Property Catastrophe Model Blending

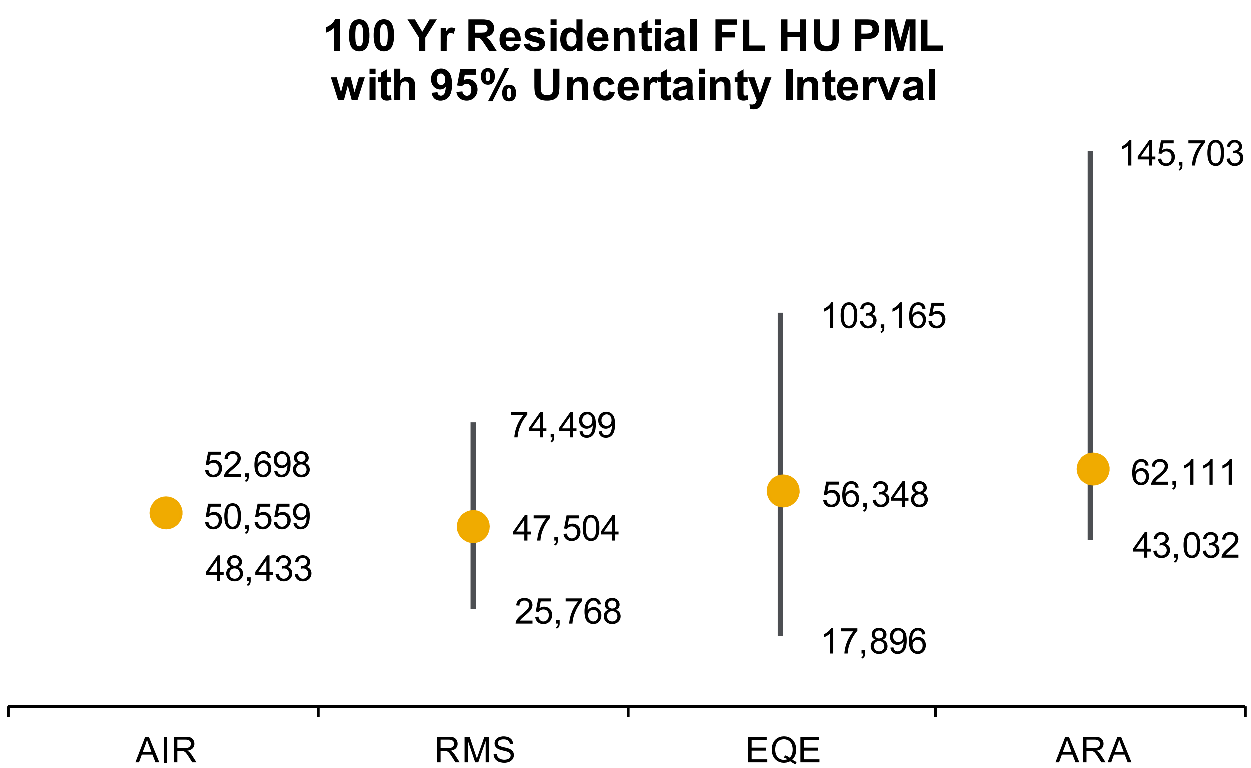
2013 CAS Ratemaking and Product Management Seminar

March 11-13, 2013

Agenda

Section 1: Why Blend Models?

Which Answer Is Best?



*2007 Florida Hurricane Catastrophe Fund's zero deductible statewide aggregate personal residential exposure data

source: Florida Commission on Hurricane Loss Projection Methodology, 2009 Standards

Catastrophe Model Customization and Blending – Why?

- Purpose of blending or customization is to better reflect a company's specific loss history or internal view of catastrophe risk

- Benefits of customization of model outputs:
  - Allows a company to develop a view of catastrophe risk that fits their actual claims experience (e.g. unique structures, loss adjustment practices)
  - Select best model for different sub-portfolios or perils
  - Minimize large changes due to vendor model changes
  - Reduce model risk that results from a reliance on a single vendor model's opinion

Catastrophe Model Customization and Blending – How?

- Adjustments should be based on:
  - A review of the science behind models
  - Model performance compared to claims
  - An understanding of notional model testing
- Desire for a customized loss curve that can be used throughout:
  - Reinsurance placement, ERM, reinsurance allocation, rate filings, rating agency reporting
- Implementation in a simulation environment provides flexibility

Custom Model PML Table

Probability of Exceedance	Return Period	Model 1	Model 2	Custom Model
99.90%	1,000	779.7	1,152.4	1,000.5
99.80%	500	499.7	812.9	715.1
99.60%	**250**	**371.7**	**547.5**	**433.6**
99.50%	200	333.5	471.4	380.5
99.00%	**100**	**179.6**	**280.9**	**226.5**
98.00%	50	105.6	153.2	124.6
96.00%	25	58.7	75.1	65.9
90.00%	10	20.9	22.4	21.7
80.00%	5	6.6	7.1	6.8
Average Annual Loss		**12.0**	**16.1**	**14.0**
Standard Deviation		57.3	93.9	76.6

Custom Model Event Loss Table

Trial	EventID	Model	Net Pre Cat Loss	Net of RI Loss
1	1101	Custom	79,115,935	79,115,935
1	2101	Vendor 1	221,557	221,557
1	2102	Vendor 1	211,948,148	100,000,000
2	3201	Vendor 2	90,476	90,476
2	1201	Custom	4,725,664	4,725,664
3	1301	Custom	76,590	76,590
⋮	⋮	⋮	⋮	⋮
249999	324999901	Vendor 2	200,790	200,790
249999	324999902	Vendor 2	26,215,545	26,215,545
250000	125000001	Custom	165,686	165,686
250000	125000002	Custom	137,798,385	100,000,000

Rating Agency Views on Model Blending

In our view, using multiple models would increase transparency in the market…We therefore consider that a multiple-model approach would give existing and potential investors a better perspective on the range of potential outcomes. While it would not eliminate uncertainty, it should provide a greater insight into the risk a deal presents, and to some extent, address the perceived issue of "model shopping."

- S&P Press Release, September 6, 2011

When companies provide output from multiple catastrophe models, A.M. Best's baseline approach is to take the straight average. This, however, can be adjusted to a weighted average in cases where more refined information is available that supports greater reliance being placed on a given model. In either case, A.M. Best expects a company's management to be able to explain why it has utilized the output selected to best represent its catastrophe exposure.

- Best's Briefing, March 10, 2011, "Catastrophe Models and the Rating Process FAQ"

Model Blending in Rate Filings

- For **hurricane**, most companies still file based on a single model, either AIR or RMS
  - Some companies do blend the two models, most often using a 50/50 blend
- For **earthquake** and **fire following**, EQE is more commonly used than it is for hurricane, either independently or blended
- **All other** US perils are predominately priced based on experience
  - Models are starting to see use, particularly for territorial ratemaking
- Model blending isn't permitted by the Florida OIR

Section 2: Vendor Model Testing

Model Testing and Calibration Framework

Review of Vendor Model Assumptions	• Review model documentation highlighting key model differences for stochastic event sets, storm parameters, event frequency, and vulnerability • Reasonability check underlying hazard assumptions against the historical record (e.g. HURDAT)
Notional Portfolios	• Loss cost map data: a single notional risk in each postal code • Vulnerability comparisons: multiple notional risks with different primary characteristic combinations at different postal code locations
Industry Portfolio	• Produces vendor/version comparisons at a macro level • Industry level impact of key assumptions: event frequency, storm surge, etc. • Compare results to historical PCS industry losses
Company Portfolio	• Company specific results that can be compared across peers and industry averages • Produces company specific vendor/version comparisons by peril at a granular level

Model Validation: Comparison to Historical Events

Comparison of Actual and Estimated FL Res Industry Loss ($M)

Storm	Year	Trended PCS Estimate[1]	RMS Estimate[2]	% difference
Andrew	1992	38,883	38,175	-1.8%
Erin	1995	815	603	-26.0%
Opal	1995	3,168	1,343	-57.6%
Georges	1998	570	180	-68.4%
Charley	2004	7,646	8,602	12.5%
Ivan	2004	5,039	1,355	-73.1%
Jeanne+Frances	2004	8,688	11,583	33.3%
Wilma	2005	10,908	11,548	5.9%
Katrina	2005	594	783	31.8%
Dennis	2005	794	554	-30.2%
Sum of All Storms		77,105	74,726	-3.1%

[1]Property Claims Services estimate of losses. Losses for Florida are normalized to 2011 values, represent residential lines and includes demand surge and excludes loss adjustment expense.

[2]RMS estimates for residential lines and are based on RMS Industry Exposure for 2011. Losses include demand surge and exclude loss adjustment expenses.

source: Florida Commission on Hurricane Loss Projection Methodology, 2009 Standards

Historical vs. Stochastic AALs: Mind the 'Gap'

What is a reasonable sized 'Gap'?

Model	Historical FL Res AAL ($B)	Stochastic FL Res AAL ($B)	AAL 'Gap'
RMS v11	2.67	3.47	1.30
RMS v10	2.80	3.26	1.16
AIR	2.84	3.62	1.27
EQE	3.26	3.99	1.22
ARA	4.13	5.28	1.28

Limited number of years

Limited event footprints

Limited storm intensities

Skewed distributions

*2007 Florida Hurricane Catastrophe Fund's zero deductible statewide aggregate personal residential exposure data

*Stochastic results use long term frequency rates; source: Florida Commission on Hurricane Loss Projection Methodology, 2009 Standards

Section 3: Customization and Blending Examples

Key Inputs to the Process

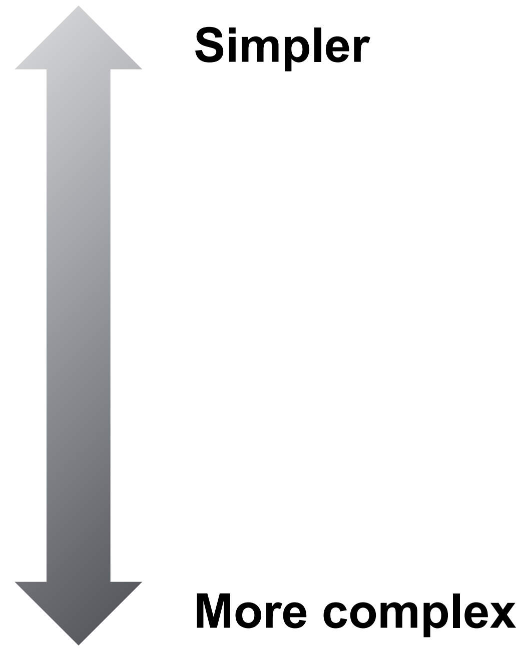
- Event Loss Tables (ELTs)
  - Collection of all the losses for each cat model peril analysis
  - An ELT will be produced for each peril
  - Hold all the information needed to produce PML/EP, AAL, pure premium to a layer, and standard deviation of each metric

ELT Structure by Vendor	**A**	**B**	**C**	**D**
All events have same frequency	Y	N	N	N
Events are assigned to a specific year	Y	N	N	N
Losses for each event are a probability distribution	N	N	N	Y

Problem of model blending reduces to how to adjust and then combine the ELTs

Illustrations of Blending Methods

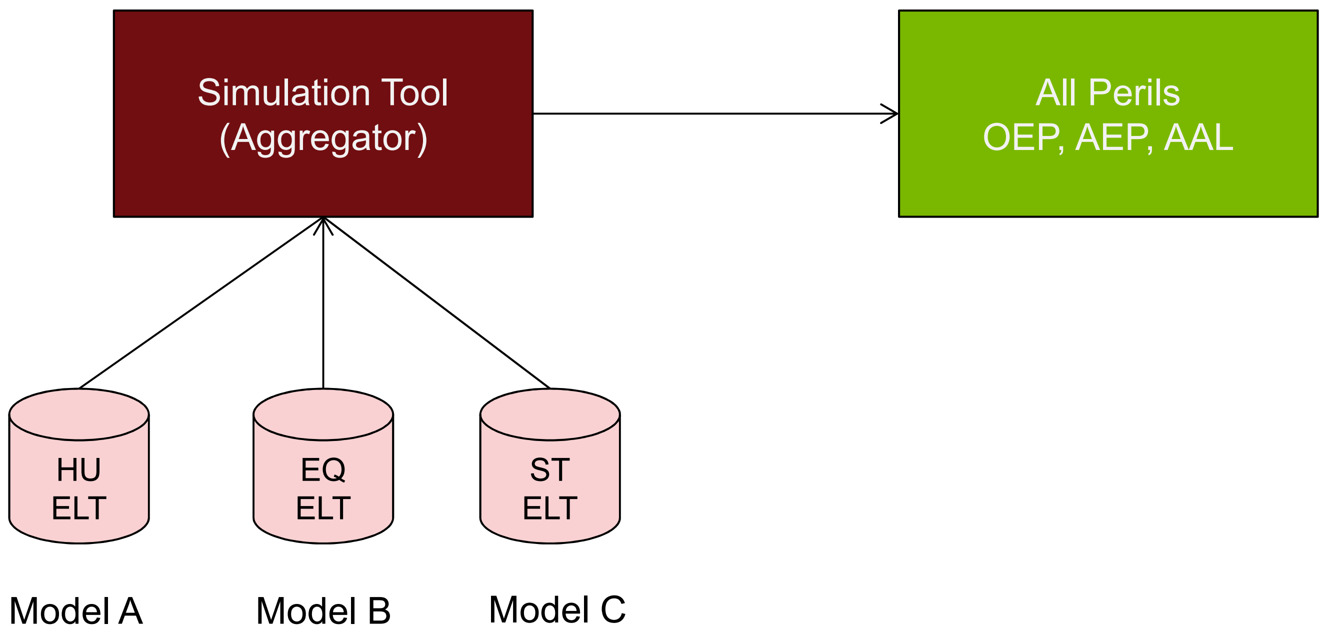
1. Using different models for different perils
2. Blending multiple models within a single peril
3. Adjusting event rates
4. Blending primary and secondary perils
5. Blending across business units



1. Different Models for Different Perils

- **Problem**: Calculate a combined occurrence and aggregate EP curve using Model A for Hurricane, Model B for Earthquake, and Model C for Severe Thunderstorm

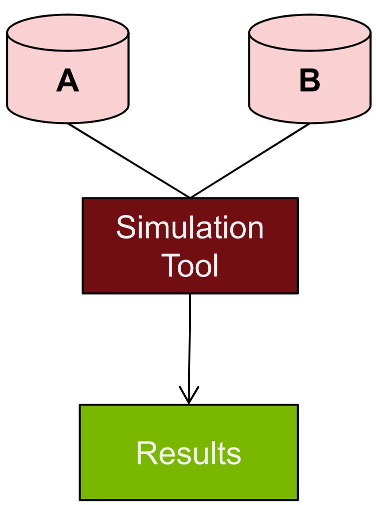
- **Solution**: Simulate trials (years) of losses from the original ELTs using preferred simulation tool



2. Blending multiple models within a single peril

- **Severity Blending**: Simple weighting of AALs and EPs
  – Blended EP = 50% of Model A EP + 50% of Model B EP (or AAL)

- **Frequency Blending**: Sampling years from different models
  – Sample from each of Models A and B for 50% of the years
  – Produces a proper probability distribution which can be used in other contexts



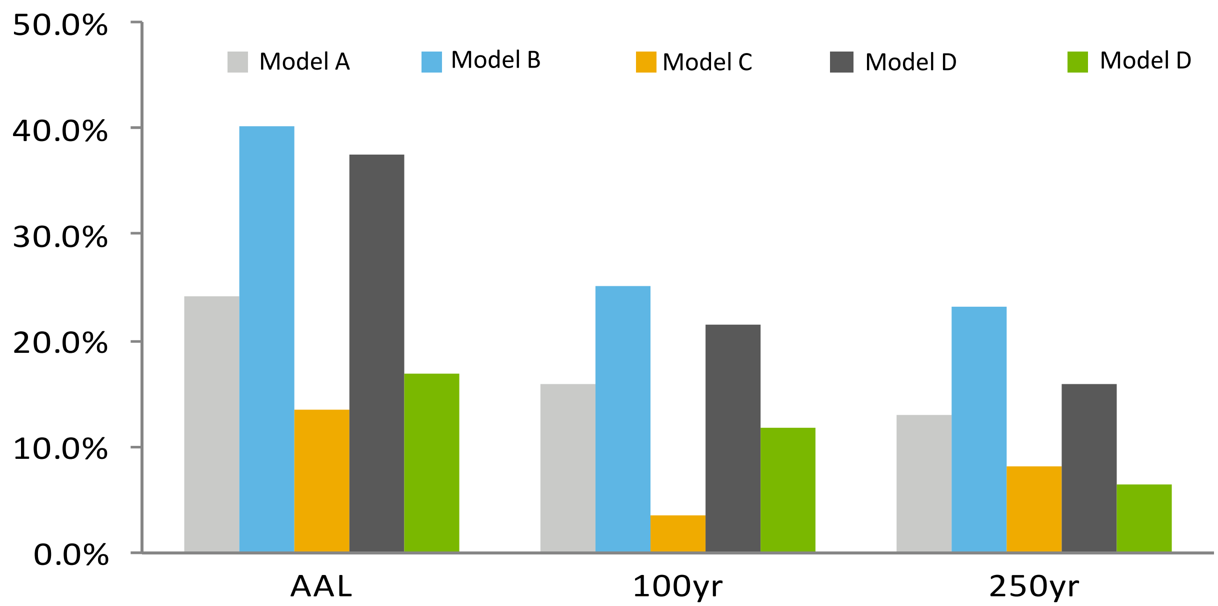
Net Pre Cat EP Summary

Probability of Non-Exceedance	Return Period (Year)	Model A	Model B	50/50 Average of Results [1]	Blended* Net Pre-Cat Loss [2]	[1] / [2]
Occurrence Loss						
99.99%	10,000	93,568,293	253,585,771	173,577,032	191,538,126	0.91
99.90%	1,000	46,497,641	70,348,136	58,422,889	55,824,577	1.05
99.60%	250	24,097,451	21,857,702	22,977,576	22,962,547	1.00
99.50%	200	20,701,917	18,639,485	19,670,701	19,475,609	1.01
99.00%	100	12,458,382	7,750,439	10,104,410	9,999,998	1.01
98.00%	50	5,342,460	2,310,319	3,826,390	3,827,784	1.00
95.00%	20	732,979	317,173	525,076	462,667	1.13
90.00%	10	29,657	62,002	45,829	53,725	0.85
Average Annual Loss		**431,301**	**392,261**	**411,781**	**411,356**	**1.00**

*Results based on 400,000 ReMetrica simulated years (50% using Model A, 50% using Model B)

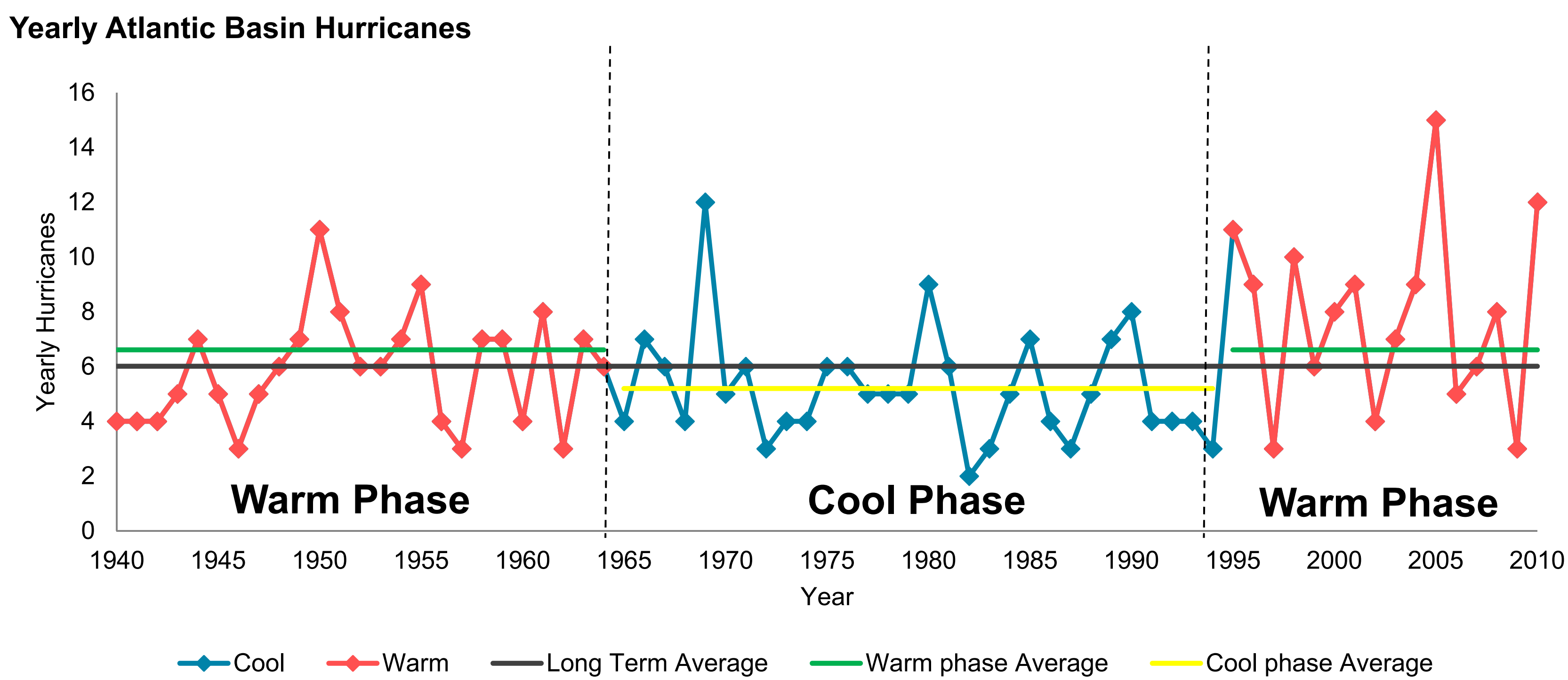
Long-Term and Near-Term Hurricane Frequency Impact by Model

Near Term Frequency Impact

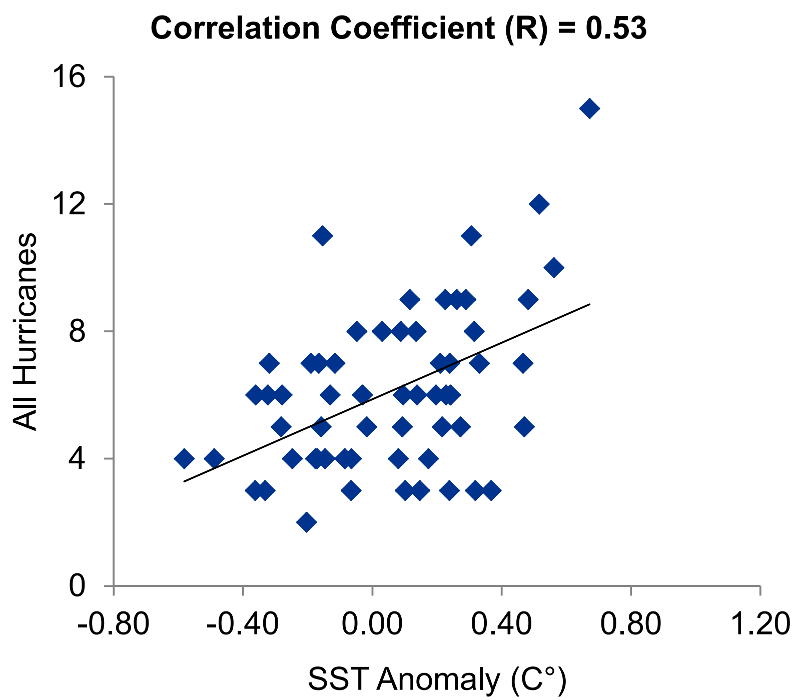


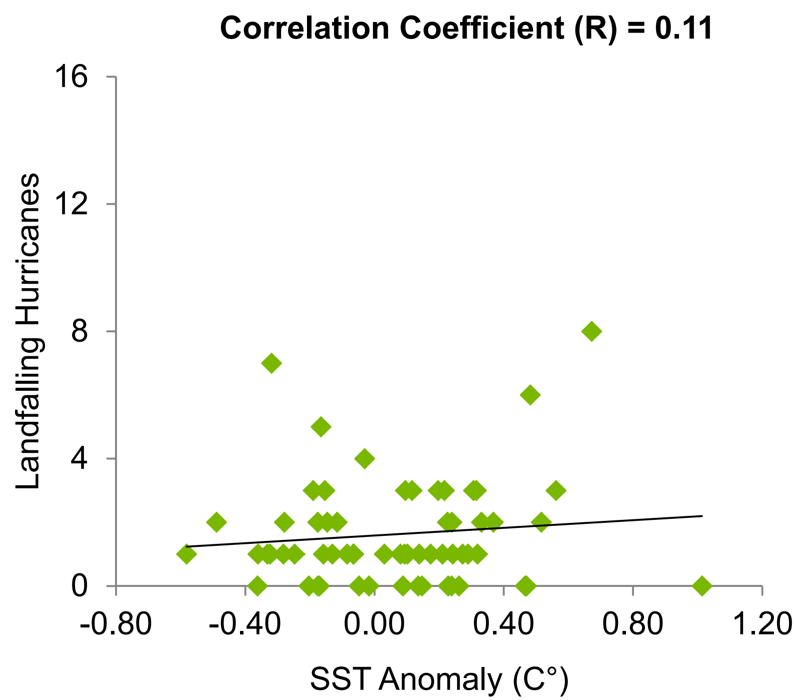
	AAL	100yr	250yr
Model A	24.2%	16.1%	13.1%
Model B	40.4%	25.3%	23.2%
Model C	13.7%	3.7%	8.3%
Model D	37.5%	21.7%	15.9%
Model E	16.9%	12.0%	6.4%

Atlantic Basic Hurricane Activity – Warm Phase vs. Cool Phase



Relationship Between SST Anomalies and Hurricanes





Hurricane Frequency Research

Frequency and Loss Analysis of U.S. Landfalling Hurricanes: Long Term versus Warm Phase

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Abstract

By reviewing recent lit
relationship between al
However, less research
that are statistically mo
on the hypothesis that l

Table 7: Comparison of increase (1- ratio) for frequency and AAL between long term and warm phase conditions

Storm Category	Landfall Frequency Percent Change	AAL Percent Change
1	15	15
2	14	16
3	11	15
4	13	17
5	16	21
All	13	17

Published in the Journal of Risk Finance in 2012

3. Adjusting Hurricane Frequency – I

- **Problem**: An insurer prefers to use Model A for hurricane, but believes that Model A overstates the impact of near-term (NT) v. long-term (LT) landfalling hurricane frequencies

Sum of Event Rates	Long-term [1]	Near-term [2]	Ratio [2]/[1]
Model A	1.76	2.20	1.25
Selected Ratio			1.13

- **Simple approach**: Adjust Model A long-term event rates by 1.13
  – Simple, but misses event- and basin-specific information

- **Better approach**: If you have identical events in NT and LT sets, adjust event rates as follows

$$\text{rate}_k^{adj} = \text{rate}_k^{LT} + \lambda\,(\text{rate}_k^{NT} - \text{rate}_k^{LT})$$

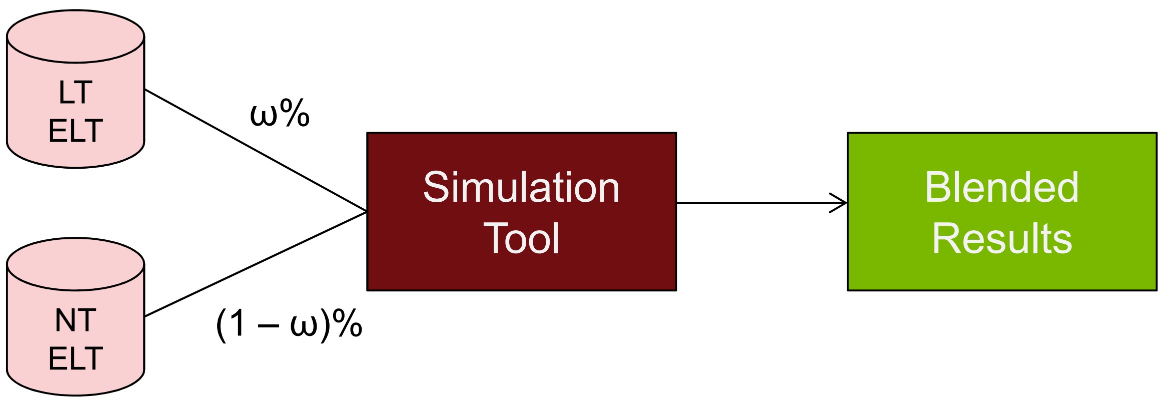
α = Model A ratio ([2] / [1] above) = 1.25

β = Selected ratio ([2] / [1]) = 1.13

$\lambda = (\beta - 1) / (\alpha - 1) = (1.13 - 1) / (1.25 - 1) = 0.52$

3. Adjusting Hurricane Frequency – II

- **Third approach**
  - Include both NT and LT event sets, rather than a blend of the two
  - Solve for a weight ω such that
    - $\omega + (1 - \omega)\,\alpha = 1.13$
    - [$\alpha = 1.25$, so $\omega = 0.48$]
  - Using simulation tool, draw from LT set ω% and from NT set (1 - ω)% of the trials



- **Benefits**
  - Method works for vendor models where LT and NT event sets differ

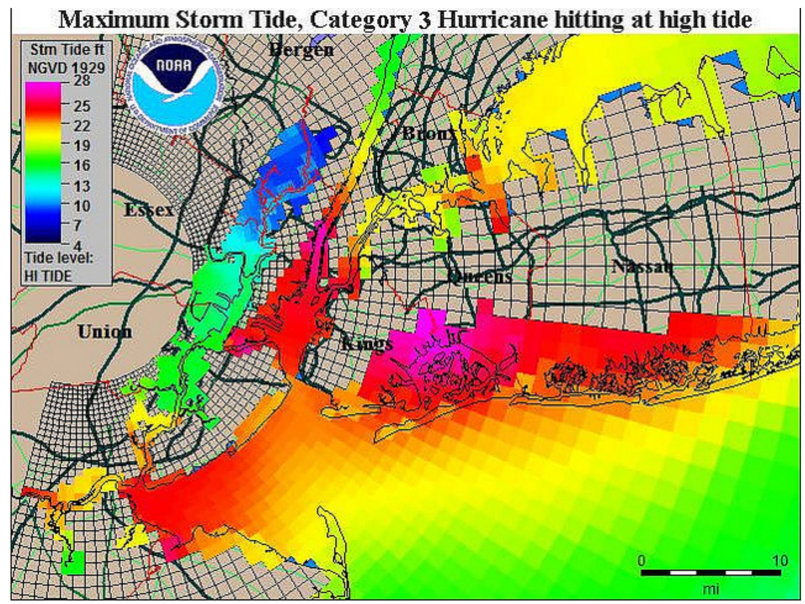
Superstorm Sandy – Storm Surge

2/3 of all New York City homes damaged by Superstorm Sandy were outside of FEMA's existing 100-year flood zone.

- *Wall Street Journal*

The highest storm surge measured by tide gauges in New Jersey was 8½ feet over normal levels at Sandy Hook, though it likely was higher because the storm knocked out the gauges.

- *USA Today*



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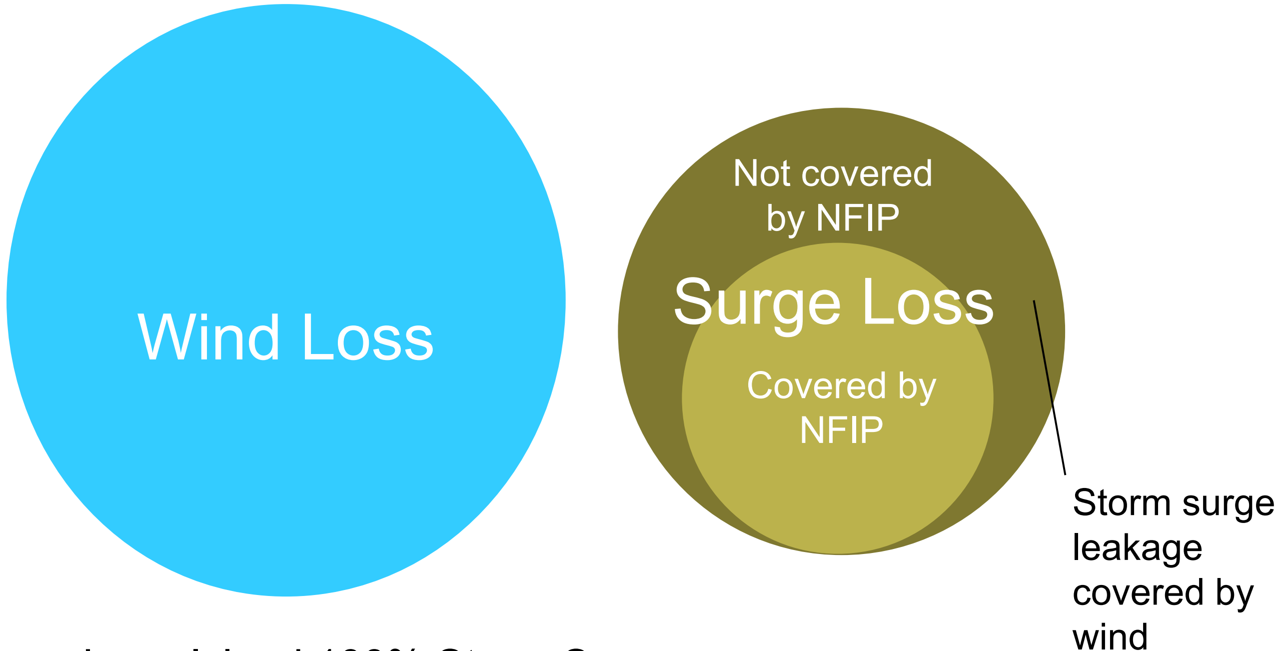
Modeling Hurricane Storm Surge

SLOSH vs. MIKE 21?

NFIP Take-up Rates?

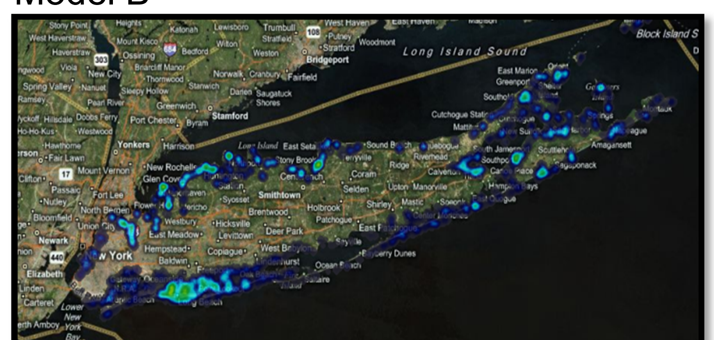
Leakage Factor?



Long Island 100% Storm Surge

Model A

Model B



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4. Blending Primary and Secondary Perils

- **Problem**: One model is preferred for a primary peril, another for an associated secondary peril
  - Hurricane / storm surge , Shake / fire following
- **Example**: Hurricane from Model A, storm surge impact from Model B

AALs	HU Only	HU + Storm Surge	SS Factor
Model A	22,755,246	26,956,836	1.185
Model B	15,125,000	16,032,500	1.060

- **Approach 1**
  - For each EventID, k, in the Model A ELT, adjust HU mean losses to be

$$loss_k^{adj} = loss_k^{HU} \times 1.060$$

  - Note that all events get the same storm surge “lift”
- **Approach 2** (Better)

$$loss_k^{adj} = loss_k^{HU} + \lambda\,(loss_k^{HU,SS} - loss_k^{HU}), \text{ where}$$
$$\lambda = (1.060 - 1) / (1.185 - 1) = 0.324$$

4. Blending Primary and Secondary Perils – Example

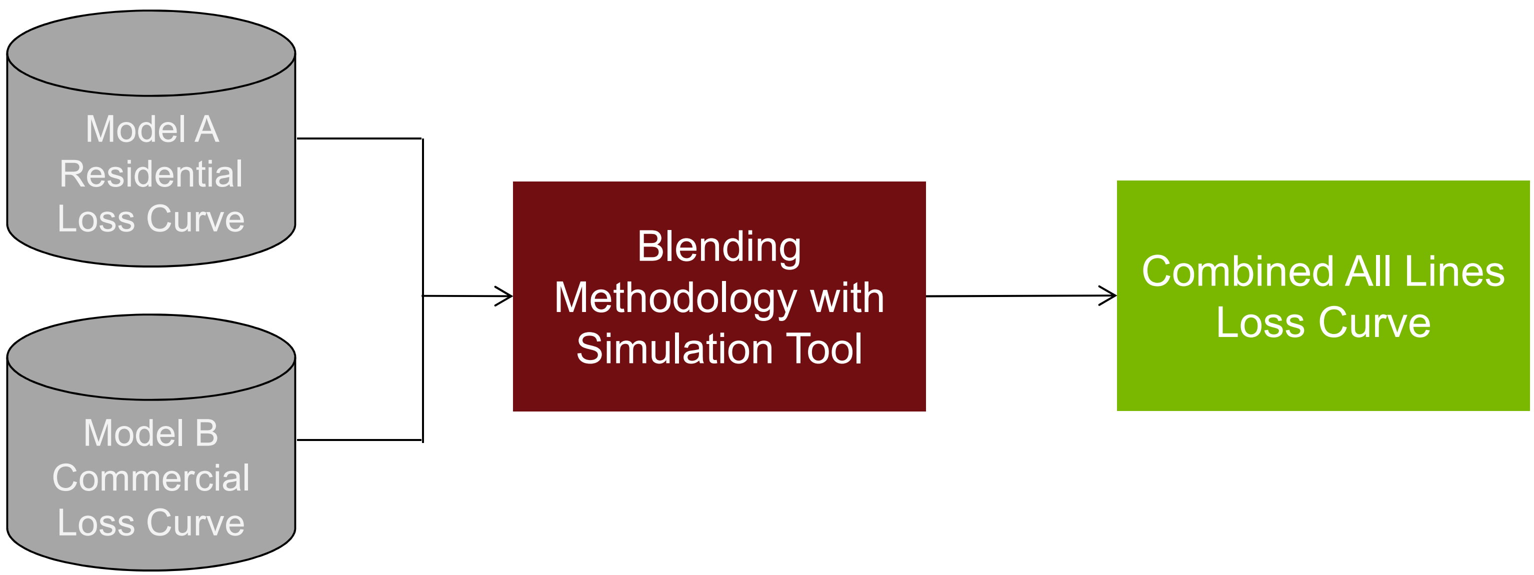
Occurrence Loss Summaries (losses in $000s)

	[1]	[2]	[3]	[4]	[2] / [1]	[3] / [1]	[4] / [1]
Return	**Model A**		**Model A, with adjusted SS**				
Time	**no SS**	**with SS**	**Approach 1**	**Approach 2**			
1000	$465,660	$496,949	$493,600	$475,130	1.067	1.060	1.020
500	$371,586	$400,967	$393,881	$380,218	1.079	1.060	1.023
250	$289,582	$317,068	$306,957	$297,530	1.095	1.060	1.027
200	$265,913	$292,500	$281,868	$273,590	1.100	1.060	1.029
100	$199,343	$222,913	$211,303	$206,048	1.118	1.060	1.034
50	$144,589	$164,618	$153,264	$150,160	1.139	1.060	1.039
25	$99,651	$116,088	$105,630	$104,192	1.165	1.060	1.046
10	$52,030	$62,641	$55,152	$55,261	1.204	1.060	1.062
AAL	$22,755	$26,957	$24,121	$24,121	1.185	1.060	1.060

5. Blending Models for Different Business Units

- **Problem:** Aggregating results from a single peril where each business unit uses a different model

- **Solution:** Map the event IDs of one model to the event IDs of another model by matching event characteristics
  - Once events are “matched”, simulate events in one model and find matching event in second model



Event Mapping Method – Description

Map the event IDs of one model to the event IDs of another model by matching event characteristics

Parametric Approach | **Loss Approach**

Match detailed event characteristics	Match OEPs, Saffir-Simpson by gate	Match OEPs, Saffir-Simpson by Region	Match OEPs at Regional level	Match OEPs at Nationwide level

More complex | **Simpler**

Hurricane Event Charateristics Provided	Model A	Model B
Event Rate	X	X
Saffir-Simpson category	X	X
Landfall Area		
By Gate	X	X
By County	X	X
By Latitude/Longitude	X	X
Radius to Maximum Winds (Rmax)	X	X
Central Pressure	X	X
1-min sustained wind speed 6hrs pre-landfall	X	X
Landfall Angle		
Degrees		X
Qualitative: N, NE, E, etc	X	

Event Mapping Method – Match OEPs (Ranks) by Region Example

1. Calculate full OEP curve for Model A (rank events)

2. Calculate full OEP curve for Model B (rank events)

3. Map the events of Model A to the events of Model B by matching occurrence exceedance probabilities (ranks)

4. Results in a mapping of Event IDs that approximately preserves both loss distributions

Model A — OEP Curve

EventID	OEP	Return Period	Loss ($B)
270090991	0.01%	10,000.5	112.5
270002754	0.02%	5,000.5	84.8
270039393	0.03%	3,333.8	70.5
⋮	⋮	⋮	⋮
270171135	0.38%	263.7	19.8
270206220	0.39%	256.9	19.5
270139068	0.40%	250.0	19.5
⋮	⋮	⋮	⋮
270264922	1.97%	50.8	5.5
270061574	1.98%	50.5	5.5
270246902	2.00%	50.0	5.4
⋮	⋮	⋮	⋮

Model B — OEP Curve

EventID	OEP	Return Period	Loss ($B)
2868396	0.00%	20,893.8	113.7
2855790	0.01%	7,972.3	109.5
2871434	0.01%	7,972.1	102.2
2860055	0.01%	7,811.5	101.9
⋮	⋮	⋮	⋮
2877060	0.38%	261.8	25.6
2869578	0.38%	261.4	25.3
2861752	0.40%	250.0	24.9
2868952	0.40%	247.0	24.5
⋮	⋮	⋮	⋮
2862887	1.98%	50.6	4.5
2877465	1.98%	50.5	4.5
2857990	2.00%	50.0	4.5
2873568	2.01%	49.8	4.5
⋮	⋮	⋮	⋮

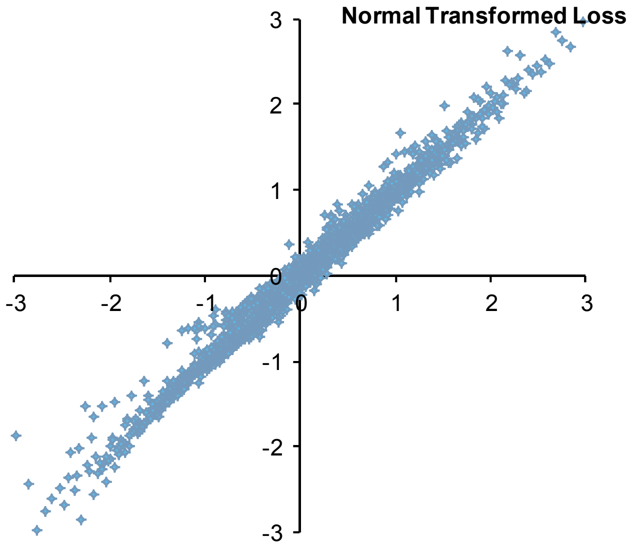
Mapped Events

Model A EventID	Model B EventID	Event Rate
270090991	2868396	6.17E-06
270090991	2855790	7.76E-05
270090991	2871434	3.18E-09
270090991	2860055	2.58E-06
⋮	⋮	⋮
270139068	2877060	5.33E-06
270203993	2869578	4.55E-06
270139068	2861752	9.85E-06
270044732	2868952	2.14E-04
⋮	⋮	⋮
270099438	2862887	3.69E-05
270103717	2877465	3.23E-05
270246902	2857990	2.78E-05
270166203	2873568	9.28E-06
⋮	⋮	⋮

Validation of Event Mapping

Single Model

Model B RES (x-axis) vs. Model B COM **1364 Observations**

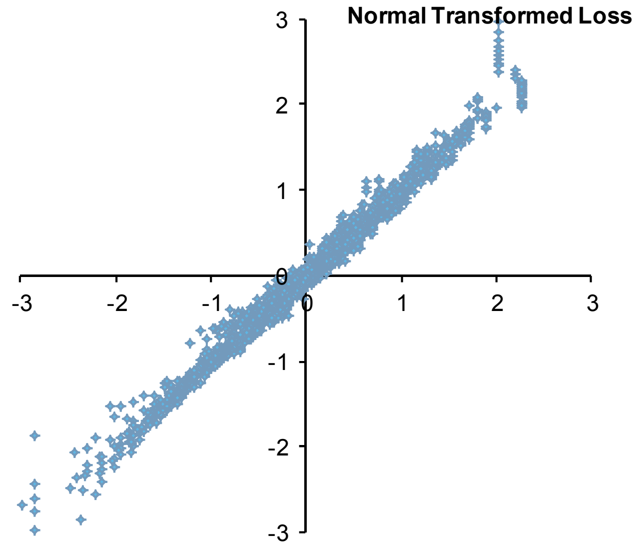


Association Summary

Linear Correlation, rho	98.1%
Rank Correlation	99.1%
Rank Correlation from rho	97.9%
Normal-Transformed Correlation	99.0%
Kendall Tau	92.2%
Tau from rho	87.6%

Multiple Models – Mapped Events

Model A RES (x-axis) vs. Model B COM **1364 Observations**



Association Summary

Linear Correlation, rho	93.1%
Rank Correlation	99.4%
Rank Correlation from rho	92.5%
Normal-Transformed Correlation	99.1%
Kendall Tau	93.4%
Tau from rho	76.2%

Approximately preserves dependence structure

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Section 4: Recap

Property Catastrophe Model Blending

Goals

- Adjusting, blending, or customizing, the output of vendor catastrophe models in a fact-based, thoughtful manner
- Better reflect a company's specific loss history or internal view of catastrophe risk

Approaches

- Range from the simple to complex
- Examples shown today are just some of the ways to blend models
- Any approach chosen should reflect specific company goals, underlying reasons for blending, and the best science

Benefits

- Enable company to develop view of risk that fits claims experience
- Select best model for different sub-portfolios or perils
- Minimize large changes due to vendor model changes
- Reduce model risk inherent from reliance on a single model