AN EVENT-BASED MODELLING APPROACH FOR ASSESSING DOWNBURST RISK TO STRUCTURES

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ABSTRACT

This paper proposes a stochastic event-based modelling approach for estimating downburst wind hazard. Unlike existing models it makes use of large scale atmospheric information to build upon observational records so that a broad range of input model parameters can be generated. Coupling this information into such a model means it may be applied in regions where no observational records currently exist, or they are of poor quality. Progress towards full model development has thus far focused primarily on the methodological approach required to couple atmospheric and observational data so that input model parameters can be developed. An example of this coupling is provided for the south east Queensland region of Australia, and estimates of annual downburst-producing storm counts are generated. This example shows the proposed model can reasonably replicate historic trends in mean annual event counts, but was unable to capture the full inter-annual variability in these counts. Future work will refine this approach and continue to develop the full hazard/risk model.

KEYWORDS

Downburst, wind, reanalysis, wind risk, wind hazard.

INTRODUCTION

Localized high intensity wind storms (downbursts) damage buildings and infrastructure throughout the world every year. Transmission line networks are particularly vulnerable to this type of wind storm and numerous large-scale failures have been reported (Letchford and Hawes 2000, CIGRE 2012). Figure 1 shows an example of such a failure (CIGRE 2012). In fact, downbursts, as opposed to larger scale cyclones, govern the wind statistics of importance for the design of a range of structures in many parts of the sub-tropical world (Holmes 2002). Unfortunately though, given the small spatial and temporal scale of these wind storms most measurement station records do not capture enough events to allow reliable extrapolation of wind statistics out to return periods of interest for structural design. A similar problem exists for extrapolation of tropical cyclone (hurricane, typhoon) wind statistics, but for these storms simulation-based methods have been utilized to better understand their low probability wind characteristics (e.g. Vickery et al. 2009, Yeo et al. 2014). It is proposed that similar methods could be employed to reduce (or simply quantify) the uncertainty in estimates of downburst wind hazard and risk.

In this paper an event-based modelling approach is proposed as a tool for improving understanding of wind hazard posed by severe downburst wind storms. Techniques used for tropical cyclone wind hazard estimation are modified here for application to downburst events. While many of the same concepts can be applied, downbursts are spatially and temporally quite dissimilar and must be treated differently in some respects. An example of such a difference is the sourcing and reliability of baseline data upon which any model could be built. Little information is often available for describing a region's downburst climate, and even for areas where this information is available it is often subject to observational or methodological biases that must be removed from records. As such a greater reliance on inference is required for model parameter development.

The proposed downburst hazard assessment methodology is based on event-based simulation of each storm's wind field. Unlike existing models, a method for coupling simulations with large-scale climate information is proposed so that assessment can be carried out in regions where data records are poor or non-existent. Each component of the proposed modelling is discussed and their relative strengths and challenges described. Progress to date has focused on developing a method for coupling climate information with event observations and will be discussed in some detail. Results for the south east Queensland region of Australia will be used as a case study.

Figure 1 Cascading failure of transmission lines during localized wind storm, Spain (CIGRE 2008).

BACKGROUND

Downburst Risk Models

A limited amount of research has been undertaken on probabilistic or stochastic modelling methods as applied to downburst winds. Li (2000) developed a stochastic model that simulated the interaction of downbursts with transmission line segments. Each downburst was simulated as a triangular pulse signal and required information on downburst frequency, wind speed and path length to be input. In doing this Li (2000) highlights that the difficulty in stochastic modelling of these events lies in the fact that downbursts occur (at any given point) randomly in time, and given their small spatial scale, may not load the structure or system of interest; even if only separated by small geographic distances.

Oliver et al. (2000) also developed a model for assessing risk to transmission line networks. Instead of considering the downburst as a temporal pulse though, they simulate it as a 2 dimensional spatial 'footprint' as defined by Holmes and Oliver (2000). This has the benefit that it allows the spatial dimensions of the downburst to be considered, but does require this additional layer of information to be fed into the model. Oliver et al. (2000) also provide a list of assumptions that simplify their model, negating the need for a complete understanding of all downburst characteristics. These simplifications have made their model widely useable and as such has been utilized by the transmission line industry (CIGRE 2008).

Letchford and Hawes (2000) applied the Oliver et al. (2000) model to undertake a risk assessment of the transmission network across Queensland. As a simplifying assumption they imposed a conceptual failure velocity for each transmission tower of 35-45 m/s. By assessing exceedences of this threshold the failure probability of different parts of the network could be assessed. In doing so they found failure estimates far exceeded the number of observed failures, but did find that the relative risk was accurately simulated. The authors suggest the reason for the overestimation of absolute failure risk is due to conservative estimates of extreme wind distributions within the model, as well as a general conservative design and construction process within the transmission line industry.

Harper and Callaghan (1998) also developed a downburst risk model for the south east Queensland region, but in their case it was for use by the insurance industry. This model conceptually appears to be similar to that of Oliver et al. (2000), but includes a time component to the downburst events. Additionally, multiple downbursts can be simulated for each event; as often occurs in reality. Comparison with wind records at the Brisbane Airport show good agreement with modelled results, and given the extensive effort the authors put into accurate characterization of the regional climatology, the positive comparison highlight the importance of using high quality meteorological information to inform model development.

Assessing the wind climate in Brazil, Ponte and Riera (2010) developed a Monte Carlo based approach for simulating downburst wind events using the wind field model described in Ponte and Riera (2007). Similar to the Harper and Callaghan (1998) model they sample a range of storm parameters that influence the resultant surface wind conditions and simulate a large number of plausible storm events impacting a given region over a predefined time period. Comparing output from their model with observational data at two sites in Brazil they find reasonable replication of wind speed distributions. However, given many of the important storm variables (and their distributions) used to drive their model are only approximated, the resultant wind climate is not well enough replicated to make it suitable for structural design or risk assessment application without further refinement.

Relationship between Environmental Parameters and Severe Storms

The occurrence of downbursts is generally poorly recorded. Some information can be inferred from anemometer records (Lombardo et al. 2009), but extraction is not straightforward and is only available (in a statistical sense) when an anemometer has been operational for an extended period of time. This is not a problem confined to estimation of wind statistics, most attempts at estimating any severe storm climatologies (e.g. tornado, hail) run into observational bias issues and inference or smoothing techniques are required to arrive at a solution.

Brooks et al. (2003), based on weather forecasting practice, proposed a method that uses large scale weather information output from global reanalysis models (e.g. Dee et al. 2011) to assess the relative frequency of severe storm activity across large areas. In essence they used spatially and temporally uniform (globally) historical reanalysis databases to develop pseudo severe storm climatologies. This was done by looking back through the simulated climate records to find times when large scale climate indicators suggestive of storm activity were present. Typically the joint occurrence of both high atmospheric instability and high values of shear were considered necessary for storm development, and so convective available potential energy (CAPE) and atmospheric wind shear have typically been used as indicators. Numerous researchers have since used similar techniques to assess severe storm climatologies across broad regions to assess spatial, cyclic and long-term occurrence of these events (e.g. Allen et al. 2011, Brooks 2009, Grunwald and Brooks 2011).

While this approach is useful for application to estimating the relative frequency of downburst events, it must be modified to account for the fact that not all days when the environment for storm activity existed led to downburst event/s. This can be done by 'training' the approach in regions where high fidelity observational records exist, so that the relative risk assessment approach discussed above can be used in an absolute sense. By doing this, large scale climate information previously unused by engineering-based risk models can be fully coupled into these assessments. This is useful not only for event frequency information, but supporting data for estimates of storm intensity and tracking can also be drawn from reanalysis data, as will be discussed in section 3.1.

PROPOSED MODELLING APPROACH

The proposed approach for modelling downburst wind hazard follows that used by researchers for assessing tropical cyclone wind hazard (e.g. Vickery et al. 2009, Yeo et al. 2014). It conceptually divides the modelling process into pre-, model and post- modelling tasks, with the former designed to estimate the climatological information needed to inform the model itself, based on the coupled reanalysis-observation data approach, and the latter encompassing a statistical analysis and validation of the model output. The sequential set of modelling steps required for assessing the downburst hazard in a given area are:

1. Pseudo-climatology development (Pre)
2. Event genesis modelling (Model)
3. Event/downburst track modelling (Model)
4. Wind field modelling (Model)
5. Statistical analysis and validation (Post)

Each step is described further in the following sections, with the results of work carried out towards step 1 discussed in the Results section of this paper.

Pseudo-climatology Development

Due to the lack of reliable climate information, a pre-modelling step is required to develop the pseudo-climatology from which statistical parameters necessary for modelling can be drawn. Global reanalysis data is coupled with high fidelity observational records to hindcast a pseudo-downburst climate for a given period of time. Probabilistic estimates of annual (or sub-annual) event frequencies, track direction, forward speed and downburst intensity can be drawn from this pre-modelling step to inform steps 2 and 3.

The approach for estimating downburst event frequencies is based on the concept that the probability a downburst will occur can be conditionally assigned based on the presence of large scale environmental conditions. These conditions may be as simple as a surface wind speed above a defined threshold, or as complex as integrals of multiple variable through the atmosphere. However, as discussed earlier, the most widely used predictors are atmospheric instability and vertical wind shear (i.e. the difference between winds at ground level and those at an elevation in the atmosphere). For this paper two commonly used versions of these predictors (indices) are used, Lifted Index (LI100) and Deep Vertical Wind Shear (DVWS) (Mason and Klotzbach 2013).

To build the pseudo climatology, dates and times of downburst observations within a given spatio-temporal domain are extracted and the associated atmospheric indices calculated using the reanalysis database. By doing this a bivariate probability density function (or frequency histogram) can be developed describing the environments conducive to downburst occurrence. Dividing this by the parent histogram for that region then allows an empirical estimate of the probability an event will occur conditional on the joint occurrence of LI100 and DVWS. These probabilities allow estimates of the mean annual number of downburst events given the joint occurrence of variables in the parent reanalysis database. This can be done for a broader area and longer time period than observations alone would allow. Additionally it potentially allows estimates of future hazard using climate change projections.

In addition to calculating indices, storm movement can be inferred using known relationships with upper level winds sourced from the reanalysis database. When coupled with observations, this data can be used to determine conditional probabilities (based on the event occurring) for storm direction and movement speed. These probabilities must be tied back to the information within the parent distribution so that inference can be made on these variables in the absence of observational data.

Maximum downburst intensity is more difficult to estimate. Initially, however, the approach taken by other researchers (e.g. Allen et al. 2011) may be a sensible start. Given there is great uncertainty in estimates of storm maximum wind speeds, even for well recorded storms, intensity can be classified into two sub-categories, severe and significant severe. This is done based on the exceedance or not of a given threshold (typically around 34 m/s) by the recorded or estimated maximum downburst wind speed. This allows for events where damage survey work has determined stronger wind speeds than recorded at anemometer sites to be more suitably classified. Some judgement about the distribution of events within each of these subsets will still be required, but it does allow more information stored within the reanalysis data to be drawn out than simply assuming a distribution of maximum intensities for the entire family of downbursts. Globally there is still a lack of understanding about the distribution of maximum wind speeds for a family of downburst events and further research is required.

As a final point, all the analysis described in this section should be done on a sub-annual basis. Downbursts occur under different meteorological conditions throughout the year and as such the indices that best estimate their occurrence will also differ on these timescales.

Event Genesis Modelling

Using event frequency information derived from step 1, generation of events within a defined spatial domain can be simulated assuming a Poisson process. A similar approach to this was used by Haigh et al. (2014) (and many others) for modelling tropical cyclone occurrence around Australia. For estimating long-term wind statistics this is a suitable approach. However, if the inter-annual variability is of importance (e.g. for considering fluctuations in loss statistics), clustering of events (i.e. non-independence) may also need to be considered. Analysis of the independence of events and the suitability of a Poisson sampling process can be done, again, by analyzing the occurrence of indices (or joint indices) in the reanalysis database. Allen and Karoly (2013) undertook a similar assessment to ascertain the role of ENSO on the occurrence of severe storms in Australia, and a similar procedure could be followed here.

Depending on the way a genesis model was spatially developed, some weighting of event genesis location may be required. This would be required because there exist non-meteorological features, such as topography, that play an important role in determining where severe storms generate and track. Research is again needed to determine how topography (likely coupled with wind direction and moisture content) influences genesis, but empirically the observational set of downbursts discussed earlier could be coupled with radar analysis, topographic, and reanalysis data to inform this relationship.

Event Track Modelling

To a first approximation, bulk storm movement is linear. Given downbursts are relatively short lived, their tracks can also be approximated as linear segments. Fujita (1985) shows that this is not always the case, but for the current modelling procedure it is considered representative. This also follows the inherent assumptions made by Holmes and Oliver (2000) and Oliver et al. (2000) when deriving and applying their downburst wind footprints. Following, given the movement of a storm is predominantly driven by bulk winds in the upper atmosphere (though systematic deviations do occur), these data should be drawn from a reanalysis database to inform model development. Some research will be required to determine what subset to use, but as with event frequency this could be conditioned on the occurrence of bulk indices (or joint indices).

A further point to consider is the occurrence of multiple downbursts during a single severe storm event. This is not uncommon and Harper and Callaghan (1988) showed that in the Brisbane region (Australia) up to five individual storm systems were often identified on days with severe storm activity. This process will need to be captured and research is underway to determine how this could be achieved.

At this point a random (or conditional) sampling of track variables through a stochastic procedure similar to that used by Li (2000) can be used to develop a stochastic set of representative downburst tracks. Track number, length (which will be a function of forward speed and intensification/decay variables) and direction will need to be simulated.

Wind Field Modelling

A number of existing empirical/analytical downburst wind field models exist (e.g. Abd-Elaal et al. 2013, Chay et al. 2006, Holmes and Oliver 2000, Vicroy 1991). Each can generate a maximum wind speed footprint or simulated spatio-temporal wind speed time histories for wind load/risk calculations. All simplify downburst outflow physics to some extent and poorly simulate the time-varying changes in outflow structure (Mason et al. 2010b). From a statistical hazard modelling stand point this may not be a significant issue, but careful consideration is required when assessing the loads these events apply to structures. Whether a more complex wind field model would significantly change (mean) model results is unclear, but is an area that must be explored.

A further point to consider with wind field modelling is the way downbursts interact with topography and terrain. This differs from the interaction that occurs within traditional wind fields (Mason et al. 2010), and must be considered within any model. This difference is not restricted to changes in topographic amplification or the mechanical influence of surface roughness, but is routed in the types of structures that such a downburst risk model may be required to analyze. For example, probably the most common use of downburst risk models to date is for the analysis of risk to transmission line systems. Many of these are embedded within surrounding terrain features, such as shown in Figure 2. This siting completely changes the loads seen by these structures and unless considered suitably the resultant risk to such a line system would be grossly incorrect.

Figure 2. Example of structure embedded within terrain. http://www.foresthiker.com/wp-content/uploads/2011/02/bpa-lines.jpg.

Accounting for all these features, a representative wind field must be assigned to each simulated track within the stochastic event set. Depending on the final use of these data this could be done through a maximum wind speed footprint, or as a series of geo-spatial wind speed time histories (or the wind field model variable to generate these) that describe the three dimensional evolution of each simulated storm. The former would be adequate for development of wind exceedance probability curves, but the latter may be required for performance based analysis of structures (or networks) or generation of potential damage statistics.

Statistical Analysis and Validation

For a given region a stochastic set of representative storms, track and footprints should be generated for a period of, say, 10,000 years. Given the length of the synthetic record, typical statistical analysis techniques can be used to analyze downburst wind hazard at individual points, or over a linear or regional area. Simple structural risk modelling could be done if vulnerability could simply be defined by a threshold wind speed, but further research developing appropriate load/response vulnerability relationships would be recommended if extending the proposed model to that point

As with all modelling work, validation is essential for ensuring the integrity of output. The simplest way this can be done is through comparison with existing wind records. Some complexities exist when doing this in that only the wind gusts generated by downbursts must be extracted from parent wind records. This is not always straightforward but must be done for any validation exercise to be useful. Of course only the low return period range of the curve will have data to validate against, but it is important to at least ensure that this regions is well replicated. Through this type of validation Harper and Callaghan (1988) showed the ability of a modelling approach similar to that proposed here to generate wind statistics that fit observed data with small overall errors.

RESULTS

To date research has focused on the development of a methodology for estimating pseudo-downburst climatologies (step 1). The aim of this research was to identify the most appropriate indices to use for model development and generate regional hindcasts. The latter would allow the assessment of the expected average annual number of downburst generating storms within a defined area (this is not necessarily the number of downbursts). For this paper, results for the greater south east Queensland (SEQ) region are presented.

Following the procedure outlined earlier, observational data and reanalysis fields were extracted from the Bureau of Meteorology's Severe Storm Archive and the ECMWF ERA-Interim databases (Dee et al. 2011), respectively. This was done for the 1989-2011 period, which was shown to be stationary through a change point analysis. A wide range of climate indices were calculated using the extracted reanalysis data and the respective predictive skill computed by assessing the separation between the joint density functions for those time steps when downbursts occurred and those when they did not. Figure 3 shows these data plot for SEQ when using LI100 and DVWS as variables. This combination was shown to perform well for the SEQ region and was subsequently used to develop the hindcast for this region.

To determine the conditional probability of event occurrence in the two-dimensional LI100-DVWS phase space, the bivariate event frequency distribution (Fig. 3) was divided by its parent. Figure 4 shows the resultant probability surface for SEQ during the warm season. The same solid grey line as used in Figure 3 is shown for reference. It is immediately clear that the probability a downburst will occur given any combination is low. This follows similar findings by Brooks (2013) and reflects the inability of a simple two variable analysis to capture all the complex physics required to actually generate a severe thunderstorm.

Considering the full reanalysis period (i.e. 1979-2012) a hindcast was made for the SEQ region to estimate historical downburst producing storm activity. To arrive at a hindcast, the full reanalysis database was analyzed and LI100 and DVWS were calculated for each time step. Segregating the data into individual years, the estimated mean number of downburst events expected in any given year was calculated using:

$$E = \sum_{I,S}\left(\sum_j \left[A(I,S)_j = X(I,S)\right] \cdot P(WS|X(I,S))\right) \tag{1}$$

where E is the mean estimated annual event count, $P(WS|X(I,S))$ is the conditional probability of downburst windstorm (WS) occurrence for a given combination of I (instability – LI100) and S (shear – DVWS), $X(I,S)$, and the summation of all true occurrences of the conditional statement within the Iverson bracket, […], represents a count of the number of time steps where the reanalysis data yields a multivariate combination, $A(I,S)$ equal to $X(I,S)$. Summations are done over all time steps, j, and for each I-S combination.

Figure 5 shows the hindcast results for SEQ warm seasons (October - March). Inspecting the period following 1990 it is seen that the mean trends are followed reasonably, but the large inter-annual peaks are not particularly well represented. Given it has already been suggested that not all the physics that drive severe storm activity are represented in the two indices used, this is not surprising. From a modelling standpoint it is also not entirely detrimental in that these peaks can be considered a random process on top of the underlying mean estimations.

Prior to 1990 the simulation generates much larger event numbers than observed. This highlights a particular sampling bias that existed in the observational record during this period, and is not a systematic overestimation by the model. In fact it appears that this period may in fact have been characterized by greater storm activity than recent years.

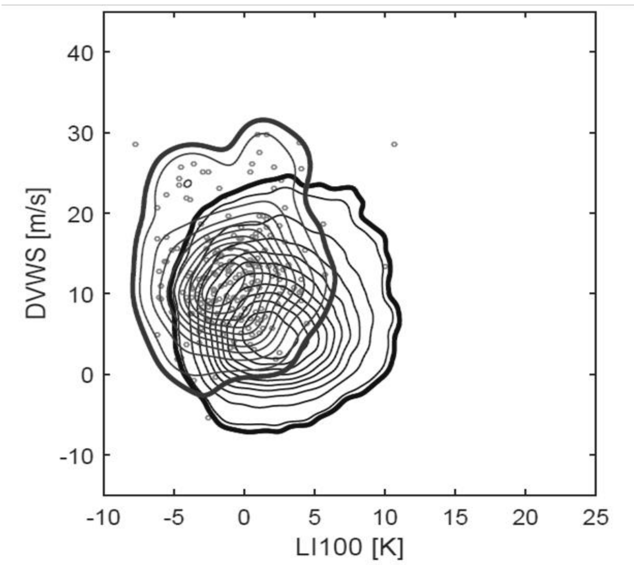

Figure 3. Joint PDFs for SEQ showing the environments that generate downbursts (light grey) and those that don't (dark grey).

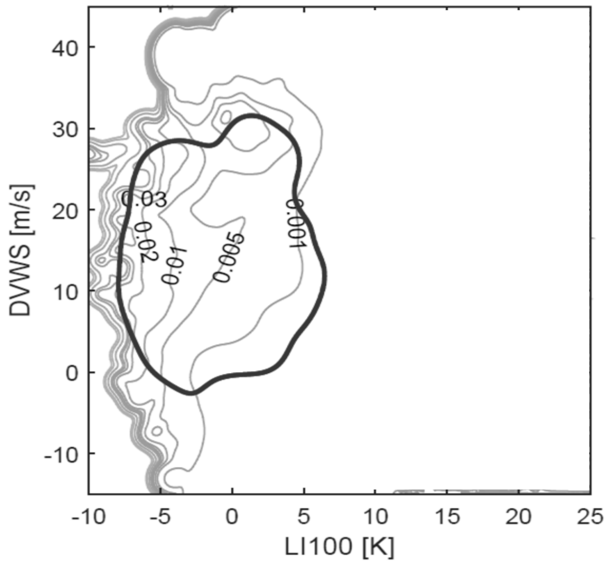

Figure 4. Event probability surface for SEQ.

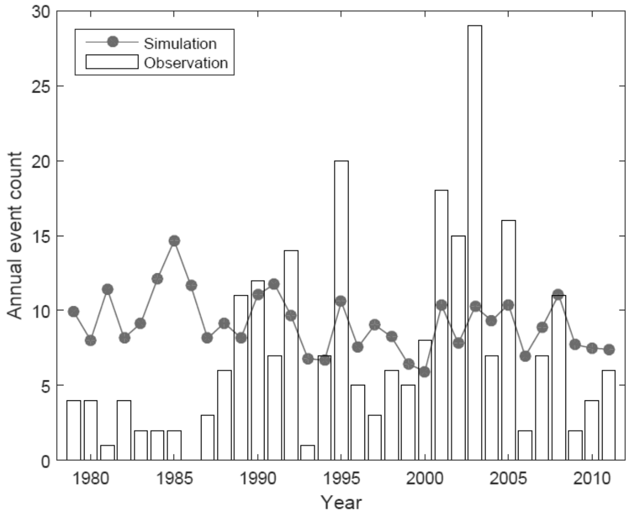

Figure 5. Hindcast of estimated annual (warm season) count of downburst producing storms in SEQ.

CONCLUSIONS

This paper proposes a methodology for building a stochastic event-based wind hazard model to estimate the risk downbursts pose to structures. Unlike existing models it couples large scale atmospheric information and observational records to generate model parameters. This extension allows the hazard model to be applied in regions where no observational records currently exist. Current progress towards full model development has focused on the methodological approach required to couple these data and integrate them into the wider hazard model. An example was provided for the south east Queensland region where it was shown that the proposed model can reasonably replicate historic trends in mean annual event counts, but was unable to capture the inter-annual variability in these counts. Future work will refine this approach and continue to develop the full model proposed.

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REFERENCES

Abd-Elaal, E.S., Mills, J.E. and Ma, X. (2013). "A coupled parametric-CFD study for determining ages of downbursts through investigation of different field parameters". *Journal of Wind Engineering and Industrial Aerodynamics*, 123, 30-42.

Allen, J.T., Karoly, D.J. and Mills, G.A. (2011). "A severe thunderstorm climatology for Australia and associated thunderstorm environments". *Australian Meteorological and Oceanographic Journal*, 61, 143-158.

Allen, J.T. and Karoly, D.J. (2013). "A climatology of Australian severe thunderstorm environments 1979-2011: inter-annual variability and ENSO influence". *International Journal of Climatology*, 34: 81-97.

Brooks, H.E. (2009). "Proximity soundings for severe convection for Europe and the United States from reanalysis data". *Atmospheric Research*, 93: 546-553.

Brooks, H.E. (2013). "Severe thunderstorms and climate change". *Atmospheric Research*, 123: 129-138.

Brooks, H.E., Lee, J.W., Craven, J.P. (2003). "The spatial distribution of severe thunderstorm and tornado environments from global reanalysis data". *Atmospheric Research*, 67-68: 73-94.

Chay, M.T., Albermani, F. and Wilson, R. (2006). "Numerical and analytical simulation of downburst wind loads". *Engineering Structures*, 28: 240-254.

CIGRE (2008). *How overhead lines respond to localized high intensity winds: Basic understanding*. Brochure 350. Task Force B2.06.09 CIGRE.

CIGRE (2012). *Mechanical security of overhead lines: Containing cascading failures and mitigating their effects*. Brochure 515. Working Group B2.22 CIGRE.

Dee, D.P., 35 co-authors. (2011). "The ERA-Interim reanalysis: Configuration and performance of the data assimilation system". *Quarterly Journal of the Royal Meteorological Society*, 137: 553-597.

Fujita, T.T. (1985). *The Downburst*. SMRP Research Paper Number 210. University of Chicago.

Grunwald, S. and Brooks, H.E. (2011). "Relationship between sounding derived parameters and the strength of tornadoes in Europe and the USA from reanalysis data". *Atmospheric Research*, 100: 479-488.

Haigh, I.D., MacPherson, L.R., Mason, M.S., Wijeratne, E.M., Pattiaratchi, C.B., Crompton, R.P., George, S. (2014). "Estimating present day extreme water level exceedance probabilities around the coastline of Australia: tropical cyclone-induced storm surges". *Climate Dynamics*, 42: 139-157.

Harper, B., Callaghan, J. (1998). "Modelling of severe thunderstorms in South East Queensland". *Proceedings of the Sixth Australian Severe Storms Conference*, Brisbane: Australia.

Holmes, J.D. (2002). "A re-analysis of recorded extreme wind speeds in Region A". *Australian Journal of Structural Engineering*, 4(1): 29-40.

Holmes, J.D. and Oliver, S.E. (2000). "An empirical model of a downburst". *Engineering Structures*, 22: 1167-1172.

Letchford, C.W. and Hawes, H. (2000). "Risk assessment to improve reliability of transmission facilities exposed to sub-tropical high wind storm events". *Proceedings of CIGRE Session 2000*, Paris: France.

Li, C.Q. (2000). "A stochastic model of severe thunderstorms for transmission line design". *Probabilistic Engineering Mechanics*, 15: 359-364.

Lombardo, F.T., Main, J.A., Simiu, E. (2009). "Automated extraction and classification of thunderstorm and non-thunderstorm wind data for extreme value analysis". *Journal of Wind Engineering and Industrial Aerodynamics*, 97: 120-131.

Mason, M.S. and Klotzbach, P. (2013). "A preliminary analysis of convective windstorm environments across Australia". *Proceedings of the 16th Australasian Wind Engineering Society Workshop*, Brisbane: Australia.

Mason, M.S., Wood, G.S., Fletcher, D.F. (2010). "Numerical investigation of the influence of topography on simulated downburst wind fields". *Journal of Wind Engineering and Industrial Aerodynamics*, 98: 21-33.

Mason, M.S., Fletcher, D.F., Wood, G.S. (2010b). "Numerical simulation of idealized three-dimensional downburst wind fields". *Engineering Structures*, 32: 3558-3570.

Oliver, S.E., Moriarty, W.W., Holmes, J.D. (2000). "A risk model for design of transmission line systems against thunderstorm downburst winds". *Engineering Structures*, 22: 1173-1179.

Ponte, Jr J., Riera, J.D. (2007). "Wind velocity field during thunderstorms". *Wind and Structures*, 10: 287-300.

Ponte, Jr J., Riera, J.D. (2010). "Simulation of extreme wind series caused by thunderstorms in temperate latitudes". *Structural Safety*, 32: 231-237.

Vickery, P.J., Wadhera, D., Twisdale, L.A., Lavelle, F.M. (2009). "U.S. Hurricane wind speed risk and uncertainty". *Journal of Structural Engineering*, 135(3): 301-320.

Vicroy, D.D. (1991). *A simple analytical axisymmetric microburst model for downdraft estimation*. NASA Technical Memorandum 104053. NASA.

Yeo, D.H., Lin, N., Simiu, E. (2014). "Estimation of hurricane wind speed probabilities: Application to New York City and other coastal locations". *Journal of Structural Engineering*, 140(6): 0414017.