Meteorological extremes

by

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This entry discusses briefly basic principles of extreme value (EV) estimation (*see* **Extreme value analysis**), the role of simulations for the development of relevant meteorological data sets, the interaction between the practical application of the meteorological data and the extreme value modeling process, and specific EV estimation issues pertaining to wind, snow, ice, and ocean waves. Modern treatments of EV theory are covered in detail by Castillo [5] and Beirlant et al. [4].

Epochal and 'Peaks-over-threshold' Approaches: Extreme Value Distributions

Classical results on EVs were obtained by Fréchet [10], Fisher and Tippett [9], Gumbel [13] and Gnedenko [12] for sets of *epochal* values. These consist of the extreme value for each of the equal periods, or *epochs*, into which it is reasonable to divide a stationary **time series**. The time series is referred to as the *parent population* of the extremes. For meteorological data it is common to avoid seasonal effects by considering one-year epochs. For asymptotically large values, depending upon the distribution of its parent population, a population of statistically independent EVs is described by one of only three possible distributions: EV type I (Gumbel), EV type II (Fréchet) and EV type III (reverse Weibull) [12] (*see* **Generalized extreme value distribution**). The application of these distributions to recorded data such as annual meteorological maxima yields EV estimates that are approximate in so far as, by definition, real data do not satisfy the theoretical requirement that they be asymptotically large. Nevertheless, it appears that estimates of meteorological extremes based on EV theory are reasonable by and large.

In the more recently developed *peaks over threshold* (POT) approach (*see* **Exceedance over threshold**) the EV set consists of all independent values of a stationary time series that are equal to or exceed a sufficiently high threshold. For any meteorological record, a POT set with threshold equal to the smallest value of the corresponding epochal data set–that is, a POT set comparable with the epochal set in terms of the magnitude of the extremes–has the advantage of being larger in size than the epochal set. Consider, for example, two years in which the observed wind speeds equal to or larger than $33\,\mathrm{m\,s^{-1}}$ are $34\,\mathrm{m\,s^{-1}}$, $36\,\mathrm{m\,s^{-1}}$ for the first year and $33\,\mathrm{m\,s^{-1}}$ for the second year. In the epochal approach the two-year data set is $\{36\,\mathrm{m\,s^{-1}}, 33\,\mathrm{m\,s^{-1}}\}$; in the POT approach, for a $33\,\mathrm{m\,s^{-1}}$ threshold, it is $\{34\,\mathrm{m\,s^{-1}}, 36\,\mathrm{m\,s^{-1}}, 33\,\mathrm{m\,s^{-1}}\}$. Increasing a POT data set by decreasing the threshold results in the inclusion of data points so small as to violate unacceptably the assumption, inherent in EV analyses, that the data are asymptotically large. Conversely, thresholds that are too high result in small data sets and, therefore, large sampling errors. In practice a sample size is judged to be satisfactory if the estimates do not vary significantly as the sample size is increased (or, equivalently, as the threshold is decreased). As is the case for epochal sets, the distribution of POT sets can be shown to approach asymptotically one of the three EV distributions [5].

A meteorological time series generally includes data of distinct physical origins, some of which may be irrelevant from an EV viewpoint (e.g. for a parent population consisting of daily maxima, morning breezes as opposed to thunderstorm winds). In practice a parent population that may be used as a theoretical basis for the selection of an EV model may therefore be impossible to define.

In some climates where the meteorological quantity of concern (e.g. the wind speed) can be associated with distinct types of meteorological phenomena (e.g. thunderstorms and tropical cyclones), it is reasonable to model that quantity by a mixed distribution consisting of a weighted sum of EV distributions. Each distribution corresponds to a distinct meteorological phenomenon, and its relative weight is estimated as the ratio of the number of EV data associated with that phenomenon to the total number of EV data.

Sampling Errors and their Reduction

Inherent in EV estimates are sampling errors due to the finite size of the data samples. The estimated standard deviation of the sampling error is a function of probability distribution, and is proportional to the estimated standard deviation of the EV sample and inversely proportional to the square root of the EV sample size.

In general, the most appropriate probability distribution of the population from which an EV record is drawn cannot be determined confidently from the analysis of that record alone. Owing to sampling errors, a sample that belongs to an EV population whose true distribution is say Gumbel may be fitted best by a reverse Weibull or a Fréchet distribution [21, 23]. This important fact, which can be verified easily by Monte Carlo simulations (*see* **Simulation and Monte Carlo methods**), has been overlooked by some statisticians [11].

The unfavorable effect of sampling errors on the selection of the appropriate EV distributional model can be reduced by considering a sufficiently large number of meteorological stations with data records, provided that these are (a) mutually independent and (b) meteorologically homogeneous (i.e. generated by the same type of meteorological phenomena: nonhurricane winds for all stations, as opposed to nonhurricane winds for some stations and a mixture of nonhurricane and hurricane winds for others). If the numbers of station records best fitted by EV I, EV II and reverse EV III distributions are roughly proportional to the numbers of samples of the same size generated by Monte Carlo simulation from say a reverse EV III population, then it is reasonable to conclude that the true distribution for most stations under consideration is reverse EV III with, in general, parameters that may vary from station to station.

Given the most appropriate distributional model, it is possible in principle to reduce sampling errors in the estimation of the distribution parameters by using the 'superstation' approach, where mutually independent records of neighboring, meteorologically homogeneous stations are consolidated into a single record. Independence can be difficult to verify for records of peak gusts, as opposed to records of sustained wind speeds. This is due to the strong spatial variability of peak gust speeds corresponding to a given sustained wind speed. That is, at any given time, two stations for which the respective sustained speeds are the same can have significantly different peak gust speeds, leading to the illusion that the two stations' records are independent.

Formal statistical methods for using spatial information to reduce sampling errors are described by Coles [6].

Estimates Based on EV Data Generated by Simulation

For certain meteorological quantities the number of direct observations is inadequate, and EV estimates must be obtained from larger sets of data generated by simulation. Simulations use historical information physically related to the quantity of interest and physical models that transform the information into directly usable data. For example, for hurricanes the requisite historical information consists of data on the pressure defect at the storm center, the radius of maximum wind speeds, the hurricane translation velocity, and the hurricane path, for each of a large number of hurricanes [3, 20, 24, 25]. In ocean engineering so-called hindcasting methods that use physical models of storms and of the waves they generate are based on the same principle. Hindcast-based estimates of wave characteristics are usually limited to mean recurrence intervals of 100 years or less; estimates for longer intervals, though needed for the estimation of safety margins with respect to structural collapse, cannot in general be obtained with any reasonable confidence owing to typically large observation, modeling and sampling errors.

Sampling errors inherent in estimates based on simulated data can be estimated by numerical simulation [2].

Dependence of Modeling Process on Type of Application: Examples

The type of application for which meteorological data are used may influence the EV modeling process. For example, in structural engineering applications wind speeds are commonly used to estimate wind effects, such as pressures, which are proportional to the squares of the wind speeds. It has been argued that more precise estimates of extreme wind pressures may be obtained by assuming that it is the squares of the wind speeds, rather than the wind speeds themselves, that are appropriately modeled by an EV distribution [18]. However, this argument presupposes a type of parent population distribution whose validity remains to be established.

A second example involves the dependence of wind effects on structures upon wind direction. Until recently this dependence was not accounted for explicitly in standard provisions. To account for wind direction, the largest wind speed from each main compass direction (e.g. N, NE, E, SE, S, SW, W, NW) is considered for each storm. Each of these (eight) speeds induces a wind effect that depends on the directional characteristics of the structure's aerodynamics. For each storm being considered the EV of interest is the largest of these (eight) wind effects. In practice it is convenient to analyze sets of the square roots of these largest wind effects, rather than the set of the largest wind effects themselves. This allows useful comparisons with analyses based on sets of extreme wind speeds (i.e. to within a constant of square roots of wind effects) that do not account for wind directionality [22, p. 311].

Extreme Wind Speeds

Extreme wind speeds used in EV analysis should be *micrometeorologically homogeneous*, that is, they should be (a) recorded over terrain with the same roughness characteristics over the entire duration of the record being considered, (b) either recorded at or converted to the same elevation above ground, and (c) averaged over the same time interval (e.g. 3 s or 1 min) (*see* **Atmospheric dispersion: Complex terrain**).

In the early 1970s two competing models of extreme wind speeds were widely used: the EV type II in the US and the EV type I distribution elsewhere. For long mean recurrence intervals EV type II analyses can lead to unrealistically high estimated speeds, in some cases higher than $100\,\mathrm{m\,s^{-1}}$ for sets not including hurricane or tornado speeds. Extensive comparisons between results of Monte Carlo simulations from populations with EV I and EV II distributions on the one hand, and analyses of observed data at large numbers of meteorological stations on the other, led to the conclusion that the EV I distribution is a more realistic model of extreme wind speeds. However, it was found by Ellingwood et al. [8, p. 6] that, if it is assumed the EV I distribution holds, then calculated indices of structural reliability under wind loading appear to be unrealistically low. Since failures induced by nonhurricane and nontornado winds are exceedingly rare, this suggests that the EV I description of extreme winds may be overly severe. To the extent that this is the case, and that an EV distribution is a reasonable model of extreme speeds, the distribution can only be reverse EV III, which unlike the EV I and EV II distributions has *finite* upper tail. The assumption that the reverse EV III distribution is an appropriate model of extreme wind speeds is in fact strongly supported by statistical studies of extreme wind speeds, based primarily on the POT approach [15, 21, 26]. Its use in reliability calculations yields results that, unlike those noted by Ellingwood et al. [8], are credible from a structural reliability viewpoint [17].

It is likely that better probabilistic models of extreme wind speeds could be developed if statistics of thunderstorm and large-scale storm wind speeds could be developed separately and combined in a *mixed distribution*. Efforts in this direction have been reported, among others, by Holmes and Moriarty [15].

The validity of the reverse EV III distribution is also suggested strongly by extensive statistical analyses of hurricane wind speeds [14]. However, EV distribution tails are longer for hurricane than for nonhurricane wind speeds. This has important implications on the relative magnitude of safety margins for hurricane and nonhurricane regions [17, 27].

Tornadoes contain some of the strongest winds occurring in nature. The realistic probabilistic estimation of extreme tornado wind speeds is a difficult if not impossible task. First, to date, no tornado wind speed near the ground has ever been measured reliably. Second, because in the past tornado observation capabilities were relatively weak, large numbers of tornadoes appear to have been unrecorded, particularly before the 1970s. Estimates of tornado occurrence frequency therefore need to be corrected subjectively. Third, estimates of typical areas swept within a tornado by winds of various intensities are also highly uncertain. Fourth, tornado intensity scales in the US have been based largely–incorrectly–on the appearance of damage (e.g. on whether a roof has been blown off). This does not account for the fact that, depending upon the stringency of the criteria used in the design of the damaged structure, the same type of damage can imply very different wind speeds [19]. Estimated probabilities of exceedance of tornado wind speeds are the result of engineering judgments and guesses affected by the inadequacy of current information on tornado occurrences, structure and wind speeds. Should effective measurement capabilities be developed in the future, it would take decades before a new and more reliable tornado database could be assembled. Nevertheless, measurements will be useful for calibrating new engineering estimates of the speeds needed to cause observed damage, which in turn would help to correct past estimates of tornado wind speeds.

Extreme Snow Depths and Loads

Ground snow depth data recorded by weather stations is subjected to EV analyses similar to those applicable for wind speeds. In engineering applications information is needed on ground snow load data. In the past, records have been taken at most US stations only for ground depth data; only at about 200 stations have records been taken for both ground depth and ground load. From such dual sets of data regional empirical relations between ground snow depth and load can be developed, on the basis of which statistical estimates of ground snow loads can be obtained from EV analyses of ground snow depths [7].

Ice Data

Data pertaining to ice is of interest for engineering purposes. Structures, including wires, cables and guys, must be designed to withstand the weight of ice accretions or wind effects due to the presence of ice. No systematic data on ice loads have been collected in the US. Data on freezing rain and associated glaze ice accretion are limited and allow only largely qualitative estimates. For example, 'based on limited data it appears that glaze ice accretions greater than ... 25 mm occur approximately once every 10 years in the Midwest ... Accumulations greater than ... 50 mm are extremely rare in the Midwest' [1].

Extreme Ocean Waves

Sufficient wave data are unavailable in most cases at any given location. Estimates of extreme wave characteristics (heights, spectra, spatial coherence and directional spread) therefore need to be performed using hindcasting techniques. These techniques develop the requisite estimates from information on wind speeds used in conjunction with physical models of wind–wave interaction and wave structure. Unfortunately, much of the extreme wind speed information collected over the past 100 years is of poor quality: anemometers on ships were often placed in obstructed areas, and ships tend to stay away from high winds. Typical efforts to model extreme wind speeds and the associated waves are summarized in [16] (*see* **Hydrological extremes**).

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(*See also* **Climatology**; **Exceedance probability**; **Extremal events**; **Meteorology**; **Risk assessment, probabilistic**; **Threshold models**)

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