Wind and Structures, *Vol. 19, No. 5 (2014) 467-480*
DOI: http://dx.doi.org/10.12989/was.2014.19.5.467

Extreme wind speeds from multiple wind hazards excluding tropical cyclones

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(Received March 13, 2014, Revised July 10, 2014, Accepted August 4, 2014)

Abstract. The estimation of wind speed values used in codes and standards is an integral part of the wind load evaluation process. In a number of codes and standards, wind speeds outside of tropical cyclone prone regions are estimated using a single probability distribution developed from observed wind speed data, with no distinction made between the types of causal wind hazard (e.g., thunderstorm). Non-tropical cyclone wind hazards (i.e., thunderstorm, non-thunderstorm) have been shown to possess different probability distributions and estimation of non-tropical cyclone wind speeds based on a single probability distribution has been shown to underestimate wind speeds. Current treatment of non-tropical cyclone wind hazards in worldwide codes and standards is touched upon in this work. Meteorological data is available at a considerable number of United States (U.S.) stations that have information on wind speed as well as the type of causal wind hazard. In this paper, probability distributions are fit to distinct storm types (i.e., thunderstorm and non-thunderstorm) and the results of these distributions are compared to fitting a single probability distribution to all data regardless of storm type (i.e., co-mingled). Distributions fitted to data separated by storm type and co-mingled data will also be compared to a derived (i.e., “mixed”) probability distribution considering multiple storm types independently. This paper will analyze two extreme value distributions (e.g., Gumbel, generalized Pareto). It is shown that mixed probability distribution, on average, is a more conservative measure for extreme wind speed estimation. Using a mixed distribution is especially conservative in situations where a given wind speed value for either storm type has a similar probability of occurrence, and/or when a less frequent storm type produces the highest overall wind speeds. U.S. areas prone to multiple non-tropical cyclone wind hazards are identified.

Keywords: extreme wind; thunderstorm; probability; multi-hazard; codes

1. Introduction

The estimation of extreme wind speed values is an integral part of the wind load evaluation process for the design of structures. In earlier publications on wind speeds and other environmental variables, the extremes were analyzed on an epochal basis (e.g., annual maxima), making the analysis ideal for the extreme value (EV) family of distributions (Gumbel 1958).

The three types of distributions in the EV family, Type I (Gumbel), Type II (Frechet) and Type III (Reverse Weibull) have all been suggested at one time or another to accurately model extreme winds (Peterka and Shahid 1998, ANSI 1972, Simiu and Heckert 1996). The three types of

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http://www.techno-press.org/?journal=was&subpage=8 ISSN: 1226-6116 (Print), 1598-6225 (Online)

distributions can be expressed as a single Generalized Extreme Value (GEV) distribution. The Type I, Type II, and Type III distributions correspond, respectively, to the GEV distribution with tail length parameter c in which c =0 (in the asymptotic limit), c >0, and c <0. In the 1970s the peaks over threshold, or POT, approach used in conjunction with the generalized Pareto distribution (GPD) was developed (Pickands 1975), and used for estimating extreme wind speed in a number of studies (e.g., Lechner *et al*. 1992, Holmes and Moriarty 1999, Cook 2013).

Most studies in estimating extreme wind speeds outside of tropical cyclone regions typically involved fitting an EV distribution and/or GPD to a single set of data regardless of storm type (i.e., co-mingled). Gomes and Vickery (1978) recognized the importance of separating wind speeds by storm type (e.g., thunderstorm and non-thunderstorm) and noted that fitting distributions to both thunderstorm (T) and non-thunderstorm (NT) annual maximum wind speeds separately yielded different probability distributions. Most wind speed observations, until recently, were unlikely to contain information on storm type or it was very prohibitive to extract such information. More recent studies (e.g., Lombardo *et al*. 2009, DeGaetano *et al*. 2014) have found ways to efficiently extract storm type and related information. These studies have also noted in some cases that considering storm types independently in a "mixed" distribution (Eq. (1)) yields higher wind speed estimates at a given probability of occurrence (or n-year return period) than co-mingled data sets.

$$P[v \leq V] = \prod_{i=1}^{j} P(v_i \leq V), \ldots, P(v_j \leq V) \tag{1}$$

where j denotes the total number of storm types considered (e.g., non-thunderstorm, thunderstorm, tropical) and v, V denote wind speeds.

An example of problems associated with not separating by storm type, especially at longer n-year return periods is shown in Fig. 1. Fig. 1 illustrates an example of a Type I distribution fitted to T, NT and co-mingled (C) annual maximum wind speed data in addition to the derived mixed (M) distribution (Eq. (1)) for a station in Boston, MA. In an extreme wind climate of this type, the NT annual maximum wind speeds are relatively "well-behaved", meaning that there is relatively low variability in annual maximum wind speeds from year to year (COV ~ 10%) and therefore a "flatter" slope when fitting a Type I distribution. The NT annual maximum wind speeds also have the distinction of producing the highest annual wind speed for most years, causing the C distribution (black) to conform closely to the NT at smaller n (< 10 yr), suggesting storm type is largely irrelevant in this period. The T distribution however has a much steeper slope, a higher variability (COV ~21%) and a smaller number of years where thunderstorms produce the highest annual wind speed. However, thunderstorms produce the *overall* maximum wind speeds in the entire record and by extension become the dominant storm type at larger n (> 50-100 yr). The M distribution converges to the T distribution at larger n as well, but Fig. 1 suggests its importance (i.e., contributions from both storm types) at n = 25-100 years. As n increases, the use of C becomes increasingly unconservative. For example at n = 1700 years in Fig. 1, using the C distribution underestimates the wind speed by 15% and the wind speed squared (proportional to wind load) by 30% compared with M. At other locations, the situation could be reversed (NT dominates at large n) and the result would be the same (i.e. co-mingled data would underestimate wind speed at large n).

Thunderstorm winds are known to dominate a significant amount of extreme wind climates worldwide outside of tropical cyclone prone regions (Holmes 2007) and are responsible for a majority of natural hazard damage in the United States (Mohee and Miller 2010), making further understanding of the thunderstorm hazard an important issue for design of structures. Although tornadoes in some parts of U.S. may dominate the extreme wind climate at very large *n* ($n > 10^4$ years) they are not considered in this work. For probabilistic treatment of tornadoes in the U.S. please consult ANS (2011).

Given the potential for underestimation of extreme wind speeds by not considering storm type, Section 2 will cover treatment of multiple wind hazards excluding tropical cyclones in codes and standards throughout the world. Section 3 will discuss the data and methodologies used to analyze these multiple wind hazards in the United States. Section 4 will analyze data from the multiple wind hazards and discuss the results. Section 5 covers conclusions from this work.

2. Codes and standards

This section will give an overview on how wind load codes and standards worldwide deal with multiple wind hazards excluding tropical cyclones when prescribing a wind speed for use in structural design. In the international wind load code, ISO 4354 (ISO, 2012), no probability distribution is given, however it does state that "…extreme wind speed analyses be done for data separated into storm type".

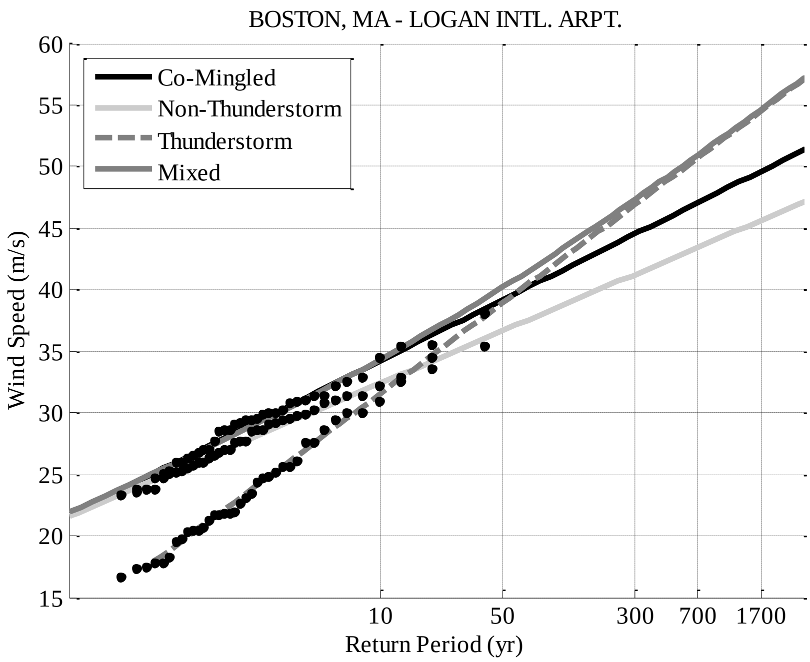

Fig. 1 T (gray-dashed), NT (light gray), C (black) and M (gray-solid) Type I fits for a station in Boston, MA, U.S.

2.1 United States

In the current wind load standard for the United States, ASCE 7-10 (SEI 2010), there are two probability distributions for non-tropical cyclone extreme wind speeds. One distribution is prescribed for the states of California, Oregon and Washington and another for the rest of the United States. When normalized by the wind speed at $n = 50$, these two distributions are the same. The distribution is Type I (Gumbel) for a 3-second gust wind speed in open terrain at 10 meter height. Annual maximum wind speeds from weather stations (Peterka and Shahid 1998) were used as a basis for the current maps. Any n-year wind speeds can be calculated using Eq. C26.5-2 found in the ASCE 7-10 standard. Newly created maps are being proposed for the ASCE 7-16 version of the standard that will consider thunderstorms explicitly and the subsequent M distribution (Pintar and Lombardo 2013).

2.2 Canada

In the National Building Code of Canada (NBCC 2010), nominally hourly annual maximum wind speeds at 10 meter height and open terrain regardless of storm type are fit to the Type I (Gumbel) distribution. Wind speeds in the code are based on historical data and are regionally representative with currently no “wind map”. Newly created maps have been proposed however (Hong *et al*. 2014). Estimates and relationships for n-year wind speeds do not consider storm type. This current distribution is found in Appendix C, pg. C-9 of the NBCC.

2.3 Australia/New Zealand

In the AS/NZS 1170.2-2011 Standard (AS/NZS, 2011), a Type III (reverse Weibull) distribution is used in all regions. The shape, or tail length parameter, “c” is either -0.045 or -0.1 depending on the region (Table 3.1 in the Standard). Other parameters in the Type III distribution (scale, threshold) vary depending on location as well. A POT methodology was used to estimate the parameters for “non-cyclonic” wind speeds for observed 0.2-s gust wind speed data at 10 meter height in open terrain. The term non-cyclonic refers to all wind speeds from all non-tropical cyclone events. The separation by “non-cyclonic” storm type into non-thunderstorm and thunderstorm winds and subsequent probability distributions was carried out (Holmes 2002). Therefore, the M distribution was calculated for the capital cities in Australia and was used for development of the wind speeds used in the AS/NZS Standard.

2.4 Japan

In the Japan code (AIJ 2006), the “basic” wind speed is defined as the 10 minute average wind speed at 10 meter height at $n = 100$ years. As Japan is prone to tropical cyclones, the coastal regions are prescribed higher basic wind speeds than those inland. Japan considers combined or “mixed” storm climates of typhoon and synoptic (non-thunderstorm) winds. Non-thunderstorm winds, estimated using observed data, are included because northern part of Japan is susceptible to strong synoptic storms (Tamura *et al*. 2003). Further separating of synoptic and thunderstorm wind speeds is not done. A reference equation (A6.12 in code) to convert the basic wind speed based on the mixed climate to those at different n-year values, follows a Gumbel distribution.

2.5 United Kingdom

The "basic" wind speed in the former British Standard, BS 6399-2 (BS 1997) is based on historical data and is at 10 meters height in open terrain for an hourly mean wind speed. This wind speed is converted into a gust wind speed for design. The basic wind speed is estimated for n = 50 years by using storm maxima converted to dynamic pressure ($0.5\rho V^2$) fit to a Gumbel distribution and then converted back to wind speed. No distinction for storm type is made in the Standard as the British extreme wind climate is generally dominated by synoptic storms where wind speeds are generally higher near the coasts and in northern regions of the UK. The relationship between any n-year speed is given in Annex D, Equ. D.1 in the standard.

2.6 Europe

The Eurocode, EN-1991-1-4 (EC, 2004) uses a 10 minute mean wind speed value at 10 meters in open terrain. The values of "basic" wind speed are to be determined by individual nations in Europe in a "National Annex" (Holmes 2007). The relationship between basic wind speeds at any n-year values is given however (cf. Eq. (4.2)), and is the same relationship given in the UK standard.

2.7 Overall

Fig. 2 shows the ratio between wind speeds at n = 10-1700 years for regions nominally outside of those prone to tropical cyclones normalized by the wind speed at n = 50 years for the codes and standards discussed above. A northern region was chosen in Japan to avoid a large contribution from tropical cyclone induced wind speeds. Although the AS/NZS code uses a Type III distribution (c = -0.1 in the figure – Region "A" in AS/NZS) its normalized values are similar to the Type I of the UK due to the method of fitting dynamic pressure to the Type I distribution. The U.S., Canada, and Japan have similar probability distributions.

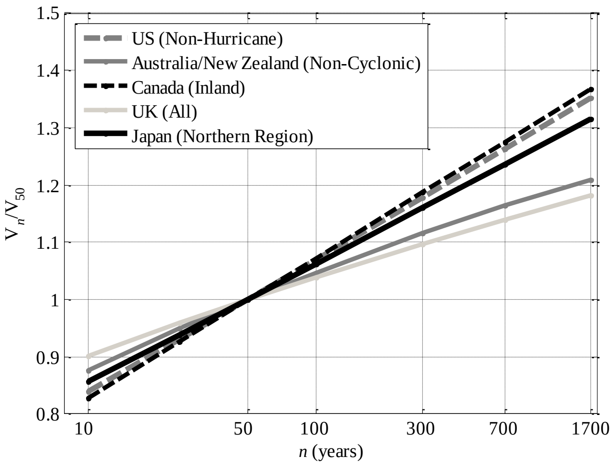

Fig. 2 Comparison of probability distributions for codes and standards nominally outside of tropical cyclone-prone regions

3. Data and methods

To analyze the multiple wind hazards excluding tropical cyclones in the contiguous U.S., data from the Integrated Surface Hourly (ISH) database 3505 was used (ftp://ftp.ncdc.noaa.gov/pub/data/noaa/). The ISH database contains a large number of meteorological data for over 20,000 stations worldwide. A subset of approximately 1,200 stations in the U.S. that contained 5-40 years of "peak" wind data and information on storm type was used (Lombardo 2012). The wind speed data were rigorously manually quality controlled and were standardized (i.e., 3-s gust, 10 m height) using provisions in SEI (2010). Both the raw and standardized data and the methods used to quality control the data are available at http://www.nist.gov/wind. The quality controlled wind data as well as corresponding metadata (e.g., anemometer height), by station, can also be found at the link above. All of the wind speed data were classified as one of three storm types: thunderstorm, non-thunderstorm, and tropical. The algorithm for classifying by storm type is discussed in Lombardo *et al*. (2009) and Lombardo (2012). Wind speeds classified as tropical were removed from the analysis in this paper.

It should be noted here that most stations used in this analysis recorded "peak" wind speed gusts with two or three distinct averaging times over the course of its operation. The first period, typically 1970's to 1990's, was prior to a station becoming automated (i.e., Automated Surface Observing System or ASOS). Pre-ASOS wind speeds were collected via cup anemometer/chart recorder system. These recorded wind speeds had no digital filtering and the averaging time was dependent on the mechanical properties (i.e., response) of the anemometer, the response of the chart recorder, and the wind speed (McKee *et al*. 1996). For high wind speeds, "effective" averaging times are approximately 1-3 s (Miller 2007). Given then that the effective averaging time was approximately 3 s or less, conservatively, no averaging time corrections were applied when standardizing the data. During the second period after ASOS commissioning, which typically ranged from the mid-1990's to the mid 2000's, the wind data, measured by a cup anemometer, were digitally sampled at 1 Hz and a 5-second block average was then recorded. The averaging time correction to 3 s ($\approx$ 1.03) was applied using the Durst curve (SEI 2010). In the third and final period, beginning in the mid to late 2000's, the data was recorded by sonic anemometers. Data are sampled at 1 Hz and digitally output a 3 s moving average and no corrections were made. Further information can be found in Lombardo (2012).

The first method for analyzing the U.S. data did not deviate substantially from ASCE 7-10. Annual maximum wind speeds from available stations were separated by storm type (thunderstorm (T), non-thunderstorm (NT)). Type I probability distributions were then fitted to each storm type separately and a "mixed" (M) distribution estimated. A Type I distribution was also fitted to the co-mingled data (C) as this is the basis for wind speed values in ASCE 7-10. In the second method, POT-GPD was used to analyze the available data. Again the data to be analyzed consisted of distinct T and NT, C and the derived M. Since the data are not analyzed in calendar year blocks in the POT-GPD analysis, the data had to be de-clustered to account for correlation between data points (Lombardo *et al*. 2009). For this work data had to be separated by at least a given time period (t). The maximum wind speed value within t was used. For this work, t = 0.5 days for T and t = 4 days for NT and C were used similar to Lombardo *et al*. (2009). A starting threshold, u, was set as the 90th percentile of the wind speed data for T, NT and C at each station. Due to the large amount of stations, this method is preferable to estimating a threshold at every location (Beguería *et al.* 2011). If u at the 90th percentile did not contain 30 or more wind speed values above u, u was reduced by 0.45 m/s (1 mph) until this condition was met.

4. Analysis

4.1 Annual Maxima (Type I)

Analyses initially were run for the C distribution as nearly 20 years of additional data have accumulated since the analysis that served as the basis for ASCE 7-10. Fig. 3 shows the square of the ratio (proportional to wind load) between wind speed values at n = 10-1700 years normalized by the wind speed value at n = 50 years (i.e., $R = (V_n/V_{50})^2$). The R values were calculated for 558 stations that had 15 or more years of both T and NT annual maximum wind speeds. The gray line is the R prescribed in ASCE 7-10. This ratio is an important parameter in reliability-based wind load design (Ellingwood and Tekie 1999). As illustrated in Fig. 3, the distribution in ASCE 7-10 is fairly conservative when compared the majority of the 558 stations used at n > 50 years. For n < 50 years the ASCE 7-10 distribution produces lower R values than a majority of the 558 stations. Compared with other distributions used worldwide (Fig. 2), the ASCE 7-10 distribution at n < 50 years would also produce lower wind speed values. Empirical probability distributions are also shown on the right side of Fig. 3 for n = 300, 700 and 1700 years for the ratio R. These distributions show the increasing variability of R as n increases.

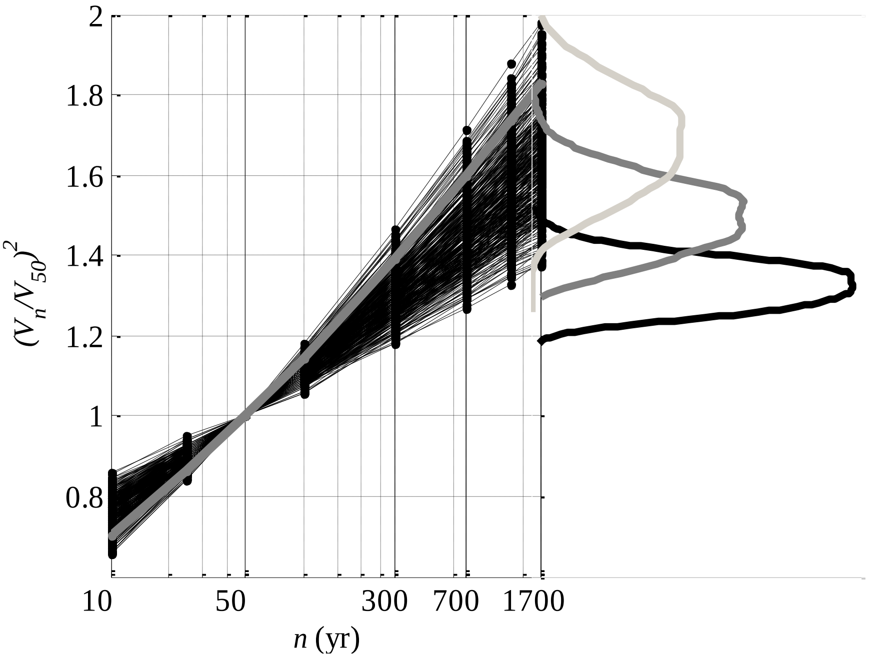

Fig. 3 Wind speed ratio squared for 558 U.S. stations for C distribution. Empirical probability density function of the ratio for n = 300 (black), n = 700 (dark gray) at n = 1700 (light gray) also shown

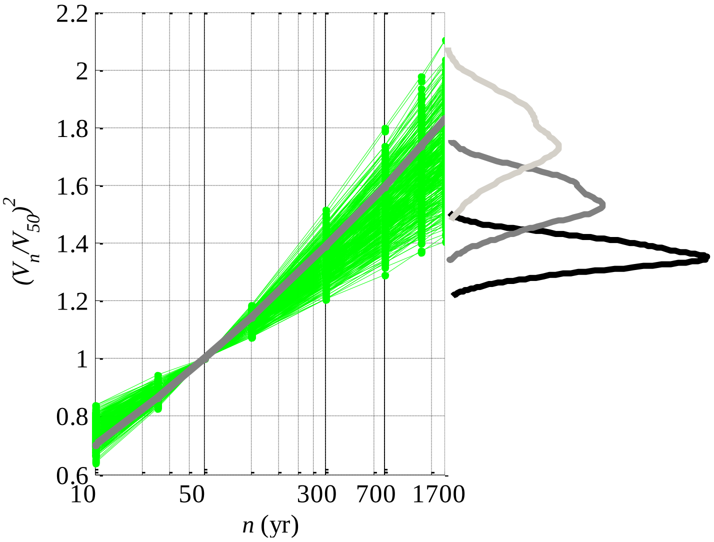

Fig. 4 Wind speed ratio squared for 558 U.S. stations for M distribution. Empirical probability density function of the ratio for n = 300 (black), n = 700 (dark gray) at n = 1700 (light gray) also shown

The R values considering storm type are shown in Fig. 4. The distribution in ASCE 7-10 is shown again as a gray line for reference. Visually comparing the M distribution with C (black, Fig. 3), it is observed that M distributions, on average, are higher than C and therefore the ASCE 7-10 distribution becomes less conservative. This also suggests that the M distribution is a more conservative methodology in the U.S. when estimating extreme wind speeds, especially for large n. As in Fig. 3, Fig. 4 illustrates the M distribution also shows higher variability as n increases. Comparing the R values in Figs. 3 and 4, ratios for M and C for n = 1700 years are 1.95 and 1.89 for the 95th percentile and 1.75 and 1.68 for the 50th percentile respectively.

This analysis demonstrates that on average the M distribution is a conservative measure when analyzing extreme wind speeds. As the 558 stations used in the analysis above were spread out across the U.S., analysis was undertaken to determine specific geographical areas where failing to account for multiple non-tropical cyclone wind hazards may be worse than others. Regionality in the U.S. extreme wind climate has been identified in Cheng (1998) and Lombardo (2012).

As a general illustration, Fig. 5 shows the percentage of U.S. annual maximum wind speeds caused by thunderstorms. With tropical systems not considered, the southeastern portions of the country as well parts of Arizona receive nearly all of their annual maximum wind speeds from thunderstorms. The Pacific coastal states, areas in the Rockies and the far Northeast rarely see a thunderstorm generated annual maximum wind speed. Areas such as the Plains, Intermountain West, and the Mid-Atlantic see contributions from both storm types. Although Fig. 5 gives no information about the magnitude of the events, it does suggest possible areas where failing to consider multiple non-tropical cyclone wind hazards is unconservative. For example, Boston (Fig. 1), an area where not accounting for thunderstorms was shown to underestimate extreme wind speeds, had the annual maximum wind speed belonging to a thunderstorm in only 7 of 38 recorded years (i.e., 7/38 ≈ 18%).

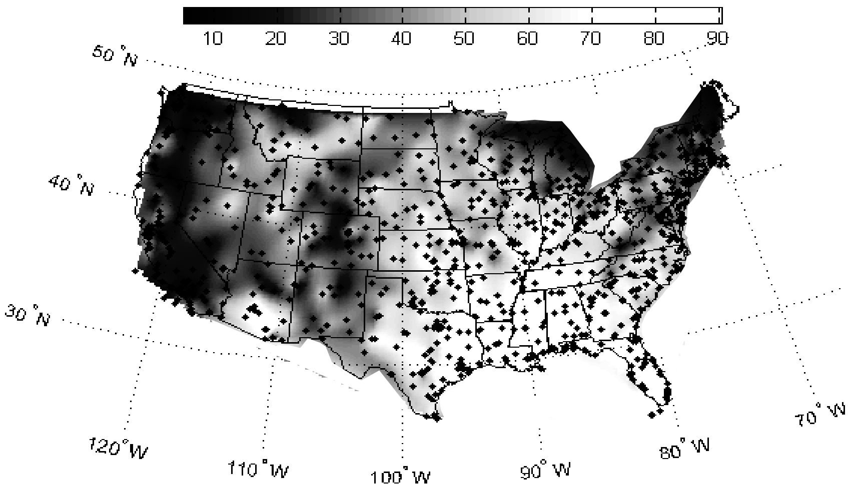

Fig. 5 Percentage of annual maximum wind speeds from thunderstorm events

The next step was to show where not accounting for storm type would lead to highest underestimation of extreme wind speeds using *R* values for both M and C (i.e., $R_2 = R_{Fig.4}/R_{Fig.3}$). Fig. 6 shows locations where, for n = 1700 years, R_2 is greater than 1.10. In general, the majority of ratios in the U.S. are 1.10 or less suggesting small differences between the mixed wind climates (M) and those without considering storm type (C). It is noticed that areas with ratios greater than 1.10 are shown as mixed climates (i.e., areas with contributions from both storm types) in Fig. 5. Some of these areas include the entire Northeast Corridor (Washington, DC to Boston) as well as Chicago, IL and San Francisco, CA.

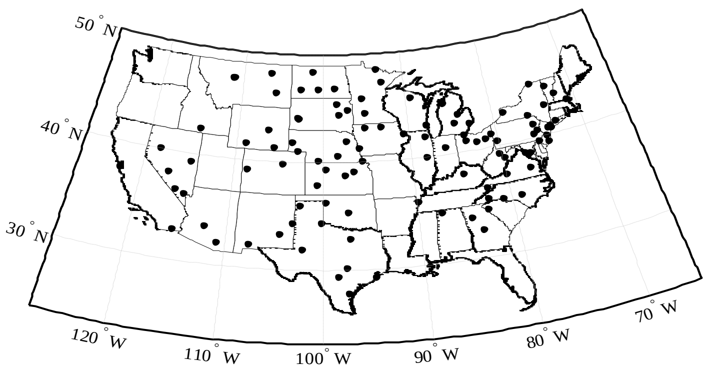

Fig. 6 Locations where $R_2 > 1.10$

4.2 POT (GPD)

In the second method, data was analyzed using POT-GPD. Due to increased number of data points able to be used in the POT-GPD method, 829 stations were used. The shape parameter (tail length, or c) and scale parameter, a, were estimated by maximum likelihood (Castillo 2006) while the threshold, u was estimated as discussed in Section 3. Fig. 7 shows the values of both a and c parameters for T ('+') and NT ('.') as well the equal probability contours of the 95th percentile of the joint cumulative distribution in bold lines. It should be noted that the first and second order moments of the GPD are undefined at $c > 1.0$ and 0.5 respectively. A large scatter regardless of storm type is exhibited, illustrating the some of the difficulty that has been noted when fitting the GPD to observed data (Castillo and Hadi 1997). Regardless of the scatter, a relationship appears to exist between the two parameters regardless of storm type. This relationship is expected based on the parameters joint relationship between the mean and standard deviation of the excesses over u (Simiu and Heckert 1996). Also a majority of the GPD fits regardless of storm type have c<0 as has been noted in a number of studies (e.g., Steinkohl *et al*. 2013). Clearly illustrated in Fig. 7 is the notion that different storm types have different probability distributions. The C parameters, although not shown, appear to be an average representation of the T and NT distributions. This 'averaging out' was also noticed in Type I fits in Section 4.1. The T distribution appears to have on average a higher value of a, or the scale parameter for any c value, and the differences become more pronounced for lower c values (Fig. 7). This suggests that on average, wind speeds classified as T have more variability than those classified NT. This higher a value was also noticed for the Type I annual maximum distribution for Boston in Fig. 1 and in Fig. 4, on average, for the entire U.S. Given the large scatter in the data, and to test the differences in estimating extreme wind speeds given storm type differences in Fig. 7, a hypothetical GPD was set up for both T and NT using Eq. (2) (Davison and Smith 1990).

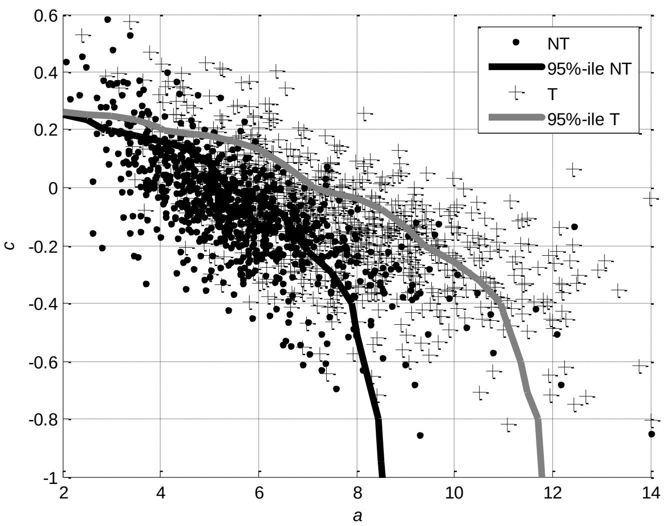

Fig. 7 Parameter estimations for 829 U.S. stations using POT-GPD for T ('+') and NT ('.') winds. 95th percentile joint cumulative distributions of the parameters are shown as bold lines

$$V_{NT,T}(n) = \left\{-a[1-(\lambda_{NT,T}n)^c]/c\right\} + u \tag{2}$$

In this example, u = 20 m/s (45 mph) and c = -0.05 for NT and T, both representative values from the GPD fitting process, were input into Eq. (2). The lambda parameter (λ), in Eq. (2), is the rate of crossing over the threshold, u. Based on the information from the Boston case (Fig. 1) it is assumed that the NT rate (λ_{NT}) is four and one-half (4.5) times greater than the T rate (λ_T). For this case λ_{NT} = 9 and λ_T = 2. The a values for NT and T were then set to approximately their 95th percentile value (6, 8) when c = -0.05 based on Fig. 7. Fig. 8 shows the relationships between these probability distributions. Fig. 8 also shows how this representative set of GPD parameters – with more data points being used – still leads to the M distribution being a more conservative estimation of the extreme wind climate for the n values shown. In the case of Fig. 8, contributions from both storm types (M) are important over a much larger range of n than for Boston in Fig. 1.

Realization of a mixed wind climate in the POT-GPD case will be highly dependent on the value of c for each storm type however. Regional dependence in GPD parameters was only revealed in the threshold parameter (u), for example, because a percentile-based threshold was used. For example, a c value could be ~ 0 for one storm type but ~ -0.2 for another storm type with all other parameters being equal. This arrangement would leave minimal contributions from the storm type with a lower c value especially at larger values of n. Of the 829 stations used in the POT-GPD methodology, only slightly over 40% (352) of stations had c values for both NT and T data within a range of (-0.2, 0.2). Values outside of this range would give unreasonable estimates of wind speeds at large n. This large range of c values, even with the use of more data points, suggests the use of a single or narrow range of c values when using this method.

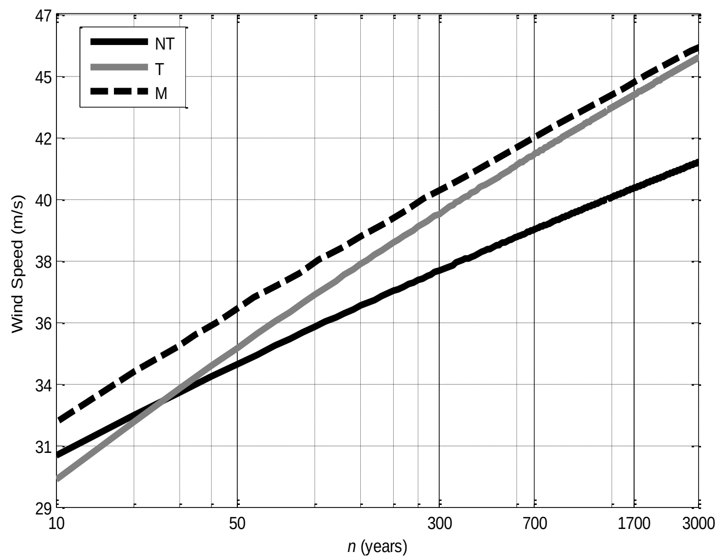

Fig. 8 GPD of NT (black), T (gray), and M (black dashed) given certain fixed parameters representative of storm type

5. Conclusions

This paper describes the potential for multiple wind hazards to significantly affect the extreme wind climate in non-tropical cyclone prone regions. This description starts with an overview of how non-tropical cyclone wind hazards are prescribed in worldwide building codes and standards. This overview is followed with a detailed non-tropical cyclone multi-wind hazard analysis for the United States using both annual maxima and POT methods.

The analysis showed that most countries of the world do not explicitly account for multiple non-tropical cyclone wind hazards (i.e., thunderstorm, non-thunderstorm), although some areas do experience contributions from both storm types. In the United States, considering multiple non-tropical cyclone wind hazards separately in a “mixed” distribution is a more conservative estimation procedure than using a single probability distribution based on co-mingled data especially for n > 50 years. The current probability distribution in ASCE 7-10 is based on co-mingled data. Contributions from multiple wind hazards were noticed in certain areas of the U.S. such the Plains, Intermountain West and the Mid-Atlantic. Some of these same areas showed that not accounting for storm type led to underestimates of extreme wind speed, and by extension wind load at large n. This underestimation typically occurred when most annual maximum wind speeds were due to non-thunderstorm events however a few, and most intense wind speeds in the record were due to thunderstorms and/or occurrence probabilities were similar for both storm types at a given wind speed.

Fitting the GPD to the same data sets using POT yielded similar results from the annual maxima analysis in that different storm types were shown to have different probability distributions and using a co-mingled distribution may underestimate extreme wind speeds. Wind speeds classified as thunderstorms also were observed to have higher scale parameters (i.e., variability) regardless of extreme value method chosen in this work. Research towards incorporating multiple non-tropical cyclone wind hazards in the United States is currently ongoing for possible inclusion into the ASCE 7-16 standard.

Underestimation of extreme wind speeds could be exacerbated in the Mid-Atlantic region which also may see infrequent but intense wind speeds from tropical systems (Yeo *et al*. 2014).

As ASCE 7-10 now prescribes design wind speeds with an annual exceedence probability of 1 in 700, the wind characteristics associated with an event of this probability may be akin to thunderstorm generated wind speeds in many regions of the U.S. Recent research has suggested that thunderstorm generated wind speeds may occur at higher frequency than previously thought (Lombardo 2012), have different probability distributions within the thunderstorm classification, and have different physical characteristics (Lombardo *et al*. 2014). For example, “impinging jet” profiles (Kim and Hangan 2007), observed in thunderstorm events, were found to have the maximum overall wind speeds as low as 4 m (Lombardo *et al*. 2014). Subsequent comparisons with “boundary-layer” profiles in codes and standards suggest current code provisions for wind profiles could underestimate wind loading for low-rise buildings (< 20 m) (Lombardo *et al*. 2014). However for high-rise buildings (e.g., 100 m), boundary-layer provisions may be conservative over an impinging jet (i.e., thunderstorm) profile. All these issues are important to consider for codes and standards as they continue to be revised using the best available data.

Acknowledgements

Portions and concepts of this work were initially developed during the author's tenure as a Postdoctoral Research Associate at the National Institute of Standards and Technology (NIST). The author is grateful for support while at NIST, including from E. Simiu, D. Yeo, M. Levitan and A. Pintar.

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