The Actuarial Profession
making financial sense of the future

The latest issues surrounding catastrophe modelling
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Using Multiple Catastrophe Models

29 March 2011

What is the problem ?

- Chief Actuary to CEO "*The cat model says that our gross 1-in-200 year occurrence loss is £ 512,983,134*"
- BAS Technical Standard "TAS R: Reporting Actuarial Information" says

C.5 COMPLETENESS

C.5.1	An **aggregate report** shall include all **material** matters relating to the work being reported on.

Uncertainty

C.5.2	An **aggregate report** shall indicate the nature and extent of any **material** uncertainty in the information it contains.

C.5.3 Uncertainty may concern the results of calculations, assumptions on which information is based or other aspects. It may arise from random variations, lack of information or other sources. The extent of any **material** uncertainty may itself be subject to uncertainty.

How to address uncertainty ?

TAS R C.5.4 gives four examples

- Give range for the result i.e. “between X and Y”
  - Cat model doesn’t provide these - where do we get X & Y from ?
- Present outcomes of scenarios
  - Realistic Disaster Scenarios – valid approach but hard to tie to return period.
- Describe and explain why cannot be quantified
  - “Lots, Too hard / Black box” – not very helpful !
- Show numerical consequences of changes in assumptions
  - Sensitivity testing – changes in model assumptions key. Hard to do with single model.

Use multiple models ?

Multiple Models ?

Advantages

- Better communication (harder to hide uncertainty)
- Better understanding of models
- Possibly reduced model change risk

Disadvantages

- Trickier communication (“why can’t you just give me one number?”)
- More work running/reviewing/understanding
- Can still be misused
- More expensive ?

Using Multiple Models - Blending
Introduction

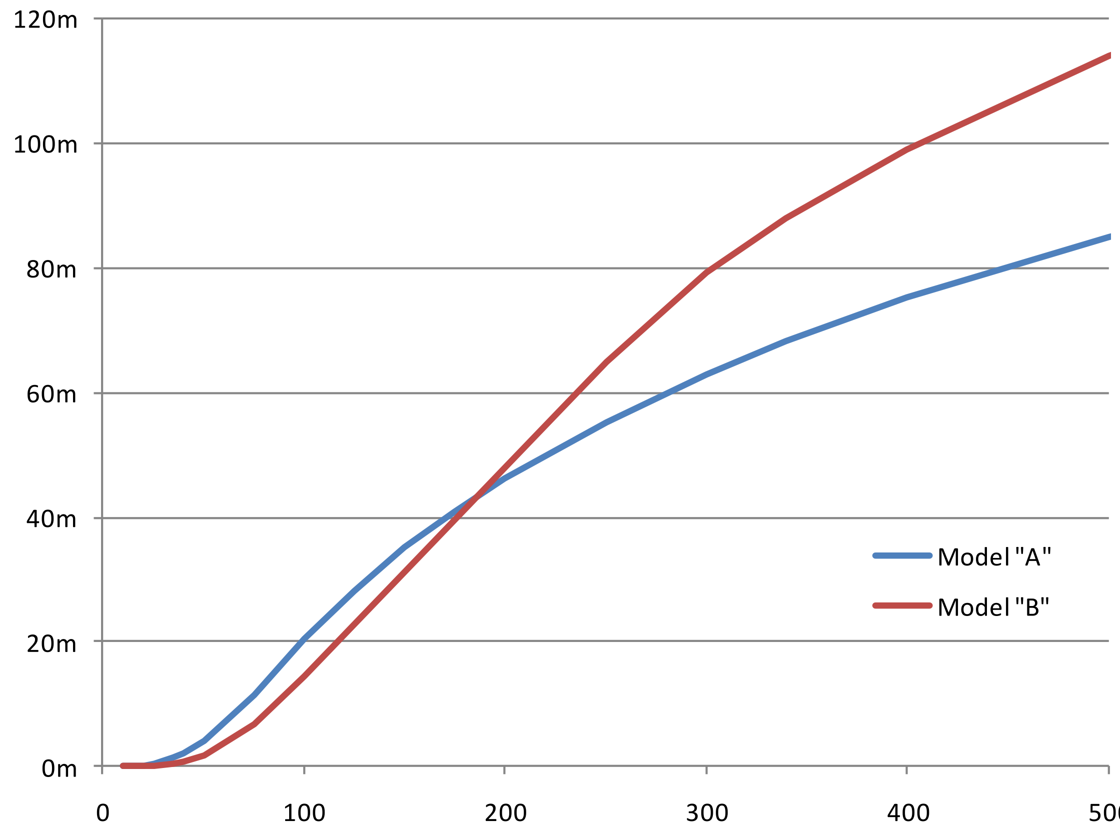
- Simple Blending (with fixed weights)
  - Common approach
  - Alternative approach
- Selecting Model Weights
- More complex blending

Simple Blending

Model Blending
Example Raw Model Output

- For illustration we take 2 sets of modelled output

OEP Comparison		
Return Period (years)	Model "A" Loss	Model "B" Loss
10	499	493
20	196,627	32,459
50	3,961,688	1,831,162
100	20,319,900	14,454,993
200	46,267,924	47,845,001
250	55,270,003	64,916,982
500	85,120,119	114,062,741
1,000	117,727,549	157,063,091



Model Blending
Common Weighting Approach (1)

- For each return period, take a weighted average of the model losses.

OEP Comparison					
Return Period (years)	Model "A" Loss	Model "B" Loss	Weight "A"	Weight "B"	Blended Loss
10	499	493	50.0%	50.0%	496
20	196,627	32,459	50.0%	50.0%	114,543
50	3,961,688	1,831,162	50.0%	50.0%	2,896,425
100	20,319,900	14,454,993	50.0%	50.0%	17,387,447
200	46,267,924	47,845,001	50.0%	50.0%	47,056,463
250	55,270,003	64,916,982	50.0%	50.0%	60,093,492
500	85,120,119	114,062,741	50.0%	50.0%	99,591,430
1,000	117,727,549	157,063,091	50.0%	50.0%	137,395,320

Model Blending
Common Weighting Approach (2)

OEP Comparison

Return Period (years)	Model "A"	Model "B"	Blended
10	499	493	496
20	196,627	32,459	114,543
50	3,961,688	1,831,162	2,896,425
100	20,319,900	14,454,993	17,387,447
200	46,267,924	47,845,001	47,056,463
250	55,270,003	64,916,982	60,093,492
500	85,120,119	114,062,741	99,591,430
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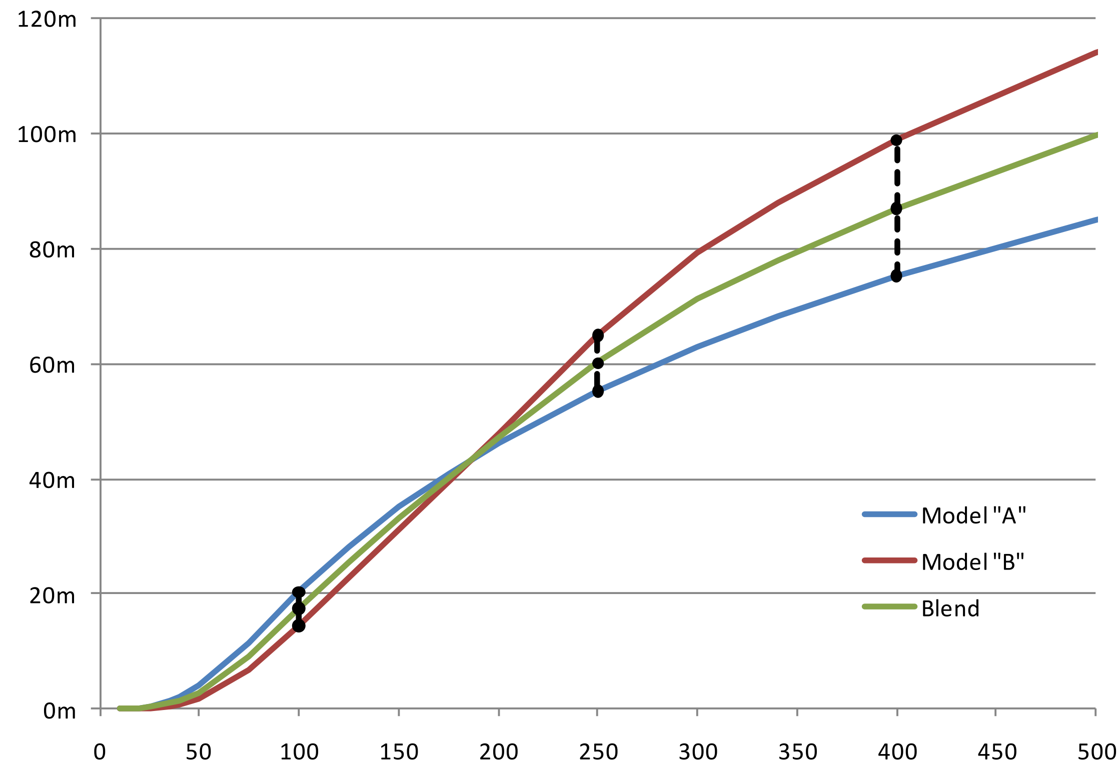


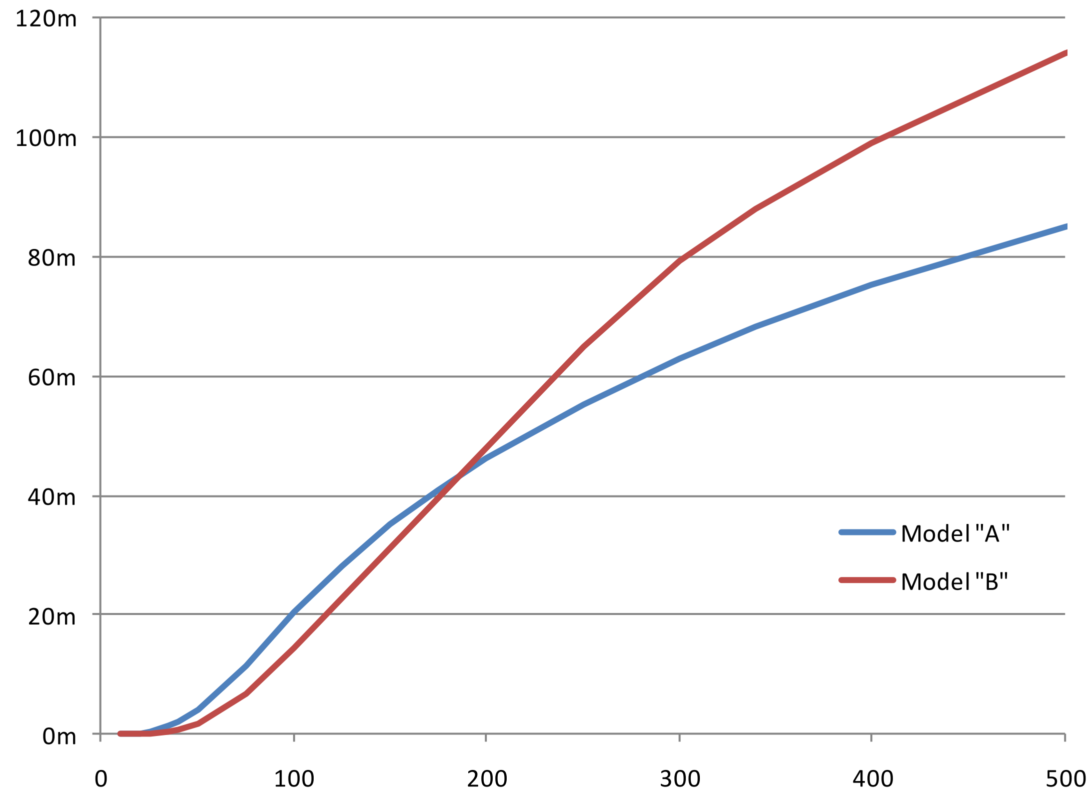
Model Blending

Example Raw Model Output (again)

- Let's present the curves original curves a different way

OEP Comparison

Loss (m)	Model "A" Return Period	Model "B" Return Period
1	31	43
2.5	42	54
5	55	67
10	71	86
20	99	116
40	170	176
50	220	206
80	446	302
100	691	407



Model Blending
Alternative Weighting Approach (1)

- For each size of loss, take weighted average of the modelled frequencies.

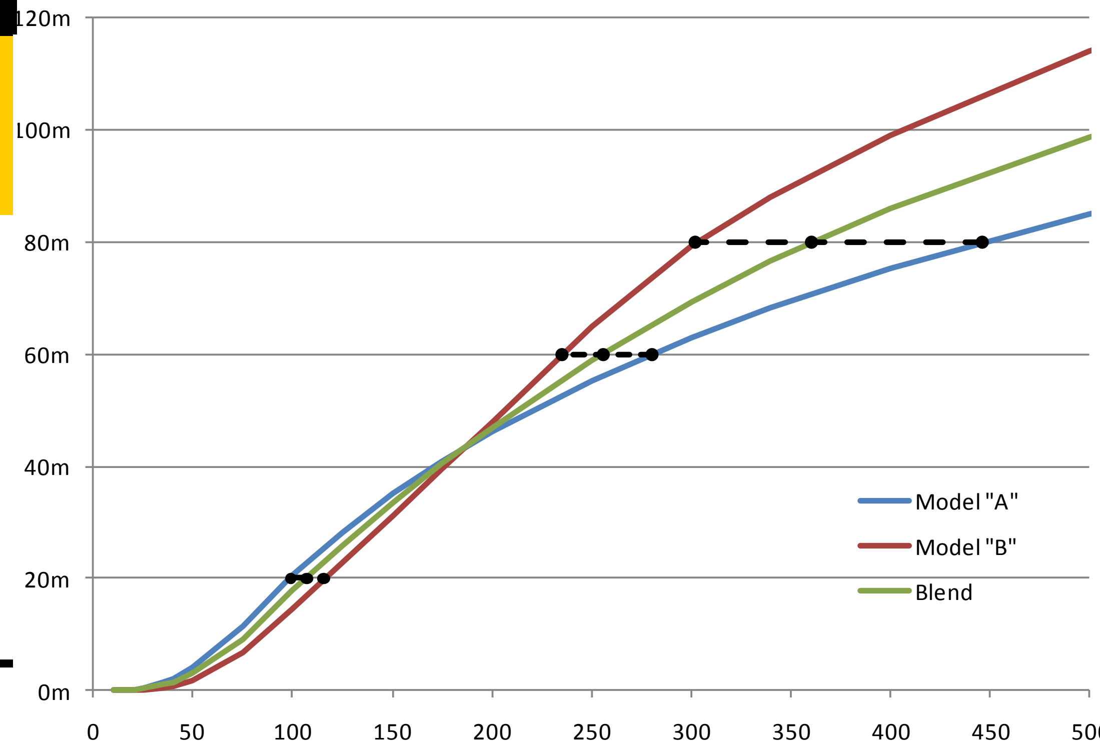
OEP Comparison					
Loss (m)	Model "A" Return Period	Model "B" Return Period	Weight "A"	Weight "B"	Alternative Blend Return Period
1	31	43	50.0%	50.0%	36
2.5	42	54	50.0%	50.0%	48
5	55	67	50.0%	50.0%	60
10	71	86	50.0%	50.0%	78
20	99	116	50.0%	50.0%	107
40	170	176	50.0%	50.0%	173
50	220	206	50.0%	50.0%	213
80	446	302	50.0%	50.0%	360
100	691	407	50.0%	50.0%	512

Model Blending

Alternative Weighting Approach (2)

OEP Comparison

Loss (m)	Model "A" Return Period	Model "B" Return Period	Alternative Blend Return Period
10	31	43	36
20	42	54	48
50	55	67	60
100	71	86	78
200	99	116	107
250	170	176	173
500	220	206	213
1,000	446	302	360



Model Blending

Common *vs* Alternative Approach

Comparison

- Are they the same ? No
- How different are they ?
  - It depends. In this case -

    up to 40% between 10-15 year return periods

    up to 3% between 250 and 300 year return periods.
- Why are they different ?
  - Common approach – weights severity distributions
  - Alternative approach – weights model frequencies
- Why bother using the alternative approach ?

Model Blending

Alternative Approach – Event Set Version

Combine ELTs into one larger ELT by weighting event rates

Model A

eventid	rate	loss mean	sd
3000001	0.00175380	18,257,179	…
3000002	0.00054733	33,196,280	…
3000003	0.00139981	53,617,849	…
3000004	0.00027257	106,984,417	…
3000005	0.00019050	133,267,576	…
etc			

Model B

eventid	rate	loss mean	sd
654321	0.00016724	70,644	…
654322	0.00010728	3,542,148	…
654323	0.00005382	10,689,570	…
654324	0.00002700	46,101,864	…
654325	0.00001354	102,821,364	…
etc			

0.0054733 * 0.5 = 0.00027366

Alternative Weighted

eventid	rate	loss mean	sd
3000001	0.00087690	18,257,179	…
3000002	0.00027366	33,196,280	…
3000003	0.00069991	53,617,849	…
3000004	0.00013629	106,984,417	…
3000005	0.00009525	133,267,576	…
654321	0.00008362	70,644	…
654322	0.00005364	3,542,148	…
654323	0.00002691	10,689,570	…
654324	0.00001350	46,101,864	…
654325	0.00000677	102,821,364	…
etc			

Model Blending

Alternative Approach – Simulation Version

For each simulation

- Sample ‘u’ from a random Uniform(0,1) distribution
- If u < 0.5
  - sample 1 year’s events from Model “A”

  otherwise
  - sample 1 year’s events from Model “B”

- Trivially generalisable to cat models with YLTs as well as ELTs

Model Blending
Common *vs* Alternative Approach

Why Bother using Alternative Approach ?

- Advantages
  - you have a ‘proper’ cat model
    - a probability weighted model
  - you have event sets
  - you have physical events & footprints
  - you have a model for correlation between portfolios
- Disadvantages
  - a little bit more work ..

Selecting Model Weights

Model Blending
selecting model weights

- Just taking straight arithmetic average is not good enough
- Using multiple models doesn’t remove the need to understand what they do or how.
- No theoretically ‘correct’ weights
- You still need to choose weights
  - Technical considerations
  - Other considerations

Model Blending
selecting model weights

Technical considerations

- Peril specific. e.g. EU WS

		Model "A"	Model "B"	Model "C"
Event Set	NWP	✓✓		
	Historical Data	✓		
	Statistical Methods	✓✓		
	Small-scale events	✓		
	Spatial Coverage	✓✓		
	Physical Mechanisms	✓✓✓		
Hazard	Orography	✓✓		
	Directionality	✓✓		
	Gust Wind Speeds	✓		
	Data Resolution	✓✓		
	Hazard Model Resolution	✓✓		
Vulnerability	Engineering Knowledge	✓✓		
	Claims Data	✓		
	Flexibility	✓✓		
	Validation	✓✓		

Model Blending
selecting model weights

Wider model considerations

- age & provenance
- frequency, magnitude & direction of model revisions
- vendor openness
- external scrutiny
- ranking of output

Other considerations

- company’s risk appetite
- process of reviewing weights

More Complex Model Blending

More Complex Model Blending
Introduction

Different Kinds of Blending

- Model Decomposition (or “Mix & Match”)
- Variable Weightings
- “Shoehorning”

Decomposition Blending
single portfolio

Traditionally

- N Poisson distribution for annual number of events
- X loss severity distribution portfolio 1, i.i.d.

Increasingly

- N frequency distribution for annual number of events
- X_i severity distribution of i'th event X_i
- $C_{i,j}$ copula for joint distribution of X_i and X_j

Perhaps Soon

- $C_{N,i,j}$ Copula for joint distribution of N, X_i and $X_{j,}$

- For multiple portfolios, C becomes even more complex

Decomposition Blending
example

Weight different components of models differently

- Can help sensitivity test specific components
- Take advantage of perceived strength of different models

e.g. a model run might consist of

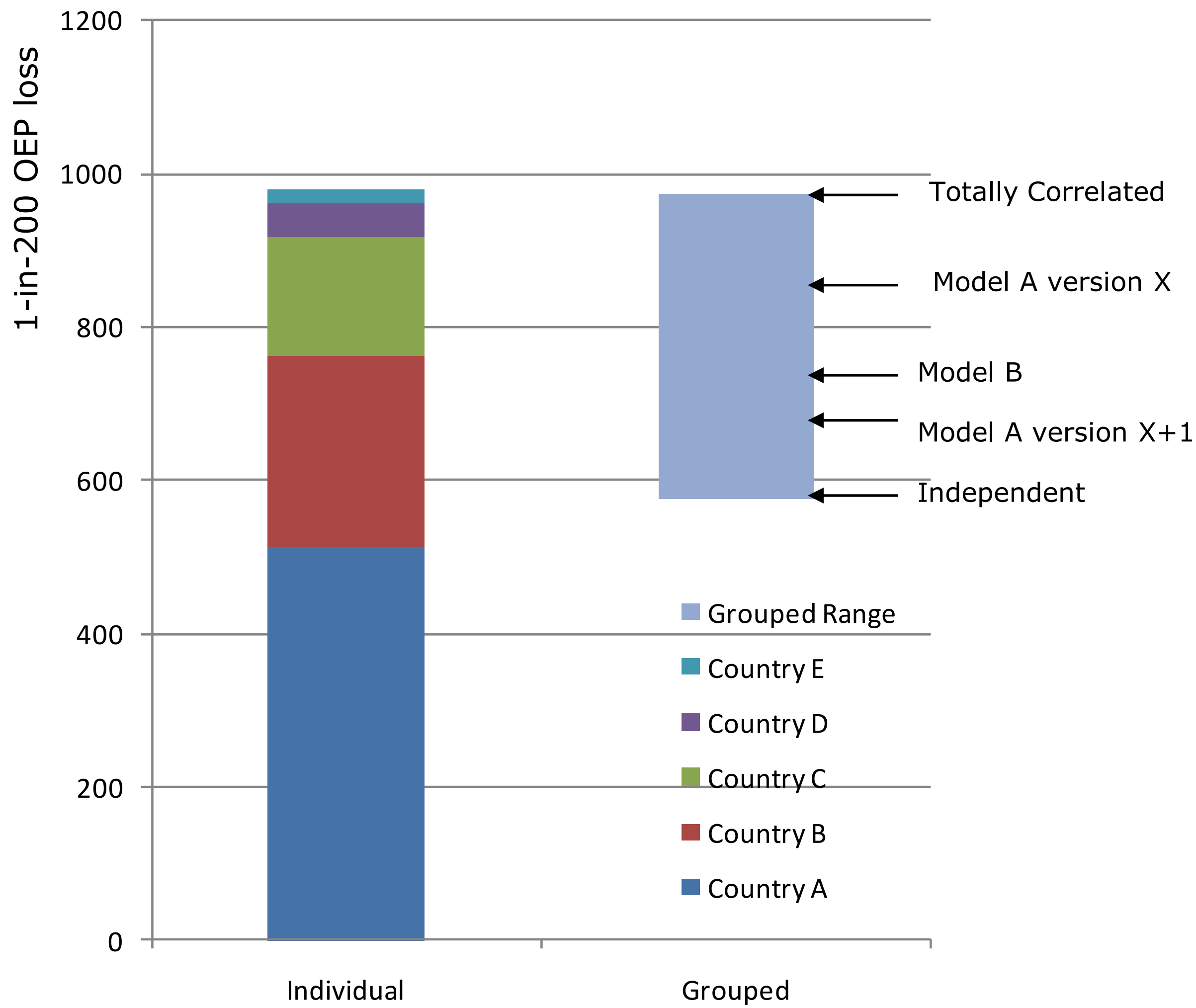
- per portfolio/country marginals
  - blend of vendor models, other adjustments and client loss experience
- correlations between portfolios/countries
  - vendor model X
- clustering (timing of events in year and correlation between events)
  - Willis ‘Kulusuk’ Windstorm Clustering Model

Decomposition Blending
example

Windstorm Correlation

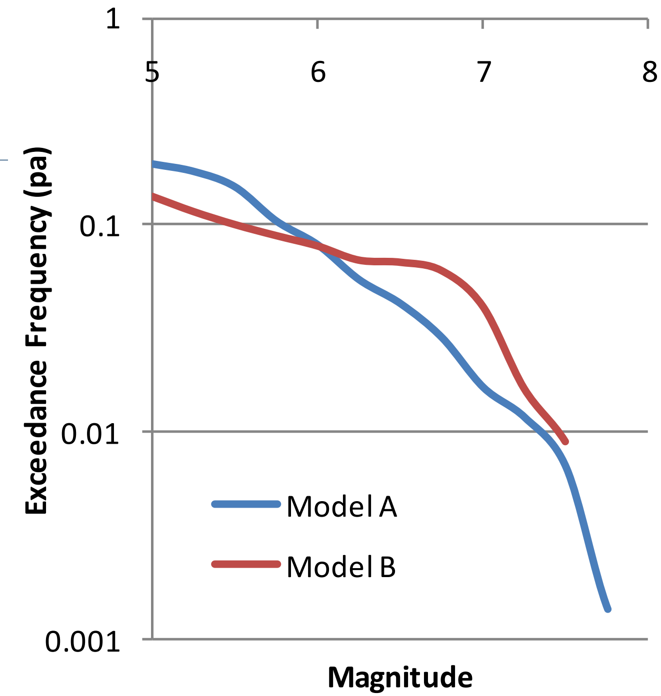
Sensitivity Testing

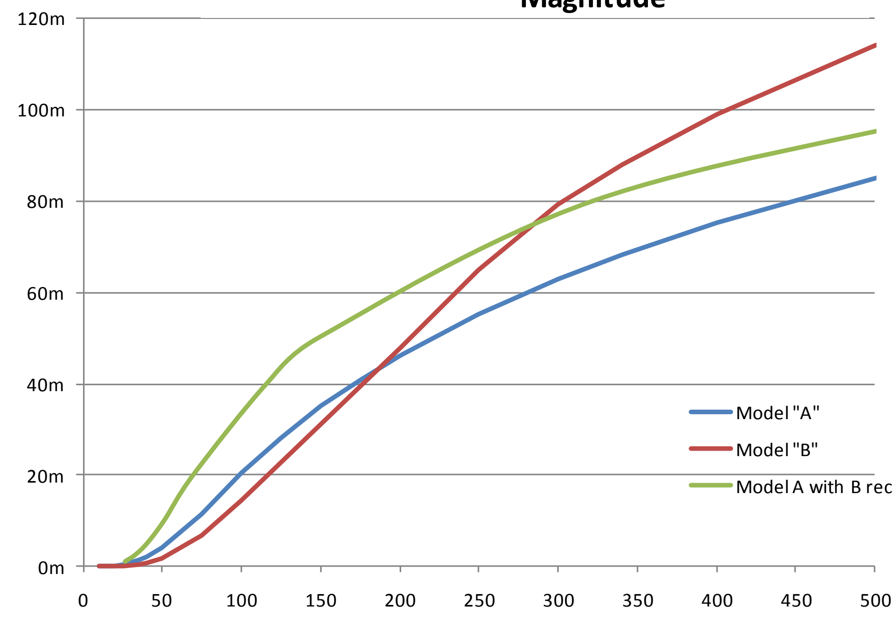
- Isolate impact of cross-country correlation on results by standardising everything else.
- E.g. use Model C for individual country results but use Models A & B for correlation.



Variable Weight Blending
physical hazard weighting

- Isolating component of model
- e.g. earthquake recurrence
  - Model B newer
  - What would our preferred model A look like with B's view here ?
- Weight each event in A's event set differently to give same relationship as B





Advanced Blending
shoehorning – example 1

Example 1a

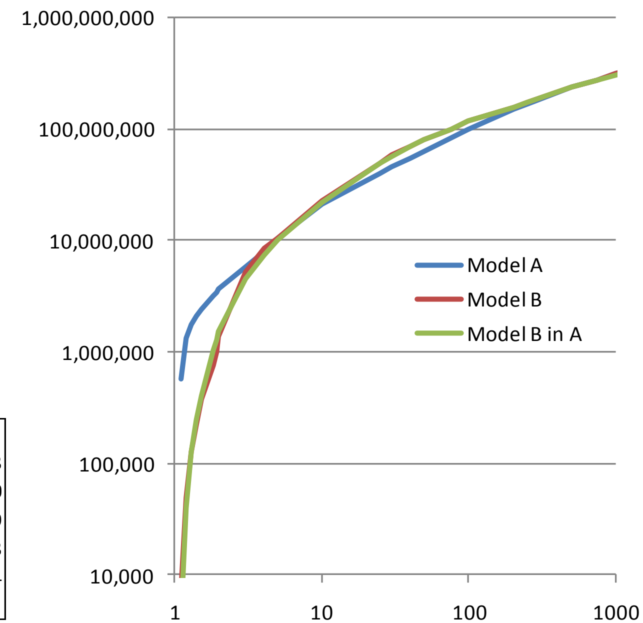
- Portfolio X run in Models A & B
- Questions
  - How can we include Model B result for X in my accumulation management / DFA platform which is based on Model A results format ?

Advanced Blending
shoehorning – example 1

- Derive transformation function $f_B(x_A)$ that for a loss x_A return the loss from Model B that has the same return period as x_A does in Model A
- For each event 'i' in the event set calculate the new loss $L^{AB}_i = f_B(\ Beta(\mu^A_i, \sigma^A_i, \lambda^A_i)\ )$
- Approximate distribution L^{AB}_i as simple beta distribution
- Now have Model A elt giving Model B results

OEP Results

Return Period	Model A	Model B
2	3,705,683	1,409,271
5	10,429,647	10,430,537
10	20,895,335	22,455,111
25	40,587,687	50,108,111
50	63,815,740	80,834,450
100	99,577,609	117,414,574
200	150,252,370	158,967,331
250	169,319,973	173,747,476



Model A event set

...					
859105	0.00003533	64,192,346	2,303,060	27,315,521	143,321,615,513
859107	0.00130700	316	236	240	52,946,240
859108	0.00007067	8,172	3,153	4,630	103,198,190
859109	0.00060070	24,990	7,762	13,485	250,961,521
859110	0.00003533	35,046	13,445	16,813	272,753,414
859111	0.00003533	3,301	2,104	1,880	41,164,697
859112	0.00003533	25,309,467	1,115,736	12,326,500	134,139,440,610
859113	0.00010600	850,460	361,305	560,448	19,839,712,189
859114	0.00028270	1,747	1,264	1,186	781,662,746
859115	0.00010600	7,283	3,019	4,092	87,886,809
859116	0.00003533	288,157	12,088	186,040	6,142,352,283
859118	0.00003533	1,139,806	24,375	730,362	23,009,866,304
...					

→

Adjusted Model A event set

859105	0.00003533	79,736,941	2,311,904	27,420,408	143,321,615,513
859112	0.00003533	29,175,376	1,540,626	17,020,634	134,139,440,610
859113	0.00010600	71,157	62,579	97,071	19,839,712,189
859116	0.00003533	5,198	109	1,678	6,142,352,283
859118	0.00003533	81,659	4,942	148,082	23,009,866,304

Advanced Blending
shoehorning – example 2

- Portfolio X run in Model A
- Portfolio Y run in Model B
    - (because Model A can't handle policy conditions)
- What might portfolio Y result look like if it were run in Model A ?

- For each event in Model B event set
    - Find event with closest footprint in Model A
    - Relabel event with Model A event ID and event rate.

- Now have Model A elt proxy result for Y.

Advanced Blending
shoehorning – example 3

- Portfolio X run in Model A
- Portfolio Y run in Model B
- What is grouped result for X+Y ?
  - (there is no possibility of running X in B or Y in A)

- This is something the Lloyd's Cat Model has to address.
- potential approaches
  - make additional assumption about correlation
  - use proxy portfolio
    - Model industry portfolio P in Model A
    - Adjust (per example 1) ELT for P in A to results of Y in B.
    - Now have proxy for Y in A elt form
    - Can group with X in A.

Solvency II Internal Models

& Multiple Cat Models

Solvency II
Passing the IMAP Tests

(Partial) Internal Model Approval

- Passing the Tests in respect of 3rd Party Models
- Sufficiently detailed understanding
  - methodology & limitations
  - assumptions

Solvency II

Passing the IMAP Tests

- options for a natural catastrophe peril
  - focus totally on output from a single catastrophe model
  - consider multiple catastrophe model outputs but use one model
  - consider multiple catastrophe model outputs and create a blended model
- Can you really claim to understand a model sufficiently if not aware of alternative approaches and uncertainty ?
- Use of single model would need more detailed understanding ?

Solvency II
Internal Model Change Governance

Policy for Changing Internal Model (IM2)

- Must define what a “major change” is
- Needs to consider change in third-party catastrophe model(s)
- Policy subject to approval by regulator

Changes to the Internal Model (IM3)

- Major change requires regulatory approval
  - Same process as for initial model approval
  - 6 months for regulators to decide

Solvency II
Internal Model Change Governance

Model Change

- Cat model change could have a bigger impact on insurer's solvency than a major cat event.
  - US WS up 100% ?
  - EU WS down 50% ?
- Would all new model releases be a major change ?
- How long will vendors support older model versions ?
- Could a regulator "unapprove" an internal model using version X of a cat model when the vendor releases a significantly different version X+1 ?

Solvency II
Final thought

- If reliant on a single model, should the risk of model change be explicitly modelled in an internal model ?
- Impacts on
  - capital requirement ?
  - cost of re-underwriting portfolio ?
  - reinsurance adequacy ?

Conclusion

Conclusion

- Models are increasing being used and relied upon
- Model results are uncertain
- There are a variety of models with different views and approaches available for cat risk
- Why just rely on one ?

- But, how independent are different models anyway …

Questions or comments?

Expressions of individual views by members of The Actuarial Profession and its staff are encouraged.

The views expressed in this presentation are those of the presenter.

All comments welcome today or via Willis Re Analytics

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