BROADLEAF CAPITAL INTERNATIONAL PTY LTD

ABN 24 054 021 117

23 Bettowynd Road
Pymble
NSW 2073
Australia

www.Broadleaf.com.au

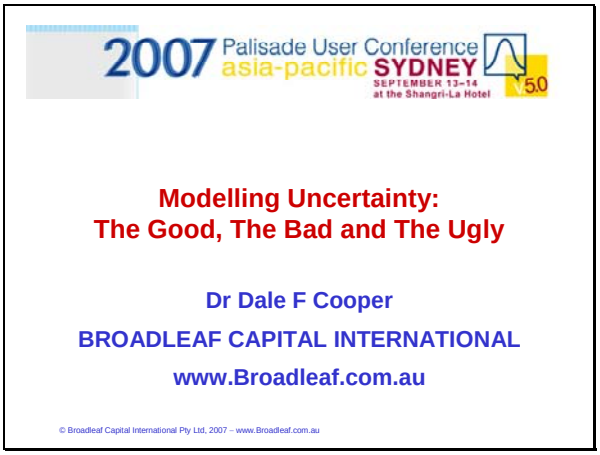
Tel: +61 2 9488 8477
Mobile: +61 4 1943 3184
Fax: + 61 2 9488 9685
Cooper@Broadleaf.com.au

Specialists in Strategic, Enterprise and Project Risk Management

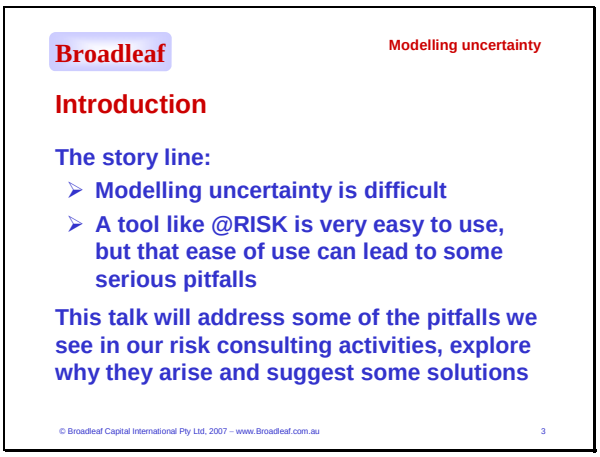
MODELLING UNCERTAINTY: THE GOOD, THE BAD AND THE UGLY

Dr Dale F Cooper
Director, Broadleaf Capital International

1 Introduction



This paper contains the edited text of a keynote address to the Palisade Asia-Pacific User Conference, held in Sydney on 13-14 September 2007.



2 Problem 1: An inappropriate focus on the tools leads to misdirected effort

… or, if you have a hammer, every screw looks like a nail.

Broadleaf — Modelling uncertainty

It is often hard to understand the real problem

The need to make a decision, or just to do something (anything!), sometimes gets lost in the technology

There is a real risk of solving the wrong problem

- Type 3 errors are all too common
- For example, I had one client who wanted to use the @RISK Fit Distributions to Data capability for medium-term forecasting of crude oil prices

 6

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Does fitting distributions to the past look sensible as a guide for the future?

WTI in constant (Jul 2005) USD, Jan 1970 – Jul 2005

 7

WTI in constant (July 2005) US dollars, January 1970 to July 2005. Sources attributed to *National Post* with data from Federal Reserve Bank of St. Louis and the Bureau of Labor Statistics.
Source: http://www.pierrelemieux.org/artoil.html

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Typical symptoms include leaping into modelling early …

… before asking why

- before identifying the purpose and decision focus of the activity

… before asking how

- before setting out a well-thought-through process for structuring the problem to achieve the desired outcomes
- and structuring the model to achieve them

 8

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and …

… before thinking about the implications of the model structure and what is needed to support it

- Information needs
- People's time (for workshops, data generation, and so on …)
- Sometimes, although less frequently now, how long it might take to run a simulation and generate reliable results

 9

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… all leading to …

Model outcomes (and the modellers!) being ignored by decision makers

… and we don't want to be ignored, now do we??

 10

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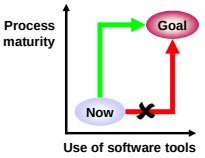
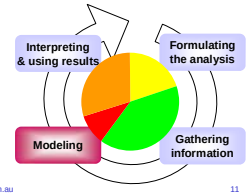
Lesson: keep the tools in their place



Understand the process before becoming immersed in tools

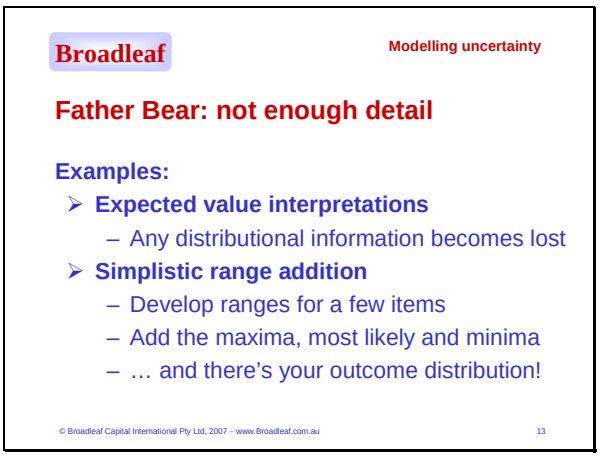


Only about 10% - 20% of effort should go on modeling

 11

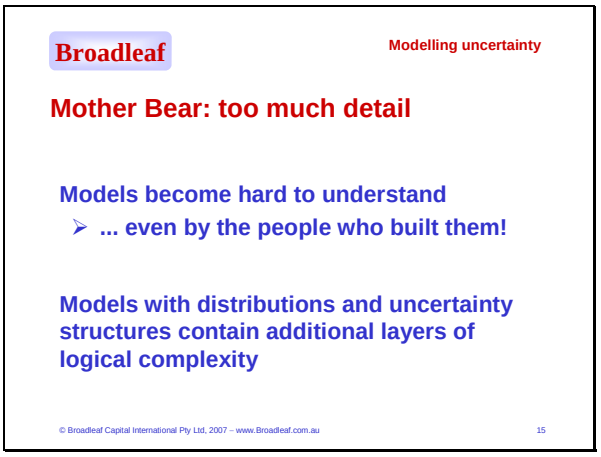
3 Problem 2: The wrong level of detail leads to simplistic perspectives or loss of understanding

… or, Goldilocks and the three modelling bears.



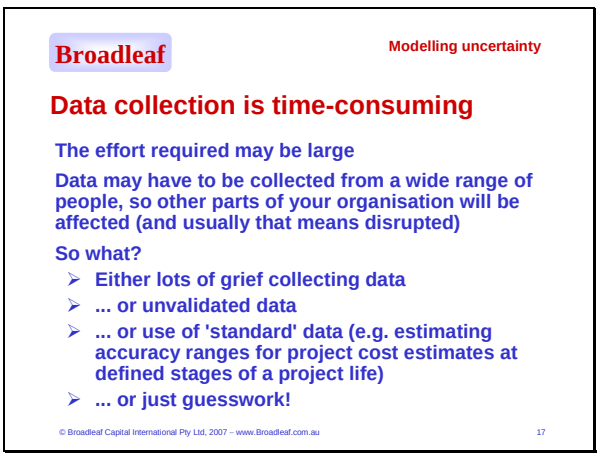
With tools like @RISK, Father Bear does not often come to the party.

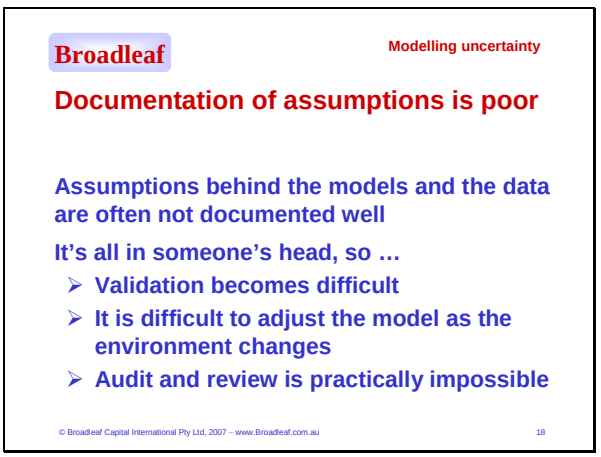
However, Mother Bear is a party animal …



Most Excel models contain errors anyway, and including distributions in the models makes validation harder.

Sources: see the website for the European Spreadsheet Risks Interest Group (EuSpRIG) at http://www.eusprig.org/ and the links provided there for information about spreadsheet errors and their consequences. Some high-profile news stories are listed at http://www.eusprig.org/stories.htm.





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The results look wrong

Often very wrong!!
- For example, a cost estimate at the concept stage of a large project had an error range of ± 3%, when the estimators thought ± 20% would have been more appropriate

… and it's sometimes hard to work out why
- In this case, because the correlation structure had been modelled poorly

 19

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Related problems and symptoms

Identifying and modelling correlation becomes difficult (and practically impossible in many cases)

… exacerbated by the large number of input variables, and by poor model structures
- Complex correlations
- Overlapping correlations
- Correlations used where simple functional relationships are better

Narrow ranges is another difficulty
- Consistent biases across the model

 20

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Baby Bear: just the right amount of detail

Enough to lead to a good understanding of the uncertainty and its effects

Enough to assist in making sound decisions

Father Bear uses only a few distributions

Mother Bear has hundreds (and sometimes thousands) of them

Baby Bear and Goldilocks like between 20 and 50 distributions for their models – that's just right

 21

4 Problem 3: Inappropriate modelling of correlation

… or *Ciconia ciconia* and the birth rate.

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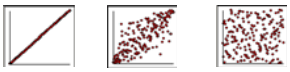
What does correlation mean in practice?

For most people, 'Not much'

Even statisticians have trouble explaining it

Scatter diagrams offer a partial demonstration and guide for estimators
- Examples …



 23

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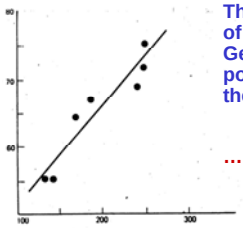
A pregnant pause before the next example



This shows how the number of storks in Oldenburg, Germany, is related to the population of the town, for the period from 1930-1936

… and the conclusion is ???

 24

Original source: *Ornithologische Monatsbereichte* 44, No 2, 1936
See also: http://www.sonoma.edu/users/l/lahme/math300b/dvb01_07.pdf

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What causes correlation?

- Statistical 'accidents' that are unrelated to causation
  - … like storks and births
- Complex cause-effect relationships that are too difficult to resolve precisely
  - 'Messy' relationships, but we know there's something there, like the links between general economic conditions and specific business drivers
- Cause-effect relationships that we can resolve and that contribute to our understanding

 25

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How is correlation best dealt with?

- Sometimes there is historical data
  - For example, in the finance sector
  - ... but then it is just a descriptive statistic
  - ... that may be useful if we expect the future to be much the same as the past
- Very often there is no reliable data
  - ... and we are usually more concerned about the future than the past
- Identifying the drivers for correlation is usually the best approach

 26

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Modelling causal drivers

- If we can understand the causes of correlation, then
  - We can model it
  - We can explore ways of managing better to reduce risk and capture opportunities
    - Post-investment reviews provide an after-the-event example of this
- Modelling process
  - Identify causal structures
    - Influence diagrams
  - Extract key drivers
- … and the effects of *Ciconia ciconia* are ??

 27

5 Problem 4: Selecting distribution shapes

… or, if in doubt, eat the fish.

You should have some rationale for selecting a specific distribution form.

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In many applications, theory provides a good guide to distribution shape

Distribution	Examples
Exponential	Component survival time; time between 'random' arrivals
Poisson	Number of arrivals in time T
Binomial	Number of faulty components in a batch
Lognormal	Outcome from a product of variables
Normal	Outcome from a sum of variables
Beta	Chance of an animal in a large herd being infected if there have been *r* infections detected in a test sample of *n* animals

 30

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Sometimes there is relevant data available

Sometimes the past is a reliable guide to the future

- For example, equipment failure rates (providing there has been no change in operating or maintenance environments …)

In other cases, unique features make extrapolation unwise

- For example, forecasting oil prices

 31

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In many project risk models, there is no clearly-stated rationale for the choice of distribution shape

Three-point estimates are a common input of choice

- Easy to use
- Easy to understand
- Familiar, common practice for other purposes

How should they be interpreted?

- Choice of shape: often triangular or Pert
- Choice of bounds: confidence interval for upper & lower estimates

 32

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Dealing with ill-specified distributions

We often need to work with three-point estimates (low, likely, high)

We test the sensitivity of the results to modelling assumptions

- Triangular vs Pert vs Lognormal vs …
- Confidence intervals for high and low points
  - Absolute limits
  - 5 and 95% limits (90-percentile confidence band)
  - 10 and 90% limits (80-percentile confidence band)

 33

6 Problem 5: Eliciting data from people requires special skills

… or, Beanz Meanz Heinz.

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Common pitfalls in estimating: some examples of heuristics and biases

Bias	Outcome
Anchoring & adjustment	Estimates remain too close to initial values
Availability	Readily retrieved information is over-weighted
Base rate	Base rates are neglected or under-weighted
Confirmation	Evidence that supports an initial hypothesis or explanation is over-weighted
Conservatism	Sample information is under-weighted
Framing	Form of data presentation influences judgement
Illusion of control	Management action can influence the outcomes of external or random events

Extensive discussions and lists of heuristics and biases are provided by many authors. A recent list appears in Louis Anthony (Tony) Cox (2007), Does concern-driven risk management provide a viable alternative to QRA? Risk Analysis, Vol 27, No 1, 27-43.

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Exercise: count the beanz!!

This exercise involves estimating the number of beans in a jar

In the exercise, the beans are not as colourful as these!!

 37

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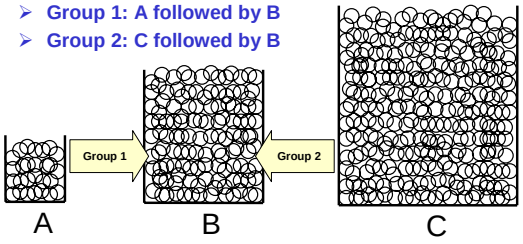
Anchoring & adjustment: an experiment

Counting the jelly beans in the jars

- Group 1: A followed by B
- Group 2: C followed by B



 38

Image source:
http://www.daremightythings.com/dc/06sept/jar200.jpg

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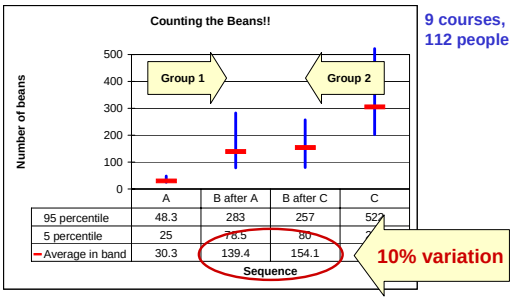
Anchoring & adjustment: results



9 courses, 112 people

10% variation

 39

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Anchoring & adjustment: implications

If you are using 3-point estimates, many people start with the most likely value

Anchoring & adjustment will probably lead to distributions that are too narrow

Avoiding the worst of the problems:

- Start with the outer values (change the sequence to reduce the anchor)
- Develop scenarios (break the adjustment)
- Develop extreme scenarios (test the limits)

 40

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Recommended elicitation process

Step	Purpose
Motivating	Introduction to the task and potential assessment biases
Structuring	Define and structure the quantities to be analysed to reduce ambiguity
Conditioning	Make assessor aware of judgement process to minimise biases during encoding
Encoding	Elicit the specific data, using response techniques appropriate for the problem
Verifying	Test and cross-check the responses using other response techniques

Source: Spetzler and Stael Von Holstein (1975)

 41

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What do you need to get reliable information from people?

A good understanding of the potential problems

A structure and plan for the elicitation process

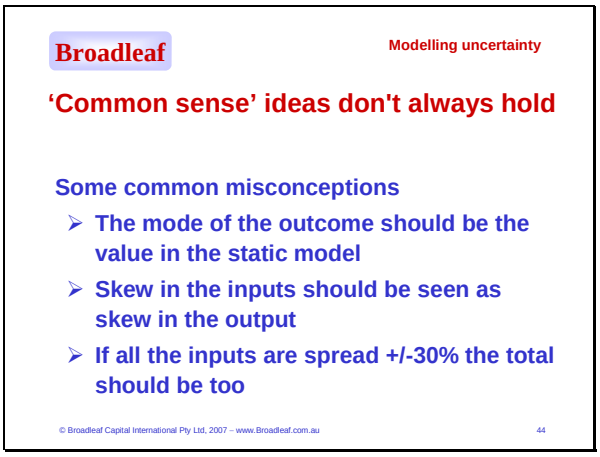
Enough time and resources to implement it properly

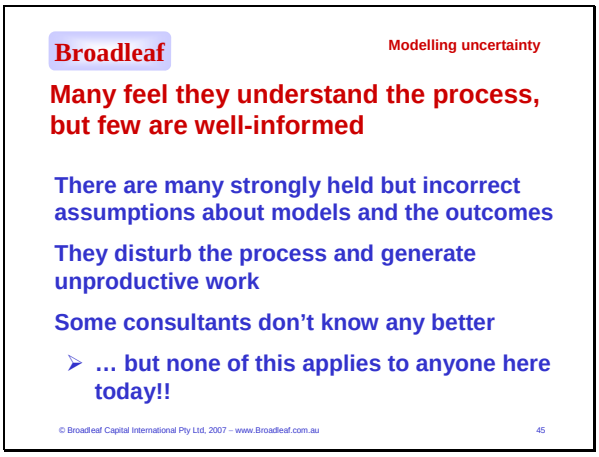
 42

Source: Spetzler, CS and CA Stael Von Holstein (1975) 'Probability encoding in decision analysis,' Management Science 22 (3) 340-358.

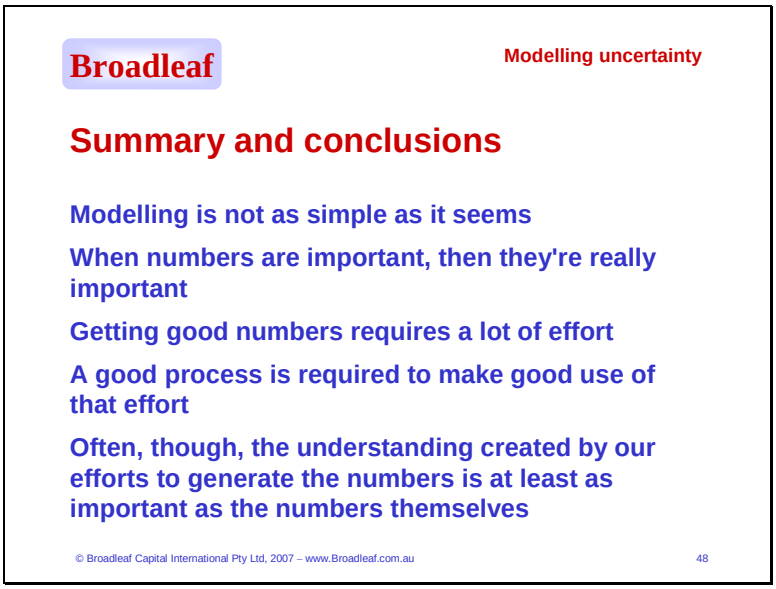
7 Problem 6: Managers don't always understand the process and its outcomes

… or, beware of Risk 36!





8 Summary and Conclusions



9 About Broadleaf Capital International

For more information about the risk management aspects of the material discussed here, please contact:

Dr Dale F Cooper	Cooper@Broadleaf.com.au
Dr Stephen Grey	Grey@Broadleaf.com.au
Mike Wood	Wood@Broadleaf.co.nz
Geoff Raymond	Raymond@Broadleaf.com.au
Dr Sam Beckett	Beckett@Broadleaf.com.au

Additional material is provided on our web site: www.Broadleaf.com.au.