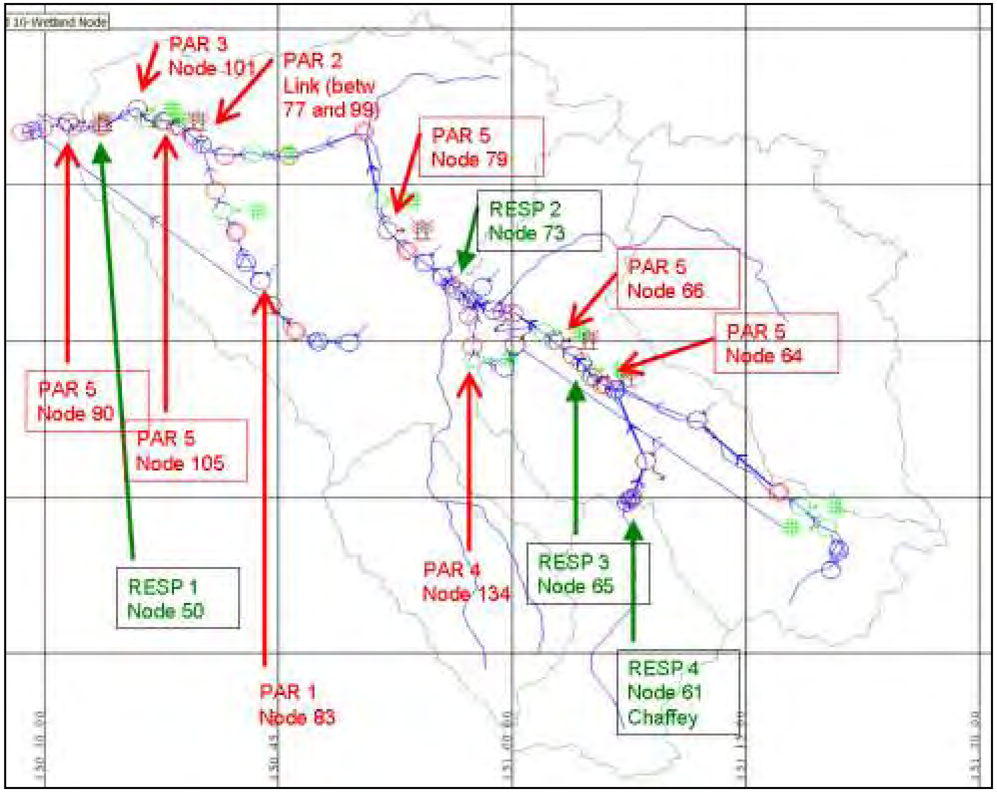
Uncertainty in Complex Models

- Water resource simulation models are complex, non linear and have many parameters
- Calibration of such models to observed data and uncertainty assessment is challenging:
  - Ill-posed → must rely on strongly informative subjective inputs
  - Models are computationally-expensive and may have less-than-ideal numerics → difficult and time-consuming to calibrate using standard methods



- How good are the predictions made by such models, particularly at locations without data?

IQQM Peel Case Study

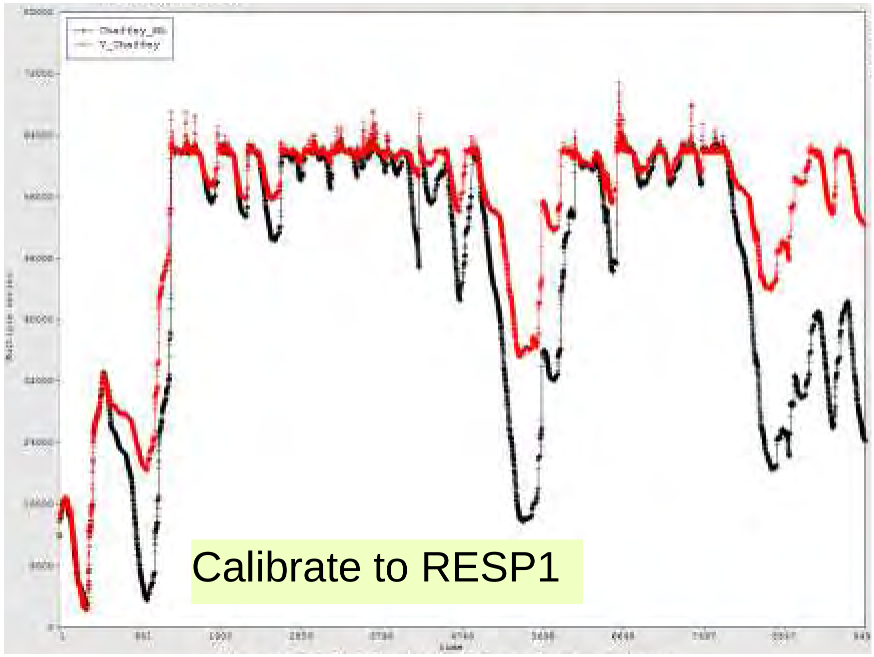


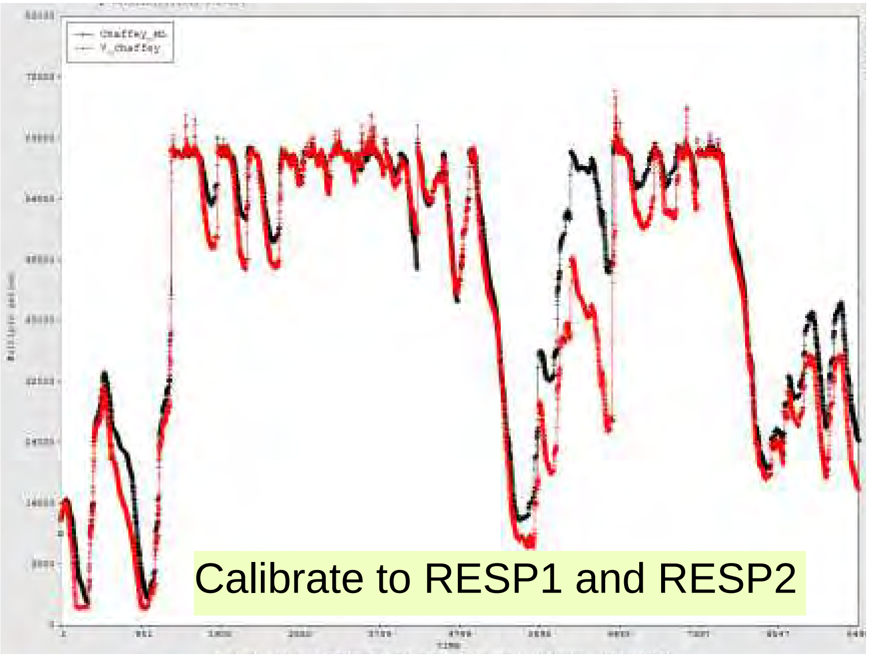
- Observed data at four sites
- Parameters affect transmission losses, irrigation demand, routing and over-ordering

- Least squares calibration of IQQM parameters to observed data at:
  - RESP1
  - RESP1, RESP2
- Check consistency of parameters and fit at RESP4, Chaffey Dam.

Internal Consistency

Simulated and observed Chaffey storage time series



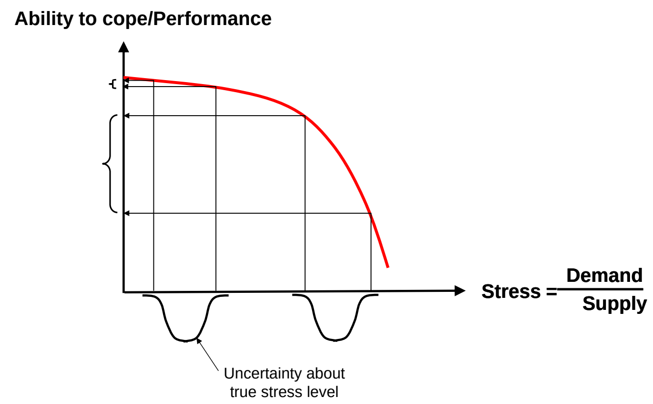


- Both calibrations produced indistinguishable fits at outlet (RESP1)
- Major discrepancies at RESP4, Chaffey dam
- Some parameters vastly different

→ An ill-posed problem with possibly large uncertainty at internal nodes

Unfinished Business

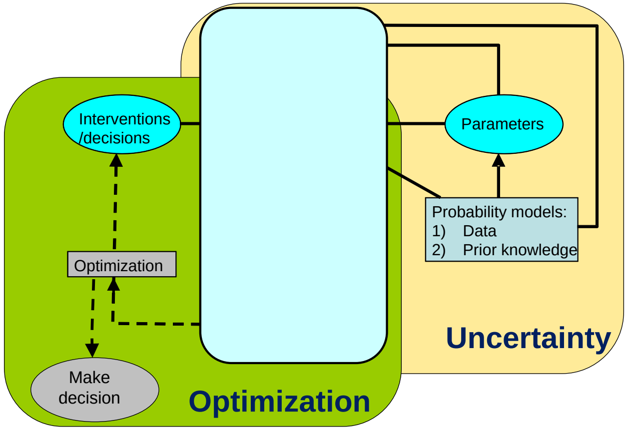
- Inclusion of uncertainty can significantly influence decision outcomes



- "Insight" decision-support system has good capability to handle intrinsic and parameter uncertainty
  – Requires adequate probability models through calibration or prior assignment
  – Requires skill in problem formulation
  – Each system is different→ need to build up experience and adapt our methods
  – Need to build up experience with inclusion of ecological objectives

Unfinished Business

- As we move closer to "unknown unknowns" the problem gets harder and our decision support gets less sophisticated:
  - Essential as this is where many decision makers "live"
  - Probability approach is unsuited to scenario uncertainty (such as future climate change, political/social settings)
  - Need to focus on efficiency versus robustness/resilience trade-offs to help identify good decisions
  - Characterizing uncertainty in large complex, nonlinear water resource models remains problematic



We need to continue adding more insight into "Insight"

Source 2012

eWater

www.ewater.com.au