J2.6 **WEATHER RISK ASSESSMENT AT THE DAWN OF ENSEMBLE NUMERICAL WEATHER PREDICTION**

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1. INTRODUCTION

Opportunities in the field of weather risk assessment continue to grow. Estimates that have been quoted in various media suggest that as much as 80 % of economic interests in the US should be considered sensitive to the atmospheric environment in some way. Weather risk can be divided more-or-less into two fundamental categories: extreme events and “regional climate anomalies”.

Examples of extreme events would include a hurricane, flood, or windstorm. Within the insurance industry and the media, such events are often referred to as “catastrophes”.

Regional climate anomalies are a consequence of weather that is both persistent (lasting weeks or months) and unusual for the region within which it occurs. The farther from normal weather conditions are, the greater the economic impact. Examples could include a drought, a heat wave or even a persistently cloudy season where the regional economy depends on a lot of sunshine. There are many other possibilities. Regional climate anomalies often include the contribution of extreme events (for example, a record-breaking cold wave); however, they may occur merely because of persistently “unseasonable” but otherwise unremarkable weather.

Traditionally, the potential costs of catastrophic risk, including those presented by extreme weather events, have been transferred, or dispersed, through various insurance instruments. This is true for both corporate interests and individuals. Understandably, the insurance industry has been interested in “catastrophic event” risk modeling and loss mitigation for a long time.

On the other hand, costs arising from regional climate anomalies have been borne by businesses under operational expenses. Recently, weather risk of this kind has begun to be addressed using financial instruments called “Weather Derivatives”, especially for the energy sector in the US. As energy markets have been deregulated, use of these instruments has increased. Weather derivatives are also beginning to emerge in other countries, especially in Europe.

Numerical Weather Prediction (NWP) models have played an important role in public safety and damage mitigation for extreme weather events for years. For example, for years they’ve been included as part of the “tool set” at NOAA’s National Hurricane Center to provide guidance in hurricane intensity, track and landfall forecasts. The emergence of ensemble NWP modeling technology has broadened the ways in which NWP models can be applied for weather and climate forecasts in general and in the area of weather risk assessment in particular.

2. BACKGROUND

Some background will be provided in this paper on weather risk assessment in the context of extreme weather events, or catastrophes. This is because it is anticipated that other contributors’ presentations in this session will be expanding on how weather derivatives can be used to “hedge” weather risk.

Within the insurance industry, a catastrophe is defined as any single event that causes insured damages exceeding $25 million. To the insurance industry, the advantages of risk modeling are manifest. An improperly insured catastrophe has the potential to bankrupt individual companies and adversely affect the industry in general. Few other events have the potential to impact company results so quickly or with such devastating results. Table 1 shows the ten largest insured losses resulting from weather catastrophes.

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TABLE 1

Year	Weather Event	Losses
1992	Hurricane Andrew (US)	19.1
1999	Storms Lothar-Martin (France Germany, Switzerland)	8.0
1991	Typhoon Mireille (Japan)	6.9
1990	Storm Daria (NW Europe)	5.8
1989	Hurricane Hugo (US, Caribbean)	5.7
1987	October Storm (UK, France)	4.4
1990	Storm Vivian (NW Europe)	4.1
1998	Hurricane georges (US)	3.6
1999	Typhoon Bart (Japan)	3.0
1972	Hurricane Agnes (US)	2.9

**(Insured losses billion $US. Source: Swiss Re Sigma, January 2000)*

Traditional actuarial methods usually require large, accurate historical data sets that are non-existent for weather-related catastrophes. In response, computer-based natural catastrophe (CAT) models began to be developed in the late 1980s. The first CAT model using a natural hazard basis estimated insured losses resulting from hurricanes making landfall on the US coast. It was not until after Hurricane Andrew in 1992 that they began to become widely used.

Combining the contributions of natural hazard and engineering-impact models (Figure 1), CAT models provide insurance and reinsurance companies a more sophisticated understanding of their risks than was possible previously. With an even modestly capable computer, a user can simulate thousands of storm scenarios. The result is a far more complete statistical picture of a range of potential-loss outcomes than can be obtained by conventional actuarial methods. Models of this type, often referred to as stochastic CAT models, are becoming increasingly sophisticated.

In recent years, firms have developed a new class of financial instruments (often referred to as "securitizations" or "CAT bonds") that transfer insurance risk to the capital markets. Approximately $12.6 billion capital-market risk transfers have been issued since 1996. A Swiss Re Sigma study sees a tenfold growth in insurance risk securitizations over the next decade. The study concludes that these securities have vast market potential. Annual issuance of catastrophe bonds, now about $1 billion, is expected to reach $10 billion by 2010.

CAT models have also been developed for real-time extreme weather events (Figure 2). Short-term CAT predictions provide information

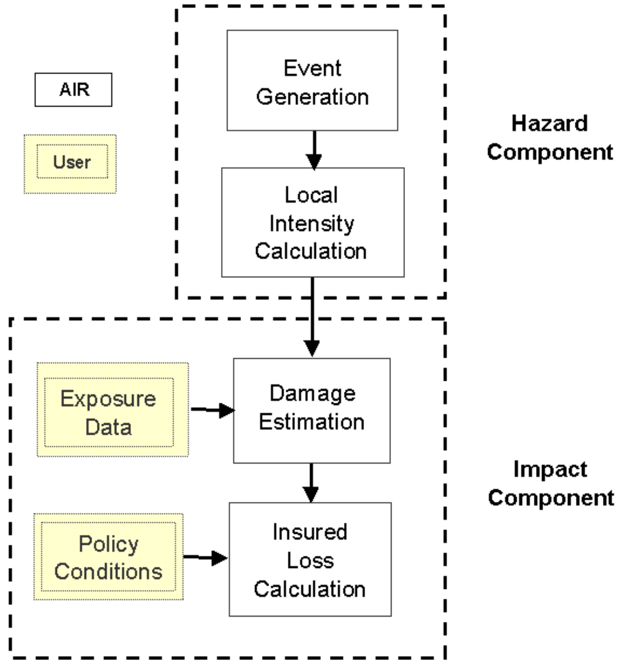

Figure 1. The CAT model loss estimation process.

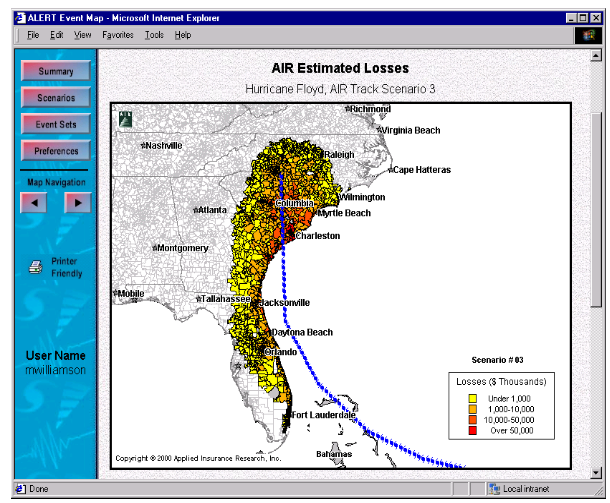

Figure 2. Real time access of loss estimates through the Internet.

that is used to reduce the costs associated with damaging storms. Preventable costs include increased efficiency in the assignment of claims adjusters, liquidation of assets (to raise cash to settle claims) and documentation of damage. Real time CAT model implementations lend themselves well to traditional applications of NWP models.

3. QUANTIFYING FORECAST UNCERTAINTY USING ENSEMBLE NWP MODELS

That NWP models have inherent uncertainty has been known for at least 40 years (Lorenz, 1963). Within a few years, this revelation was reflected in operational weather forecasts that included some gesture toward a probabilistic interpretation. One early example is the "chance of" percentages that have commonly accompanied US National Weather Service forecasts since the 1960s. Another example is “model output statistics” (MOS) in which model-predicted outcomes are statistically related to observed outcomes for a large number of forecasts.

The level of uncertainty is related to atmospheric predictability. It is well established that the atmosphere’s predictability is not constant, but depends on its initial state. Figure 3 illustrates the phase-space evolution of uncertainty on the Lorenz (1963) attractor for two different initial conditions. NWP model forecasts provided as an ensemble provide a probability distribution of possible future outcomes.

Techniques for quantifying the economic value of probabilistic forecasts in the decision-making process have been developed over the years. Recently, an international team of those working on this topic has submitted a review paper to the Bulletin (Zhu, et al., 2001). A comprehensive development on this subject in the more general context of predicting uncertainty can be found in Palmer (2000).

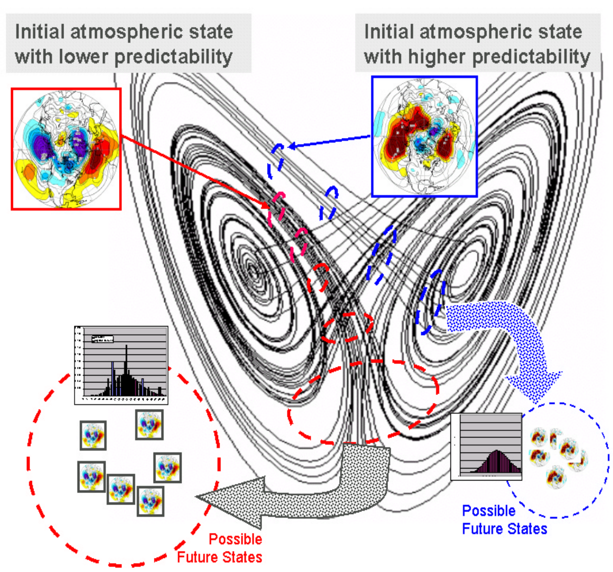

Figure 3. The Lorenz (1963) attractor.

Decision models based on cost-loss analyses of probabilistic NWP model output lead to the result that precautionary measures should be taken if

$$P > C/L_p.$$

Here P is the *calibrated* probability of occurrence (caused by the extreme events or anomalous conditions discussed earlier), C is the cost of taking the precautions and L_p is the preventable loss suffered because precautionary measures were not taken. An example of a preventable loss might be the difference between the higher cost of raising cash to pay for losses immediately after a catastrophe minus the lower cost of raising cash well before it is needed. In practice, individual organizations would determine the appropriate cost-loss ratio C/L_p criteria depending on their own situations.

It is important that the probability of occurrence be calibrated. What this means is simply that when 10 % of an ensemble’s members are predicting an event to occur, they have historically verified 10 % of the time. It should also be understood that the advantages of this approach, in many cases, would only be realized by applying it over time.

Another appealing aspect of decision models based on the cost-loss analysis theory is that it provides the highest value when the cost-loss ratio, C/L_p*, is near the climatological frequency.* It is reasonable to assume that the economic system in general, and the insurance industry in particular, are “tuned” to minimize losses based on the climatological frequency of extreme events and climate anomalies. This implies that the cost-loss ratio C/L_p (and the decision probability threshold, P) should be relatively well defined in most cases.

It is possible to apply the $P > C/L_p$ decision rule to “deterministic” forecasts based on probabilities estimated from MOS. For example, over many years whenever an NWP model has predicted a maximum wind speed at some location of 30 m/s, the observed speed exceeds 20 m/s 80 % of the time. The uncertainty associated with this traditional approach is generally higher since the statistics are applied to atmospheric states with both higher and lower predictability. Some improvement may be possible with MOS applications that include the conditional climatology of analogue initial conditions, but ensembles can account for the predictability of the current atmosphere more directly.

4. NWP MODEL ENSEMBLES AND WEATHER RISK ASSESSMENT: DEFINITIONS OF CLASS 1 AND CLASS 2 APPLICATIONS

Since uncertainty is fundamental to quantifying the state of atmosphere, a probabilistic framework can be considered appropriate, if not practical, for many NWP model applications. In this context, the notion of deterministic prediction is defined as the ability for an NWP modeling system to simulate the evolution in both the phase and amplitude of an important feature (or features) of the atmospheric circulation accurately.

The theoretical limit for deterministic prediction depends on how well the forcing, internal or external, responsible for a particular feature is known. How well the forcing is known depends on the nature (i.e., its forcing mechanisms, spatial and temporal scale) of the feature under consideration. For example, for transient internal eddies, such as the frontal waves and extra-tropical cyclones, the limit is about ten days. On the other hand, regional climate anomalies are often a result of a forced circulation. The best known examples are regional anomalies that result from changes in the large-scale atmospheric circulation forced by the El Nino – Southern Oscillation (ENSO) phenomenon.

Unfortunately, at the current state of modeling technology, no forcing mechanism can be quantified accurately (with perhaps the exception of the annual solar cycle) beyond one year. After about one-year, all forcing mechanisms dealt with in the NWP model become internal and the model is, effectively, a General Circulation Model (GCM). While a NWP model used as a GCM can be useful as a heuristic tool for understanding the Earth-atmosphere system, it has less value as a predictive tool, since all forcing mechanisms are artifacts generated internally by the model physics.

It is convenient to divide ensemble NWP model applications into two general classes: those that produce probabilistic predictions and those producing probabilistic statistics of important weather elements. The former class of applications, where the forcing mechanisms for a feature of interest are well defined, corresponds to an extension of traditional deterministic NWP model techniques into the formal probabilistic framework. One example of the latter class of applications would be determining how the mid latitude storm-climate is affected by surface anomalous (of which the ENSO phenomenon mentioned earlier is an extreme example).

4.1 *Examples of Class 1 Applicatons: Prediction of Individual Extreme Events*

Ensemble NWP model output is available from the National Centers for Environmental Prediction (NCEP) via the Internet. NCEP's Medium Range Forecast (MRF) model ensemble system runs twice per day at 00Z and 12Z. In addition to the standard 2.5°X2.5° grid, there is a high-resolution model 1°X1° grid. High-resolution MRF ensembles consist of 12 members for the 00Z cycle and 11 members for the 12Z cycle.

These files are in GRIB format. The easiest way to extract data from them is to use a utility called wgrib. Wgrib has versions that run on various computers, including computers with Windows and UNIX operating systems.

These data sets provide an opportunity to add value to real time loss estimates (Figure 2). One example, in which an ensemble of hurricane tracks has been created using high-resolution MRF ensemble model output for a hypothetical storm, is shown in Figure 4. Using an ensemble of tracks landfall probabilities can be estimated (Table 2).

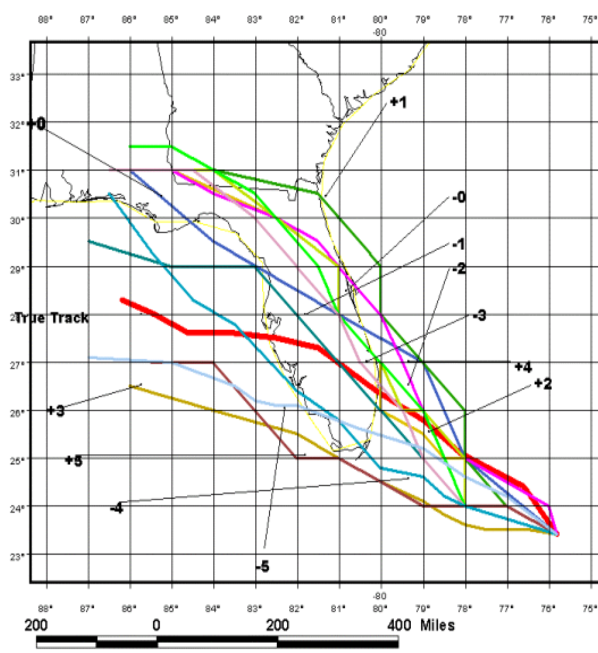

Figure 4. Ensemble of hurricane tracks determined from 12-member high-resolution MRF ensemble model output.

TABLE 2

Latitude Band	Landfall Probability
24° - 25°	0.250
25° - 26°	0.083
26° - 27°	0.417
27° - 28°	0.083
28° - 29°	0.083
29° - 30°	0.000
30° - 31°	0.083

Organizations choosing to invest in an in-house ensemble NWP modeling capability have more flexibility. By having complete control of this technology, model-system attributes such as resolution, sampling rate, model physics and number of ensemble members can be set depending on end-user requirements.

A 16-member sample of maximum-wind speed fields for the great European windstorm Daria from AIR's 55-member ensemble NWP model is shown in Figure 5. In January 1990, storm Daria devastated northwestern Europe (see Table 1). If impact models (Figure 1) are adapted to accept ensemble output, probability distribution functions (PDFs) can be produced. Figure 6 shows the PDF resulting from the loss distribution calculated using the 55-member Daria ensemble. The median loss for this ensemble was $6.3 billion.

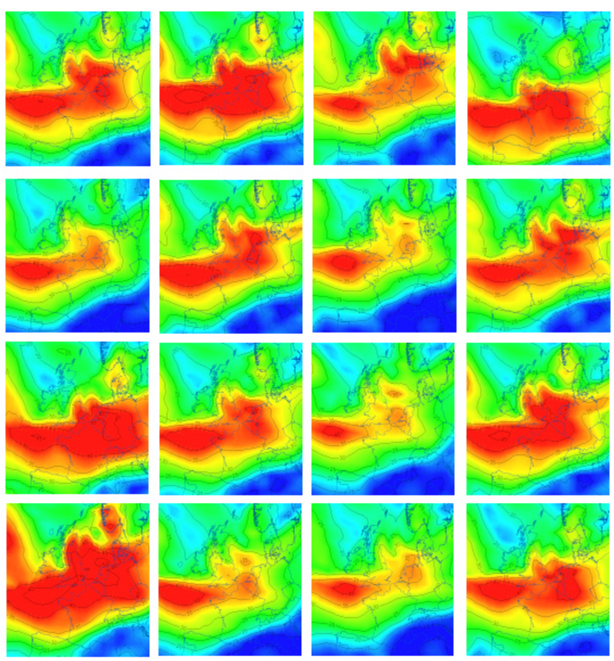

Figure 5. A subset of a 55-member ensemble of maximum wind speeds occurring during storm Daria (January 1990).

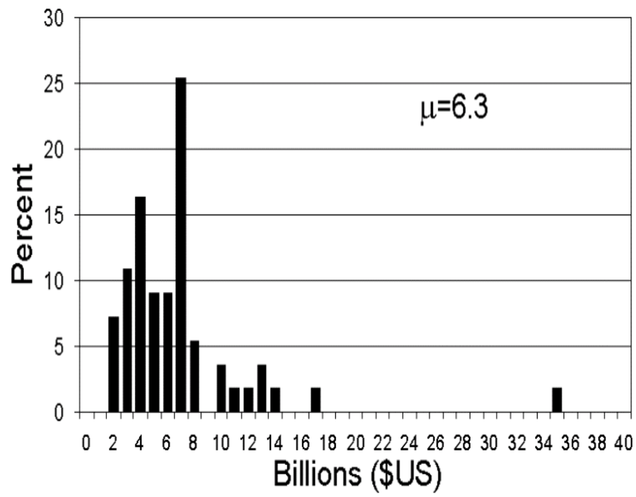

Figure 6. PDF of insured losses for storm Daria.

While most losses for this case cluster near the median, there is one notable exception. One of the results indicated insured losses in excess of $35 billion. This example illustrates an important aspect of extreme events. Very large ensembles must be generated to resolve events of this type appropriately. Although one of the 55 members indicated this enormous loss, it does not necessarily mean that there was a 1 in 55 (0.018) probability of occurrence. A much larger number of members would need to be used to resolve its probability with more certainty. Losses of this magnitude might never occur again were the ensemble increased, for example, to 10,000 members. In that case, its probability of occurrence would be reduced to 0.0001.

4.2 *An Example of Class 2 Application: Regional Extreme-Event Climate Models*

Regional climate models (RCMs) are NWP models that are nested in global-scale models. Since RCMs are run at a higher resolution than global scale models, they can be effective in determining statistics for smaller scale phenomena. This is often referred to as "down scaling". RCM applications have been developed to down scale both prognostic and global data-assimilation climate models. The example discussed here will involve an application of the latter case in order to enhance the hazard component of a stochastic CAT model (Figure 1).

While there are several global data-assimilation climate models, perhaps the best known is that of the National Center for Atmospheric Research (NCAR) and NCEP. (Kistler, et al., 2001). One motivation for the global reanalysis project is to use a single data assimilation technique and archived data to produce the most accurate and statistically stationary record of the atmosphere possible. Other global reanalysis model projects include those at the European Centre for Medium-Range Weather Forecasts (ECMWF) and NASA Goddard.

Data from the global reanalysis data is used to produce "canonical ensembles" of windstorms caused frontal cyclones affecting the European region. Canonical ensembles are families of events spawned from historical storms having similar, specific characteristics. The canonical storm events "captured" in the assimilation model process reflect the storm environment in this region over the past few decades (Figure 7). Slight perturbations to the state-of-the-atmosphere variables at the time of these events can change the trajectory of development significantly (see

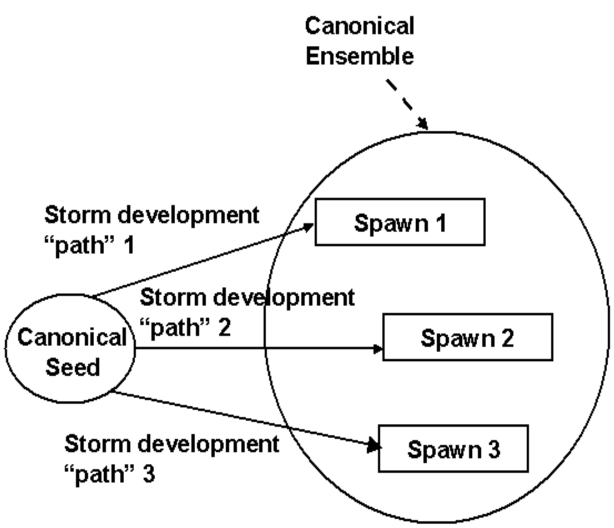

Figure 7. Schematic showing how statistics of European regional storm climate can be captured in the global reanalysis model data set.

Figure 3). A large ensemble of storm events (many thousands) can be generated, some of which will be stronger and others less strong than the historical seed events captured in the global reanalysis model data (Figure 8). Very large ensembles are practical for Class 2 applications because they need not be created in real time.

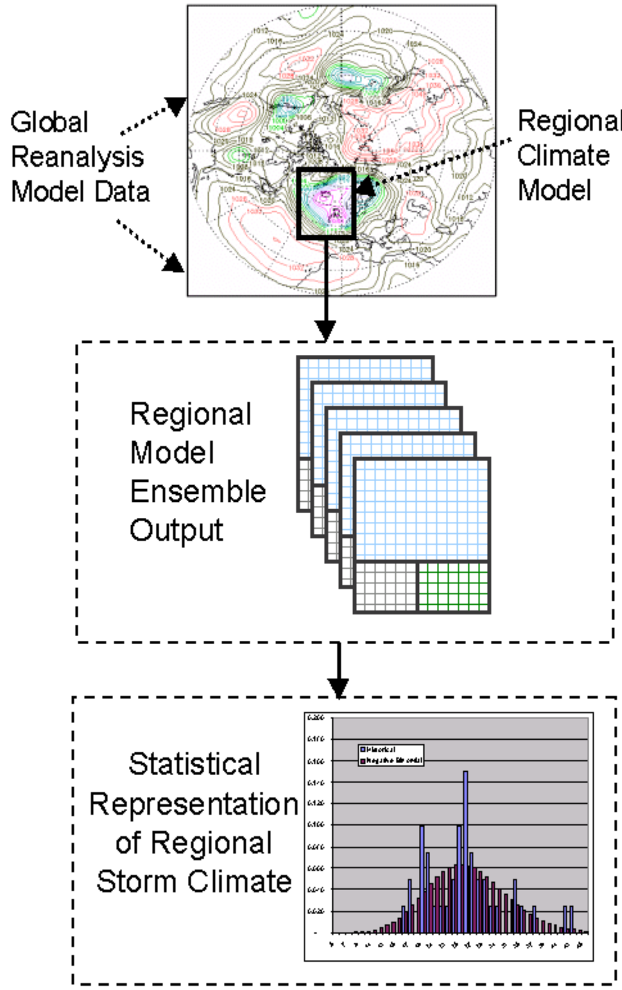

Figure 8. Schematic illustrating the canonical ensemble generation process

In one particular Class 2 application, a "generalized" reanalysis storm-wind climate for 10,000 years has been created to provide the hazard component of the "stochastic" CAT model using 40 years (1958-1997) of NCAR/NCEP reanalysis model data. Using an NWP model allows for the generation of storms that are more intense than those observed. An NWP model can also limit the intensity of potential storms through dynamical and physical constraints. Figure 9 shows the maximum-annual wind speed, down-scaled using the RCM to a 10-km footprint and an equivalent three-second gust at 10 m. It can be seen that the 40-year historical profile can be considered a subset of a generalized 10,000-year reanalysis climate.

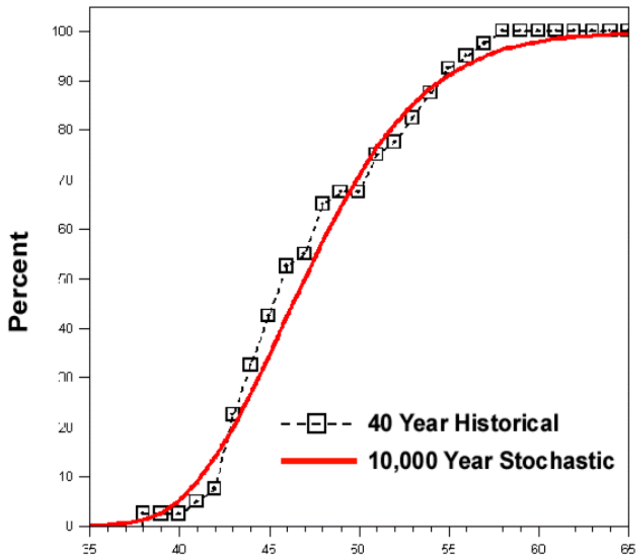

Figure 9. Exceedence distribution of maximum annual wind speeds for the 40-year and generalized reanalysis-model wind climate for northwest Europe.

5. SUMMARY

In the changing world of insurance risk management, catastrophe (CAT) models are moving to the center of quantitative weather risk assessment. These models offer significant benefits for the companies that use them through automation, and the ability to manage risks and set rates proactively. Because these models help insurance companies to better understand the complexities of their risks, they can allocate capital more efficiently than before and remain more competitive.

Ensemble NWP modeling provides the means to quantify forecast uncertainty. Using the output from the ensemble members, a probability density function (PDF) of potential losses can be created. Further, once the performance and reliability of an NWP ensemble model forecast system is characterized, its economic value as a function of cost-loss ratios (C/L_p) can be determined.

Two classes of ensemble NWP model applications have been defined for CAT loss estimation. “Class 1” applications can provide probabilistic loss forecasts for real-time extreme events. “Class 2” applications involve the characterization of the losses that would be expected within a region’s natural climate variability (often referred to as “regional loss profiles”). An example for each was discussed. Other Class 1 applications include medium range (three to seven day) predictions of individual events. Class 2 applications would include alternative regional loss profiles created from seasonal climate predictions.

CAT models are continuing to become more sophisticated, and some have begun to incorporate NWP modeling technology. As the cost of computers and networks decreases, the insurance industry should find that the benefits of ensemble NWP modeling technology more cost effective.

6. REFERENCES

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