Modelling insurance markets:
value of seasonal weather forecasts

Trevor Maynard
Phd Student at LSE (on the train) and Head of Exposure Management at Lloyd’s. But...

...these comments are personal views and do not necessarily reflect those of Lloyd’s

Not published yet, intend to present at Hurricane conference in June.
Some facts and stats

- 1960 - 1990 number of natural catastrophes doubled... insulated losses increased nearly seven times.
- Due (in part) to increased population in risky areas... but also due to an increase in the level of risk.
- 2005 was the worst year ever for property insurers
  - USD 95 bn dollars relates to the US hurricanes alone
  - the Lloyd’s incurred claims of USD 6 bn to help people hit by Hurricanes Katrina, Rita, and Wilma.
<table>
<thead>
<tr>
<th>Insured loss(^{\circ}) (in USD m, indexed to 2006)</th>
<th>Victims(^{\circ})</th>
<th>Date (start)</th>
<th>Event</th>
<th>Country</th>
</tr>
</thead>
<tbody>
<tr>
<td>71163</td>
<td>1858</td>
<td>25.08.2005</td>
<td>Hurricane Katrina: floods, dam, breast, damage to oil rigs</td>
<td>US, Gulf of Mexico, Bahamas, North Atlantic</td>
</tr>
<tr>
<td>24479</td>
<td>43</td>
<td>23.08.1992</td>
<td>Hurricane Andrew: floods</td>
<td>US, Bahamas</td>
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<td>22767</td>
<td>2662</td>
<td>11.09.2001</td>
<td>Terror attack on WTC, Pentagon and other buildings</td>
<td>US</td>
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<td>20276</td>
<td>61</td>
<td>17.01.1994</td>
<td>Northridge earthquake (M 6.6)</td>
<td>US</td>
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<tr>
<td>19940</td>
<td>136</td>
<td>06.09.2008</td>
<td>Hurricane Ike: floods, offshore damage</td>
<td>US, Caribbean, Gulf of Mexico et al</td>
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<tr>
<td>14642</td>
<td>124</td>
<td>02.09.2004</td>
<td>Hurricane Ivan: damage to oil rigs</td>
<td>US, Caribbean, Barbados et al</td>
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<tr>
<td>13907</td>
<td>28</td>
<td>19.10.2005</td>
<td>Hurricane Wilma: floods</td>
<td>US, Mexico, Jamaica, Haiti et al</td>
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<tr>
<td>11069</td>
<td>34</td>
<td>20.09.2005</td>
<td>Hurricane Rita: floods, damage to oil rig</td>
<td>US, Gulf of Mexico, Cuba</td>
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<td>9148</td>
<td>24</td>
<td>11.06.2004</td>
<td>Hurricane Charly: floods</td>
<td>US, Cuba, Jamaica et al</td>
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<td>8699</td>
<td>61</td>
<td>27.09.1991</td>
<td>Typhoon Noelle: No 19</td>
<td>Japan</td>
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<td>7918</td>
<td>71</td>
<td>15.09.1989</td>
<td>Hurricane Hugo</td>
<td>US, Puerto Rico et al</td>
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<tr>
<td>7672</td>
<td>95</td>
<td>25.01.1990</td>
<td>Winter storm Daria</td>
<td>France, UK, Belgium, NL et al</td>
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<td>7475</td>
<td>110</td>
<td>25.12.1999</td>
<td>Winter storm Lothar</td>
<td>Switzerland, UK, France et al</td>
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<tr>
<td>7305</td>
<td>54</td>
<td>18.01.2007</td>
<td>Winter storm Kyrill: floods</td>
<td>Germany, UK, NL, Belgium et al</td>
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<td>5857</td>
<td>22</td>
<td>15.10.1997</td>
<td>Storm and floods in Europe</td>
<td>France, UK, Netherlands et al</td>
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<td>5848</td>
<td>38</td>
<td>26.08.2004</td>
<td>Hurricane Frances</td>
<td>US, Bahamas</td>
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<td>5242</td>
<td>64</td>
<td>25.02.1990</td>
<td>Winter storm Viola</td>
<td>Europe</td>
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<td>5206</td>
<td>26</td>
<td>22.09.1999</td>
<td>Typhoon Bar: No 18</td>
<td>Japan</td>
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<td>4889</td>
<td>600</td>
<td>20.09.1998</td>
<td>Hurricane Georges: floods</td>
<td>US, Caribbean</td>
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<td>4398</td>
<td>41</td>
<td>05.06.2001</td>
<td>Tropical storm Allison: floods</td>
<td>US</td>
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<td>4074</td>
<td>45</td>
<td>06.09.2004</td>
<td>Typhoon Songda: No 18</td>
<td>Japan, South Korea</td>
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<tr>
<td>3999</td>
<td>125</td>
<td>26.06.2008</td>
<td>Hurricane Gustav: floods, offshore damage</td>
<td>US, Caribbean, Gulf of Mexico et al</td>
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<tr>
<td>3740</td>
<td>45</td>
<td>02.06.2003</td>
<td>Thunderstruck, tornados, hail</td>
<td>US</td>
</tr>
<tr>
<td>3677</td>
<td>70</td>
<td>10.06.1999</td>
<td>Hurricane Floyd: floods</td>
<td>US, Bahamas, Columbia</td>
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<tr>
<td>3631</td>
<td>187</td>
<td>06.07.1988</td>
<td>Explosion platform Piper Alpha</td>
<td>UK</td>
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<td>3530</td>
<td>69</td>
<td>01.10.1995</td>
<td>Hurricane Opal: floods</td>
<td>US, Mexico, Gulf of Mexico</td>
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<tr>
<td>3482</td>
<td>6423</td>
<td>17.01.1995</td>
<td>Great Hanshin earthquake (M 7.2) in Kobe</td>
<td>Japan</td>
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<td>3372</td>
<td>25</td>
<td>24.01.2009</td>
<td>Winter storm Klaus</td>
<td>France, Spain</td>
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<tr>
<td>3083</td>
<td>45</td>
<td>27.12.1999</td>
<td>Winter storm Martin</td>
<td>Spain, France, Switzerland</td>
</tr>
<tr>
<td>2917</td>
<td>28</td>
<td>10.09.1999</td>
<td>Blizzard, tornados, floods</td>
<td>US, Canada, Mexico, Cuba</td>
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<tr>
<td>2256</td>
<td>28</td>
<td>06.08.2002</td>
<td>Severe floods</td>
<td>UK, Spain, Germany, Austria et al</td>
</tr>
<tr>
<td>2195</td>
<td>28</td>
<td>20.10.1991</td>
<td>Forest fires which spread to urban areas, drought</td>
<td>US</td>
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<tr>
<td>2067</td>
<td>28</td>
<td>06.04.2001</td>
<td>Hail floods and tornados</td>
<td>US</td>
</tr>
<tr>
<td>2575</td>
<td>10</td>
<td>23.05.2007</td>
<td>Heavy rainfall, floods</td>
<td>UK</td>
</tr>
<tr>
<td>2545</td>
<td>30</td>
<td>18.06.2003</td>
<td>Hurricane Isabel</td>
<td>US, Canada</td>
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<tr>
<td>2498</td>
<td>30</td>
<td>05.09.1996</td>
<td>Hurricane Fran</td>
<td>US</td>
</tr>
<tr>
<td>2454</td>
<td>20</td>
<td>03.12.1999</td>
<td>Winter storm Anatol</td>
<td>Denmark, Sweden, UK et al</td>
</tr>
<tr>
<td>2448</td>
<td>41</td>
<td>11.06.1992</td>
<td>Hurricane Wilma</td>
<td>US, North Pacific Ocean</td>
</tr>
<tr>
<td>2361</td>
<td>21</td>
<td>29.08.1979</td>
<td>Hurricane Frederic</td>
<td>US</td>
</tr>
</tbody>
</table>

Chile EQ
New Zealand EQ
Winter Storm Xynthia

2010 update
Source Munich RE

Source: Swiss Re, sigma catastrophe database
The “near term” view

- Catastrophe modelling companies have offered conditional models
- Variety of names:
  - “Near term”
  - Warm SST conditioned
  - “Medium term”
- Typically a 5 year average
- Variety of procedures
  - Expert elicitation
  - Internal view
  - Weighted Ensemble Average
Simple model
The basic simulation examined in this paper is as follows:

- Simulate the number \((n_B \text{ from the random variable } N_B)\) of hurricanes that form in the North Atlantic Basin;
- Simulate the the number \((n_L \text{ from the random variable } N_L|N_B)\) of these that make landfall;
- Simulate the number \(n_C\) of these which hit a major city or commercial centre (see simple model below), from the distribution \(N_C|N_L;\)
- Simulate the saffir simpson strength of each storm that makes landfall \(sa_1, \ldots, sa_{n_L}\) from the iid random variables \(SA_1, SA_2, \ldots, SA_{N_L}\) - assume this is independent to landfall location, uniformly sample \(n_C\) of these, which are deemed to be the city hits, assume a 1-1 correspondence \((sa_i)\) between strength of a city hit and financial loss \((S_i = S(sa_i))\) distribution;
- Calculate the Premium charged (using a Krepps [1] formula) as \(P_0 = E(N_C)E(S) + 30\% \left( E(S)^2 \text{VAR}(N_C) + E(N_C)\text{VAR}(S) \right)^{\frac{1}{2}};\)
- Calculate the insurance (underwriting) profit as \(P_0 - \sum_{i=1}^{n_C} S_i.\)
In the control we’ll assume that $N_B \sim \text{poisson}(\lambda)$, where $\lambda = 7$, this is the average number of hurricanes per year since 1955 rounded up (to very approximately allow for over-dispersion, the true mean is 6.1 with a variance of 6.8). See the plot below which compares histogram of actual hurricane numbers to a poisson(7) distribution sample:

Figure 1: Histograms of actual hurricane counts per year (left) and simulated (right)

Assume that $N_L | N_B \sim \text{binomial}(N_B, q)$, where $q=24\%$ (based on HURDAT data).
A simple model of whether a major city is hit is defined as follows:

- The US east coast is around 12000 miles long;
- Assume that each hurricane falls into a ‘slot’ exactly 300 miles wide - so there are 40 such slots on the US coast;
- Assume there are 10 major population centres on the coast
- Say that each city is sufficiently far away from the others, so there is a zero probability of a hurricane hitting two - also assume that each city is in the middle of a coastline ‘slot’ (defined above);
- Assume that a hit on each coastal slot is equally likely, and therefore there is a 10/40 probability (call this ‘c’ below) that a landfalling storm will hit a major city - assume the loss would otherwise be zero.

Using the above model the number of city hits is \( N_C | N_L \sim \text{binomial}(N_L, c) \).

Or equivalently \( N_C \sim \text{poisson}(\lambda q c) \)
The landfall intensity distribution is calculated from the following table (based on HURDAT data from 1955 to 2009):

<table>
<thead>
<tr>
<th>saffir simson</th>
<th>landfall count since 1955</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>31</td>
</tr>
<tr>
<td>2</td>
<td>20</td>
</tr>
<tr>
<td>3</td>
<td>23</td>
</tr>
<tr>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>5</td>
<td>2</td>
</tr>
</tbody>
</table>

Assume the losses are related to saffir simson score as follows:

<table>
<thead>
<tr>
<th>saffir simson (sa)</th>
<th>loss S(sa) USDbn</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>3</td>
<td>15</td>
</tr>
<tr>
<td>4</td>
<td>70</td>
</tr>
<tr>
<td>5</td>
<td>110</td>
</tr>
</tbody>
</table>

- 2/3 rds of years have zero loss
- $P(Katrina \text{ size loss}=\text{USD40bn}) = 3.3\%$
  - ...(cf AIR 3%)
- $P(KRW=\text{USD80bn}) = 1/80$
$$N_L|N_B \sim \text{binomial}(N_B, q)$$

$$q = 24\%$$

<table>
<thead>
<tr>
<th>Saffir</th>
<th>Landfall count</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>31</td>
</tr>
<tr>
<td>2</td>
<td>20</td>
</tr>
<tr>
<td>3</td>
<td>23</td>
</tr>
<tr>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>5</td>
<td>2</td>
</tr>
</tbody>
</table>

$$N_B \sim \text{poisson}(\lambda)$$

$$\lambda = 7$$

- Generated?
- Landfalling?
- Where?
- How big?
\[ P_0 = E(N_C)E(S) + 30\% \left( E(S)^2 \text{VAR}(N_C) + E(N_C)\text{VAR}(S) \right)^{\frac{1}{2}} \]

Pricing variants:

1. Basin frequency known approximately – reduce line size
2. Basin frequency known approximately – change premium rate
3. Basin frequency known – change premium rate
4. Landfalling frequency known – change premium rate
5. Landfalling known, severity known approximately
1. Basin frequency known approximately – reduce line size

\[
f(n_B) = \begin{cases} 
\text{‘high’} & n_b > E(N_B) + k.\sigma(N_B) \\
\text{‘medium’} & n_b \in [E(N_B) - k.\sigma(N_B), E(N_B) + k.\sigma(N_B)] \\
\text{‘low’} & n_b < E(N_B) - k.\sigma(N_B) 
\end{cases}
\]

\( \sigma = \text{standard deviation, } k=0.4, \text{ so } n<6= \text{“low”}, \ n>8=\text{“high”} \)

<table>
<thead>
<tr>
<th>season frequency (f)</th>
<th>P(season frequency = f)</th>
</tr>
</thead>
<tbody>
<tr>
<td>low</td>
<td>30 %</td>
</tr>
<tr>
<td>medium</td>
<td>43%</td>
</tr>
<tr>
<td>high</td>
<td>27 %</td>
</tr>
</tbody>
</table>

Roughly symmetric

Company acts unilaterally….

\[
\text{underwriting profit} = \begin{cases} 
\frac{1}{(1 + \alpha_2)} \cdot (P_0 - \sum_{i=1}^{n_{L}} S_i) & f(n_B) = \text{‘high’} \\
(P_0 - \sum_{i=1}^{n_{L}} S_i) & f(n_B) = \text{‘medium’} \\
(1 + \alpha_1) \cdot (P_0 - \sum_{i=1}^{n_{L}} S_i) & f(n_B) = \text{‘low’}
\end{cases}
\]

In the experiment \( \alpha_1 = \alpha_2 = 10\% \).
2. Basin frequency known approximately
- change premium rate

Market acts together (else write no business?)

\[ P_2 = \begin{cases} 
P_0(1 + \beta_1) & f(n_B) = \text{‘high’} \\
\frac{P_0}{P_0} & f(n_B) = \text{‘medium’} \\
\frac{P_0}{(1 + \beta_2)} & f(n_B) = \text{‘low’}
\end{cases} \]

In the experiment \( \beta_1 = \beta_2 = 10\% \).
3. Basin frequency known
   – change premium rate

Here we assume the \( N_B \) is forecast accurately, i.e. that the insurer knows the number \( n_B \) of basin tropical cyclones in the year. In this case \( N_C \sim \text{binomial}(n_B, q.c) \)
Hence in this case (in a year where \( N_B = n_B \) the premium is calculated as:

\[
P_3 = q.c.n_B.E(S) + 30\% \left( E(S)^2.q.c.(1 - q.c).n_B + q.c.n_B.VAR(S) \right)^{\frac{1}{2}}
\]

Note in this case that \( P_3 | N_B \) is a random variable (i.e. varying each year), and that \( E(P_3 | N_B) \neq P_0 \).
Landfalling frequency known
- change premium rate

In this case we not only know the number of basin storms - but the number of them that go on to make landfall. In this case $N_C \sim \text{binomial}(n_L, c)$ and hence the premium is calculated as:

$$P_A = c.n_L.E(S) + 30\% \left(E(S)^2.c.(1 - c).n_L + c.n_L.VAR(S)\right)^{\frac{1}{2}}$$
Landfalling known, severity known approximately

In this variant we assume (as in variant 4) that the number and strength of landfalling hurricanes is known accurately but not which ones (if any) hit a city. Hence a potential loss $PL$ (an upper bound on possible losses) is known and this

$$g(PL) = \begin{cases} 
  \text{'high'} & p_l > E(PL) + k_3 \cdot \sigma(PL) \\
  \text{'medium'} & p_l \in [E(PL) - k_4 \cdot \sigma(PL), E(PL) + k_3 \cdot \sigma(PL)] \\
  \text{'low'} & p_l < E(PL) - k_4 \cdot \sigma(PL) 
\end{cases}$$

For this simulation we have set $k_3 = 0.63$ and $k_4 = 0.36$.

<table>
<thead>
<tr>
<th>landfall severity (s)</th>
<th>$P(\text{landfall severity}=s)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>low</td>
<td>35 %</td>
</tr>
<tr>
<td>medium</td>
<td>34%</td>
</tr>
<tr>
<td>high</td>
<td>31 %</td>
</tr>
</tbody>
</table>
Landfalling known, severity known approximately (continued)

5. Adjust pricing

\[ P_5 = \begin{cases} 
P_4(1 + \beta_3) & \text{if } g(pl) = 'high' \\
\frac{P_4}{1 + \beta_3} & \text{if } g(pl) = 'medium' \\
\frac{P_4}{(1 + \beta_3)} & \text{if } g(pl) = 'low'
\end{cases} \]

Note the use of $P_4$ in the above formula.

5b. Scale line size

underwriting profit = \[ \frac{1}{(1 + \alpha_4)}. \left( P_0 - \sum_{i=1}^{nL} S_i \right) \]

\[ \frac{P_0 - \sum_{i=1}^{nL} S_i}{(1 + \alpha_3).(P_0 - \sum_{i=1}^{nL} S_i)} \]

Note the use of $P_0$ in this case. In the experiment $\alpha_3 = \alpha_4 = 10\%$. 
Results
Control experiment – underwriting profits
Premium rates are lower, on average for more sophisticated methods... because lower std dev
Premium rates are lower, on average for more sophisticated methods...

..explanation

Consider for example variant 3. The premium formula for the control is:

\[ P_0 = q.c.\lambda E(S) + 30\% \, (E(S)^2.q.c.\lambda + q.c.\lambda \, \text{VAR}(S))^{\frac{1}{2}} \]

So,

\[ E(P_0) = P_0 = q.c.\lambda E(S) + 30\% \, (E(S)^2.q.c + q.c.\text{VAR}(S))^{\frac{1}{2}} \cdot \lambda^{\frac{1}{2}} \]

Compare this to,

\[ P_3|N_B = q.c.N_B.E(S) + 30\% \, (E(S)^2.q.c.(1-q.c).N_B + q.c.N_B.\text{VAR}(S))^{\frac{1}{2}} \]

So, since \( E(N_B) = \lambda \),

\[ E(P_3) = q.c.\lambda E(S) + 30\% \, (E(S)^2.q.c.(1-q.c) + q.c.\text{VAR}(S))^{\frac{1}{2}} \cdot E(N_B)^{\frac{1}{2}} \]

Now, the term \( q.c.\lambda E(S) = 5.42 \), is the same for both expectations and the term involving \( E(S)^2 \) is clearly lower for \( P_3 \) (due to the \( (1-q.c) \) term). In the specific simulation we have:

\[ 30\% \, (E(S)^2.q.c + q.c.\text{VAR}(S))^{\frac{1}{2}} = 2.061 \]

...compared to

\[ 30\% \, (E(S)^2.q.c.(1-q.c) + q.c.\text{VAR}(S))^{\frac{1}{2}} = 2.047 \]

In the particular simulation we have \( E(N_B^{\frac{1}{2}}) = 2.59 \) compared to \( E(N_B)^{\frac{1}{2}} = 2.64 \) but it is generally true that \( E(N_B^{\frac{1}{2}}) < E(N_B)^{\frac{1}{2}} \). In the particular simulation we therefore have:

\[ E(P_0) = 5.42 + 2.061 \times 2.65 = 10.88 \]

...compared to

\[ E(P_3) = 5.42 + 2.047 \times 2.59 = 10.72 \]

Therefore it is clear that the reason for the premium difference is due to the capital loading (the standard deviation part of the equation). In the case when we have more information (variant 3) the standard Kreps formula gives credit for the lower variance and hence calculates a lower premium.
Figure 6: Premium rates against number of Atlantic Basin hurricanes
Variant 3 lower triangle blank – if a given number of landfalling hurricanes has occurred at least that number of basin storms must have occurred (giving a lower bound on the premium)

Figure 7: Premium rates against number of landfalling hurricanes
Key point: even the most sophisticated methods give wide spread of premium rates – sometimes lower than the control.

But never lower than when the number greater than 2

Figure 8: Premium rates against number of city hits
Profitability (relative to control)

Premiums are on average lower

Not everyone can scale line size!
Capital requirements

spread of 0.5%ile relative to control

variant
Multi-year considerations

- These remarks in context...  
  .... typical strategy 3 years

- Pre-purchase materials? Resilience vs Optimal

- Inform building codes/ design standards

- Pre-decade preparation

- Tele-connections – changes in dependency in year

- Value of Climate Change Adaptation

- Social issues – impact of climate and man made issues (political unrest etc)
Social and other issues

- There is a lack of symmetry between positive and negative outcomes.
  - Can’t expose capital too far
  - Simple modelling suggests differential pricing could be less profitable; but may need less capital?
- Is more volatile pricing desirable?
- Formulaic use of forecasts – leads to systemic risk?
- Danger of too-accurate forecasts?
Questions?