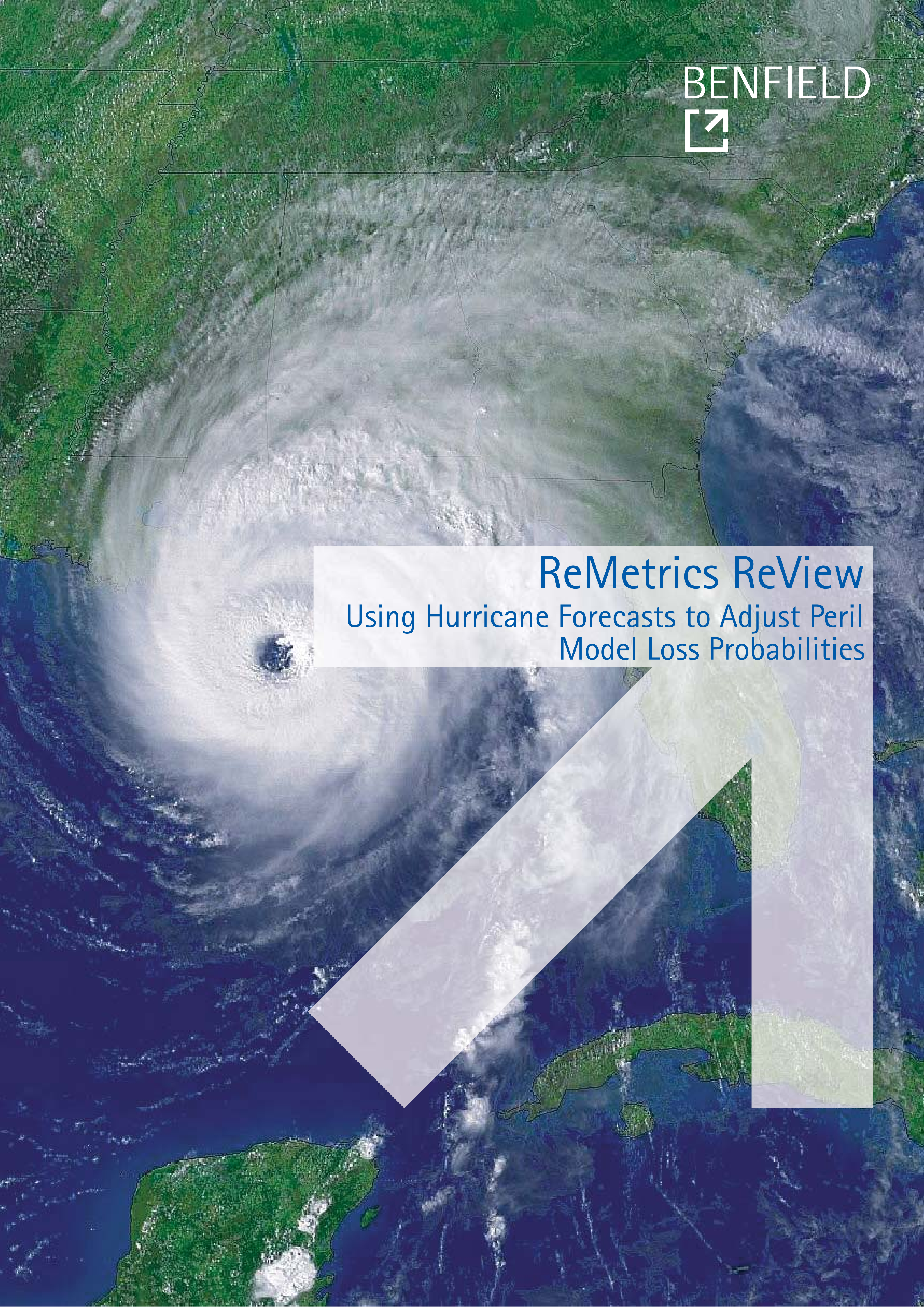

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ReMetrics ReView

Using Hurricane Forecasts to Adjust Peril Model Loss Probabilities

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Introduction

The 2005 hurricane season has highlighted once again the impotence of man before nature. The frequency of large events seems to be rising. Uncertainty over the potential impacts of global warming confuses the picture still further.

Insurers and reinsurers have made great strides in recent years to better understand US hurricane risks. Sophisticated peril models now offer a range of potential loss scenarios.

But is there more information that could be used to better assess the risks insurers and reinsurers face in the current year and so help them make better tactical decisions? Hurricane forecasts now have credibility and proven accuracy, but how can they be used?

The importance of tackling this issue has been clearly underlined by Hurricane Katrina, which is likely to prove the most expensive ever natural disaster to hit the US, with insured losses currently estimated to be between US$40bn and $60bn, and reinforced by the subsequent impacts of Hurricanes Rita and Wilma causing estimated US insured losses of between US$4bn and $7bn (Rita), and between US$6bn and $10bn (Wilma).

But even before these events 2005 had proved an unusually active season, with intense Hurricane Dennis and Tropical Storms Arlene and Cindy striking the US Gulf Coast before the end of July.

Similarly 2004 was also a very active hurricane season. In the US alone, Hurricanes Charley, Frances, Ivan and Jeanne caused estimated insured damage of US$23bn – a total which is nine times the annual average for US hurricane insured loss between 1950 and 2003.

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But while the 2004 and 2005 hurricane seasons again demonstrated the large year-to-year variability in landfalling US hurricane activity and in associated insured losses, perhaps the most significant factor from a risk management point of view is that both seasons were forecast to be unusually active well in advance.

For example, as far back as December 5, 2003, the Benfield-sponsored Tropical Storm Risk (TSR) consortium was forecasting that for 2004 there was an 68% chance of an above-average US landfalling storm season (as measured by landfalling storm wind energy), only a 26% chance of a normal year and a 6% chance of a below-average year.

Again, on December 10, 2004, for the 2005 US landfalling storm season TSR forecast an 65% chance of an above average activity season with a 22% chance of a normal year and only a 13% chance of a below average year.

By August 5 2005, the assessed probability of an above average US hurricane season had risen to 85%, with only a 15% likelihood of a near normal season and 0% probability of a below normal season.

New methodology

But how can insurers and reinsurers use these hurricane forecasts to better manage their business and, potentially, rethink business decisions?

To tackle this question, TSR and Benfield's ReMetrics team have together developed the necessary methodology to adjust the probability assessments of catastrophe models in the light of TSR's forecast information.

For illustration purposes the methodology and results presented in this paper apply to the forecast issued on August 5, 2005. However, the model can accommodate other forecast issue times appropriate to a user's needs.

The model allows reinsurers and insurers to see how the latest hurricane forecast:

- Changes the expected or average level of loss for the coming season
- Adjusts the expected likelihood of extreme losses for the coming season
- Provides a better reference for the cost/benefit of adjustments to both outwards and inwards reinsurance

But how does it do this? The answer, of course, lies in the application of the forecast data to existing hurricane models.

Peril models define a series of potential loss events, in this case US landfalling hurricanes, with an associated probability that reflects loss patterns over time. This information is then used to estimate the amounts of loss an insurer could suffer from each potential event based upon the location and type of its portfolio of business.

However, while such models enable insurers and reinsurers to estimate the average likelihood of suffering a loss over any given amount, they have never been adjusted to reflect the additional potential impact on a particular year of the specific climatic conditions which make landfalling hurricanes more or less likely during that period.

But this issue can now be overcome by using advanced financial models, such as Benfield's dynamic financial analysis modelling tools, ReMetrica or ReMetrica Limited Edition, in conjunction with hurricane forecasts.

To do this, the event level information from the peril model is imported into a purpose-built ReMetrica model which is used to create a sample of 300,000 years of 'as-if' U.S. hurricane landfall events and loss. Some of these simulated years will have low hurricane activity, others high activity. For each 'as-if' year ReMetrica logs the contributing loss-producing events which are evident from their unique event identifiers.

These 300,000 'as-if' years are then split into three sets of 100,000 years with these sets being defined so that they are consistent with a high, medium or low forecast activity year.

A high activity year is defined as being in the most active third of historical years, medium as the middle third and low as the quietest third.

This splitting process allows for the unfortunate reality that forecasts can be wrong. The high forecast set will contain some years with no land-falling events, but will contain fewer such 'null years' than the medium and low sets. Similarly, the high forecast set will have more extremely active years than the medium set which will have more than the low set.

Hurricane forecasting quality

TSR's US hurricane forecasts demonstrate real skill, as reported in the cover story of the April 21, 2005 issue of the scientific journal, *Nature* (Figure 1).

Figure. 1: TSR's cover story, Nature magazine, April 21 2005. (See Saunders, M. A. and A. S. Lea, Seasonal prediction of hurricane activity reaching the coast of the United States, *Nature,* **434**, 1005-1008, 2005).

For the period 1950 to 2004 the rank correlation between the TSR August 1 hindcasts *(a hindcast is a forecast which would have been made at a prior time based on the climate data available at that time)* for US landfalling hurricane wind energy and actual US hurricane economic and insured losses is an impressive 0.48 – but what does this level of correlation mean in practice?

If we consider the period 1950 to 2004, TSR would have correctly predicted whether US hurricane economic losses were above or below the average (median) in 41 years out of 55 (75% of the years). For insured loss the percentage is an equally impressive 70%.

Figure 2 compares the August 1 TSR hindcast for US landfalling hurricane wind energy between 1950 and 2003 with the resulting US hurricane economic and insured losses. Hindcasts and losses are shown according to whether they are above median (red) or below-median (blue).

a Economic Losses

Year	Hindcast	Loss	$ mn
1992	-	+	44,014
1954	+	+	23,302
1955	+	+	17,548
1965	+	+	16,888
1960	+	+	16,236
1969	+	+	14,584
1972	-	+	14,258
1989	-	+	13,705
1979	+	+	11,489
1961	+	+	9,536
1964	+	+	9,377
1985	+	+	8,834
1999	-	+	6,346
2001	+	+	5,579
1983	-	+	5,395
1995	+	+	4,957
1996	+	+	4,635
1970	+	+	4,439
1998	+	+	4,414
1950	+	+	3,732
2003	+	+	3,580
1957	-	+	3,251
1967	+	+	2,726
1975	+	+	2,336
1991	-	+	2,279
1971	+	+	1,612
1994	+	+	1,367
2002	-	-	1,244
1980	-	-	1,151
1974	-	-	953
1959	+	-	594
1956	+	-	466
1968	-	-	425
1976	-	-	408
1958	-	-	296
1951	+	-	242
1966	-	-	219
1963	+	-	197
1984	+	-	173
1973	-	-	126
1997	-	-	123
1988	+	-	116
1981	-	-	102
1978	-	-	100
1990	-	-	99
1993	-	-	85
1952	-	-	84
1962	-	-	56
1977	-	-	44
1986	-	-	39
1953	+	-	37
1982	-	-	36
2000	-	-	30
1987	-	-	18

b Insured Losses

Year	Hindcast	Loss	$ mn
1992	-	+	29,597
1954	+	+	18,259
1965	+	+	13,922
1989	-	+	6,845
1964	+	+	5,885
1960	+	+	5,707
1970	+	+	5,522
1979	+	+	5,160
1983	-	+	4,729
1985	+	+	4,298
1961	+	+	4,202
1995	+	+	3,710
1950	+	+	3,701
1969	+	+	3,568
1955	+	+	2,946
2001	+	+	2,667
1996	+	+	2,514
1999	-	+	2,430
1998	+	+	2,044
2003	+	+	1,775
1957	-	+	1,422
1959	+	+	1,214
1972	-	+	1,157
1991	-	+	1,117
1967	+	+	1,073
1975	+	+	946
2002	-	+	648
1980	-	-	343
1956	+	-	332
1966	-	-	255
1984	+	-	162
1976	-	-	155
1971	+	-	147
1974	-	-	143
1968	-	-	117
1953	+	-	113
1986	-	-	84
1952	-	-	67
1993	-	-	57
1997	-	-	50
1988	+	-	23
1977	-	-	14
1963	+	-	5
1987	-	-	1
1951	+	-	0
1994	+	-	0
1981	-	-	0
1990	-	-	0
1973	-	-	0
1978	-	-	0
2000	-	-	0
1962	-	-	0
1982	-	-	0
1958	-	-	0

Figure. 2: Comparison of TSR hindcast US landfalling hurricane wind energy from August 1 and US hurricane damage 1950-2003. The comparison is shown for hurricane (a) economic losses and (b) insured losses. The yearly value of each parameter is colour-coded based upon whether it is above-median (red) or below-median (blue). Rows are stratified vertically by loss and referenced by year (left column). Losses are in US $ millions at 2003 prices and exposures.

Clearly there are some misses - the losses relating to Hurricane Andrew in 1992 being the most glaring example. However, it should be noted that Hurricane Andrew was a major event in a quiet year that was actually correctly forecast to be below average in terms of number of events. Such anomalies should not be allowed to mask the fact that most years are correctly predicted.

Creating the advanced output

Returning to the modelling process, with the three sub-sets representing high, medium and low forecast years in place, the next step is to produce adjusted peril model output consistent with the latest forecast.

The three 100,000 year data sets containing their unique peril model event identifiers are loaded into the purpose-built ReMetrica model and matched to the peril model's loss estimates (with secondary uncertainty where provided) for each event.

The latest TSR forecast probabilities of a high, medium or low season are entered into the model and the 100,000 simulated years are run. For each year ReMetrica takes samples from the high, medium and low sets in proportion to the probabilities given by the hurricane forecast.

For instance, the August 2005 hurricane forecast assessed there was an 85% probability of high activity, a 15% probability of a medium activity and a 0% probability of low activity. Accordingly, when using this forecast, 85,000 of the 100,000 years were selected from the high forecast set, 15,000 years from the medium set and none from the low set.

Figure 3 shows a typical model in ReMetrica Limited Edition, a reinsurance only version of ReMetrica which was launched at Monte Carlo in September 2005.

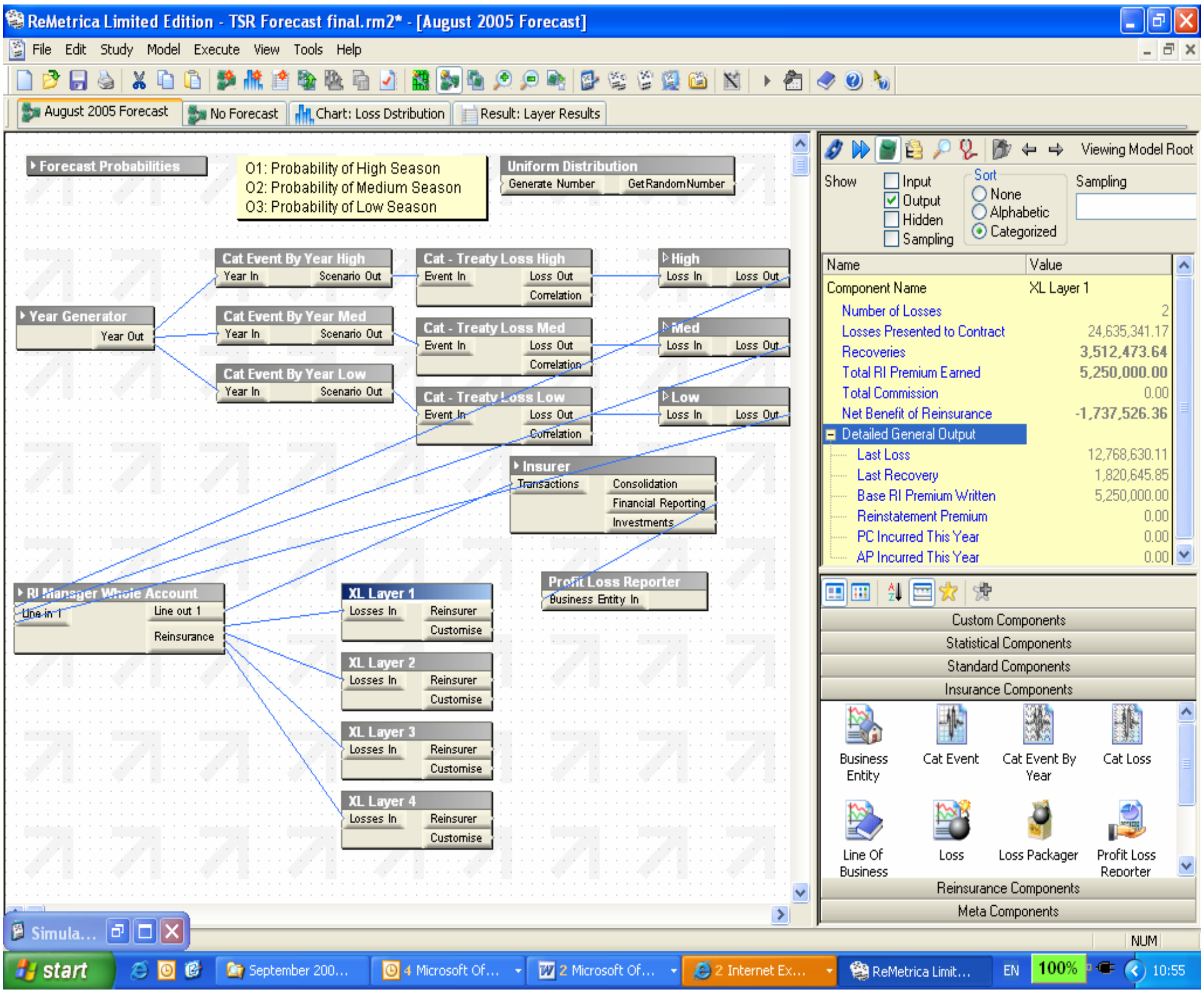


Figure. 3: ReMetrica Limited Edition – TSR Storm Forecast Model showing:

- Year generator
- 3 sets of 100,000 years consistent with high medium low forecasts
- Estimated loss amounts for each event
- Selected event subsets consistent with forecast probabilities
- Reinsurance
- Net and Gross Results

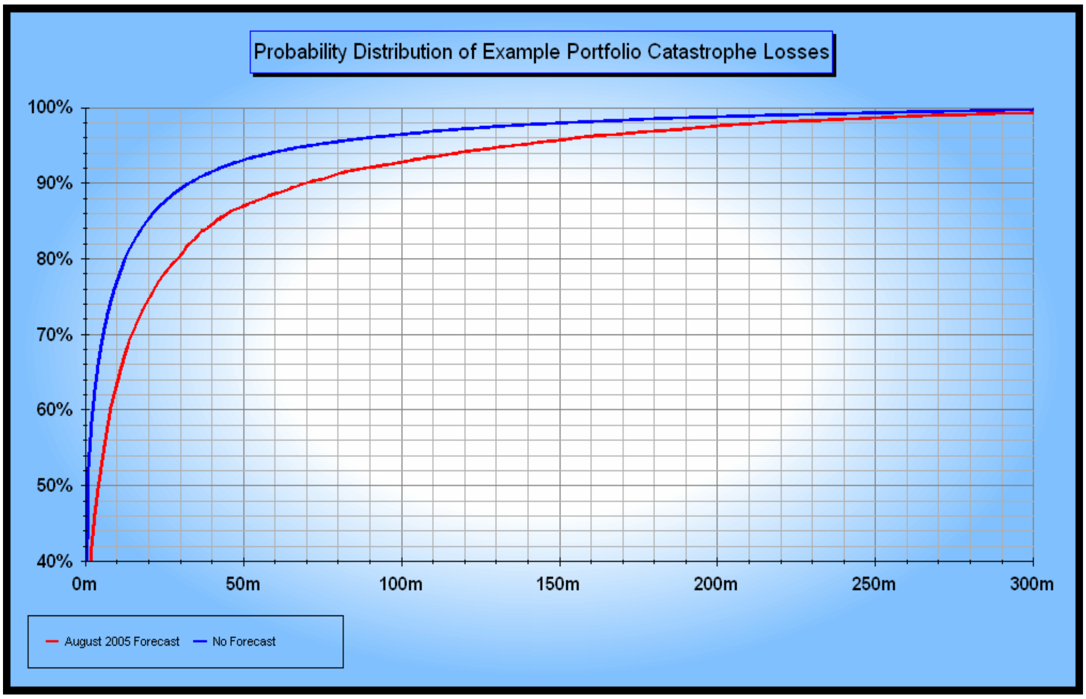
The model calculates revised average losses and extreme loss probabilities consistent with the current forecasts.

Assessing the true risk

But while this is all very interesting in theory, what does it mean in practice? To answer this we have used a sample portfolio to illustrate the impact of using the 2005 August forecast - the results are dramatic.

Looking first at the predicted probability distribution of individual hurricane losses (US only):

Figure. 4: Probability Distribution of Annual Hurricane Losses: The probability of any given loss amount is higher using the forecast information. For example there is only a 3.5% (100% - 96.5%) probability of losses over $100m ignoring the forecast but 7.1% taking the forecast into account.



In Figure 4 above, the red curve, which includes the TSR forecast, is significantly to the right of the blue curve which represents the unadjusted raw peril model output.

This means the probability of suffering a significant loss in 2005 is far higher than is implied by the output of the standard peril model. For example, prior to the adjustments for the 2005 hurricane forecasts, the peril model assesses the probability that the total hurricane loss will exceed US$100m as 3.5%. Once the hurricane forecasts are incorporated this probability doubles to 7.1%.

To further demonstrate the application of such models we have taken this output and investigated the impact on a typical reinsurance programme. The illustration is based on an actual insurer's programme, albeit simplified and scaled.

In this example, the insurer buys cover to a modelled 1 in 100 (or 1st percentile) level - roughly some US $225m if based on the unadjusted peril model output.

Table 1 illustrates the predicted results of the top and bottom layers of the insured's programme. The unadjusted column is the result using raw peril model output while the adjusted column reflects the impact of incorporating the TSR forecast.

Table 1: Effect of August 2005 hurricane forecast on a typical reinsurance programme.

Example Treaty Results	Bottom Layer			Top Layer		
	Unadjusted	Adjusted	Difference	Unadjusted	Adjusted	Difference
Mean	1,997,257	3,512,474	76%	1,541,385	3,199,050	108%
Standard Deviation	5,195,157	6,640,759	28%	10,804,913	15,490,591	43%
1 in 10 years	14,217,910	15,000,000	6%	0	0	
1 in 50 years	15,000,000	18,337,311	22%	25,821,164	90,000,000	249%
1 in 100 years	17,909,433	30,000,000	68%	90,000,000	90,000,000	0%
1st Limit : Prob Attach	16.378%	27.419%	67%	2.651%	5.374%	103%
1st Limit : Prob Exhaust	9.788%	17.573%	80%	1.043%	2.122%	103%
2nd Limit : Prob Attach	1.237%	2.509%	103%	0.025%	0.076%	204%
2nd Limit : Prob Exhaust	0.477%	1.036%	117%	0.003%	0.011%	267%
3rd Limit : Prob Attach	0.052%	0.127%	144%	0.000%	0.000%	
3rd Limit : Prob Exhaust	0.011%	0.038%	245%	0.000%	0.000%	

Clearly the performance of the programme looks radically different before and after the forecast. Estimated average recoveries increase by 76% for the bottom layer and more than double for the top layer.

The adjusted model also helps to assess the worth of 2nd or 3rd loss covers, a factor which is particularly valuable given that such purchases are often opportunistic. In this case the probability of attaching, and exhausting, each layer also increases substantially, so implying that the value of 2nd or 3rd loss covers becomes far more attractive.

But, as shown by the top layer 1st loss exhaustion probability, perhaps the single most crucial point is that the chance of exhausting the programme in 2005 is double that implied by the raw peril model. Is this a risk an insurer would be comfortable to take?

Summary

No forecast is exact, but can insurers and reinsurers afford to ignore the best advice available - especially when the growing evidence for global climate change is further feeding concerns that past experience provides an uncertain guide as to future exposures?

Advances in forecast skill and the availability of financial models like ReMetrica Limited Edition allow insurers to take “basic” peril model output and use it far more intelligently and pro-actively.

Wise insurers and reinsurers can now adjust peril model outputs to reflect the actual probabilities they are likely to face in the coming season, spotting opportunities and risks that others are unable to see or quantify.

Managers are better able to make informed decisions about whether to buy or write additional protections and, equally crucially, are armed with the necessary data to demonstrate to others why they have made their decisions - decisions that can be the difference between a company making a profit and loss … or even surviving.

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Hurricane Ivan approaching US landfall, September 2004 (courtesy NOAA).