

# Record length coefficient in up-crossing rate analysis for design wind velocities in Canada

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## SUMMARY

Access to reliable weather data is crucial for designing resilient infrastructure that responds to climates vulnerable to extreme weather events. Many Indigenous regions have short or incomplete weather records, increasing uncertainty. This study develops a record-length coefficient, implemented in the Up-Crossing Rate (UCR) analysis, to predict long-term extreme wind velocities across Canada, even for short record lengths. All weather station data are accessed from the Environmental and Climate Change Canada (ECCC) database. Record lengths are reduced to 20, down to 5 years of the most recent data, to apply a record length coefficient for long-term extreme wind predictions. Results show that incorporating the record length coefficient provides conservative predictions for extreme wind events. Fitted exponential equations for the record length coefficient were developed. This can reduce uncertainties and mitigate underestimations of extreme wind speeds in regions with constrained weather data, such as those with limited or missing hourly wind datasets.

**Keywords:** *Extreme Value Analysis, Up-Crossing Rate, Wind, Prediction, Record Length Coefficient*

## 1. INTRODUCTION

Reliable meteorological data for predicting extreme weather events is a vital component, especially in the design of safe and robust structures (Cannon et al., 2020; Hong and Ye, 2014). In Canada, many northern and remote regions face challenges to data scarcity, with data being collected on a limited or infrequent basis, resulting in unreliable accuracy for predicting extreme events, specifically for wind predictions (Reed et al., 2024). Implementing analytical techniques to estimate precise extreme wind events in data-scarce regions is essential in northern zones to overcome these limitations.

Extreme Value Analysis (EVA) for predicting long-term extreme wind speeds has been a widely utilized technique in the wind engineering field for many decades, but it relies on long-term, consistent data records (Friederichs and Thorarinsdottir, 2012; Simiu et al., 2001). For regions with short or limited data sets, these methods become problematic, facing more uncertainty and bias in estimating long-term extreme wind velocities (Cook et al., 2003; Peterka, 1992; Torrielli et al., 2013). Another approach for estimating extreme wind velocities is called the Up-Crossing Rate, which was studied by Davenport (1967) for wind engineering applications, where it overcame the limitations of the assumption of independent events, often made in EVA methods. This method was then revised by Gomes and Vickery (1977), treating wind speeds as a stationary random process, and to overcome the limitations of traditional extreme value methods (Torrielli et al., 2013). This study applies the UCR analysis to long-term data throughout Canadian regions by implementing an appropriate threshold velocity based on the specified meteorological locations. The study will then reduce their record length to the most recent dataset (i.e., 20 and 10 years) and

apply a record length adjustment coefficient towards the predicted long-term extreme mean wind velocity to seek validity in its accuracy for short-term wind records for regions with sparse or limited data. Three traditional distribution methods are employed in this study to validate the UCR method in wind speed prediction. Derived formulas for the record length coefficient based on the return period are then implemented for ease of use when data availability is limited.

## 2. CANADIAN WIND RECORD DATA

Hourly wind data has been a primary source for predicting long-term extreme wind events for locations with a well-maintained meteorological system. In this study, only hourly wind data (HY01) from the Environment and Climate Change Canada (ECCC) database is utilized (Government of Canada, 2024). Hourly wind data provides nominal hourly mean wind speeds represented by the last 2-minute mean wind speed in each hour (after 1985) and the last 1-minute mean wind speeds (before 1985). The height standardization recorded from the anemometer adjusts the wind speed measurement at a specific height to 10-m standard height by assuming either a power law or a log law for the mean wind velocity profile. Hourly wind data ranges from 2 years upwards of over 53 years (1970 – 2022). This study utilizes 204 meteorological weather station locations throughout Canada, which consist of at least 20 years of hourly wind data. For densely populated areas with many meteorological stations, stations are then grouped together based on their near-identical latitude and longitude coordinates, taking the higher of the stations' hourly mean wind velocity when combining such datasets. Missing data should be set as the previous value to avoid incompleteness when datasets are missing. This study considers hourly mean wind velocities in the ECCC database in km/hr.

## 3. UP-CROSSING RATE ANALYSIS FOR WIND SPEEDS

The Up-Crossing Rate (UCR) method has become one of the most popular methods for estimating extreme values of random processes because of the abundant use of data and solid theoretical foundation. This method requires a threshold velocity,  $v_{UCR_{Threshold}}$ , which is calculated initially from Brown et al. (2025a) as the mean of the daily maximum hourly wind velocities (i.e., the highest hourly wind speed within each 24 hours, averaged over all days in the dataset for a given location) plus 1.85 times the standard deviation of these daily maxima. This  $v_{UCR_{Threshold}}$  is established to determine each meteorological wind station's specified return period wind speed. Based on the  $v_{UCR_{Threshold}}$ , the occurrence of an up-crossing event is defined as a transition from a wind velocity below the  $v_{UCR_{Threshold}}$  to above it within the hourly time history. Based on each station and  $v_{UCR_{Threshold}}$ , each up-crossing is counted to determine how frequently the wind speeds crossed the threshold throughout its hourly time history, see an example in Figure 1. Eq. (1) can then be implemented, and the return period wind velocity estimation can be used. The up-crossing rate,  $v(v)$ , is defined as the number of up-crossings,  $N(v)$ , per unit of time,  $T$ .

$$v(v) = \frac{N(v)}{T} \quad (1)$$

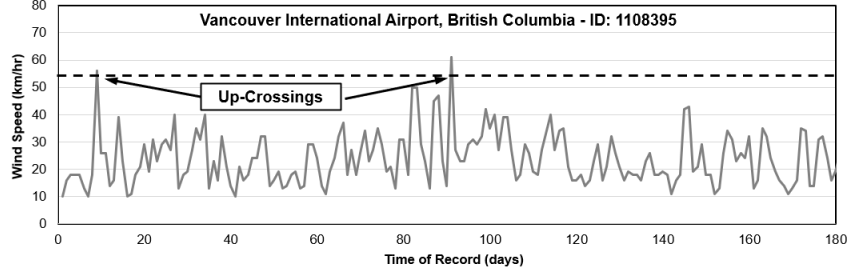


Figure 1: Time history of maximum daily wind speeds for Vancouver International Airport, British Columbia, two up-crossings with a threshold wind speed of 55 km/hr

#### 4. NUMERICAL RESULTS FOR LONG-TERM WIND SPEED PREDICTIONS

Extreme Value Analysis (EVA) for the annual maxima was conducted using the Gumbel distributions with three plotting positions (i.e., Weibull, Gringorten, and Cunnane) applied to hourly wind speed data from the ECCC database for 204 meteorological stations across the country (Cunnane, 1978; Gringorten, 1963; Weibull, 1939). The EVA distributions produce nearly identical mean wind velocity values for each station. Up-Crossing Rate (UCR) method to predict the mean wind velocity for a 50-year return period, denoted as  $v_{UCR_{50}}$  was also included. For all 204 stations, the study found that using the mean plus 1.85 times the standard deviation of their daily maxima produced  $v_{UCR_{50}}$  values in closer agreement with the EVA results, originally analyzed from Brown et al. (2025a) and revisited from Brown et al. (2025b). The  $v_{UCR_{50}}$  predictions closely match those from the three EVA distributions.

A Record Length Coefficient ( $C_{rl}$ ) was developed and implemented in this analysis when fewer than 20 years of hourly wind data are available. The  $C_{rl}$  acts as an amplification factor to adjust the UCR velocity predictions ( $v_{UCR}$ ) for long return periods, reducing the uncertainty associated with wind record availability (i.e., 5 to 20 years). Figure 2 (a and b) present graphical comparisons of the UCR velocity,  $v_{UCR}$ , derived from the full dataset (x-axis) against that obtained from the reduced dataset (y-axis), denoted as  $n_{rl}$ , shown for 10 years, for return periods of (a) 50 years and (b) 500 years for all 204 wind stations. For the data availability,  $n_{rl}$ , of 10 years,  $C_{rl}$  is equal to 1.207 and 1.256 for return periods equal to 50 and 500 years, respectively. It can be observed that for  $n_{rl} = 10$  years of available data,  $v_{UCR}$  is slightly larger in comparison to the  $v_{UCR}$  of the full dataset. When comparing  $n_{rl}$  for 20 years and the NBCC 2020 to the corresponding  $v_{UCR_{50}}$  for the full dataset, wind velocities magnifications are 1.154 and 1.128, respectively. The difference is only 2.25% for a 50-year return period, suggesting that the amplification factor ( $C_{rl}$ ) at 20 years of available data for a 50-year return period lies within an acceptable tolerance. The NBCC 2020 wind velocity values are elevated, which acts as a safety factor, accounting for engineering judgement, statistical uncertainty, and potential non-stationarity. As data availability decreases or return periods increase,  $v_{UCR}$  data exhibits greater dispersion compared to the full dataset, reflecting increased variability due to systematic amplification of wind velocity predictions. Values of  $C_{rl}$  for the 50 and 500 year return periods are presented in Figure 3 (a and b), respectively. Exponential formulations have been developed to represent  $C_{rl}$  as a function of extreme wind velocity amplification for each return period (i.e., 50 and 500 years) when utilizing the UCR method based on the record length availability, denoted as  $n_{rl}$ .

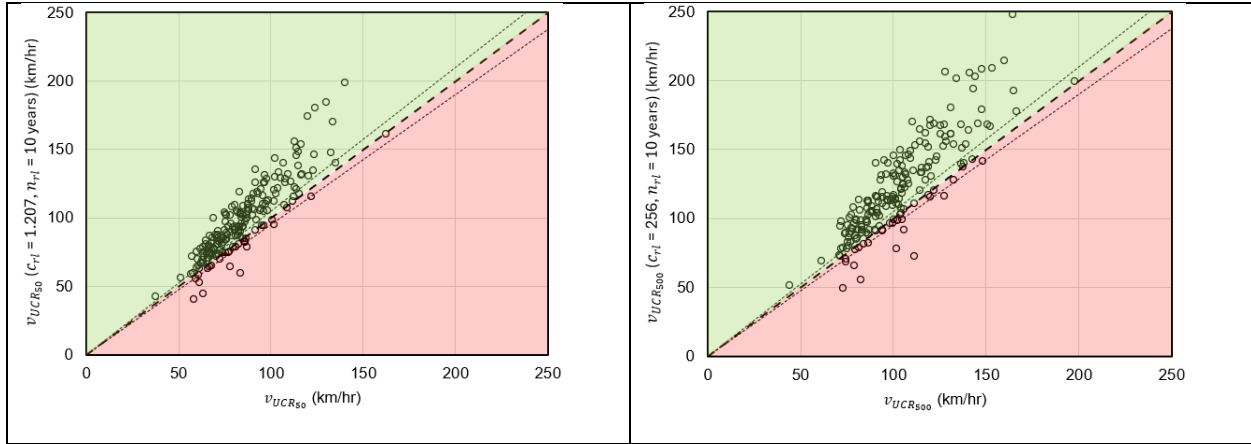


Figure 2: Graphical plot comparison of the full dataset vs. 10 years of data for (a)  $v_{UCR_{50}}$ , and (b)  $v_{UCR_{500}}$

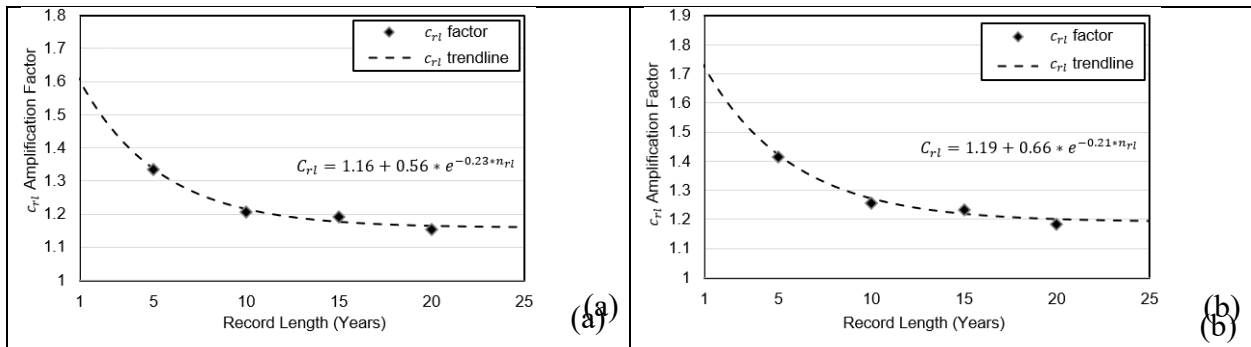


Figure 3: Record length adjustment coefficient ( $c_{rl}$ ) for (a) 50-year, and (b) 500-year return period velocity based on record length availability (years)

## 5. CONCLUSION

Up-Crossing Rate analysis was applied throughout 204 meteorological stations across Canada in predicting long-term extreme wind velocities,  $v_{UCR}$ . An adequate threshold velocity,  $v_{UCR_{Threshold}}$  of the mean plus 1.85 times the standard deviation of these daily maximum hourly wind velocity was applied and confirms close agreement in comparison to traditional Extreme Value Analysis methods. When estimating return periods of 50 years and 500 years, this method provides robustness as a reliable approach to predict extreme wind velocities. A Record Length Coefficient,  $C_{rl}$ , was then developed and applied throughout this analysis as an amplification factor in the  $v_{UCR}$  predictions to mitigate discrepancies when limited data is unavailable (i.e., less than 20 years). Results showed that the  $C_{rl}$  provides a systematic and conservative adjustment towards  $v_{UCR}$  predictions, ensuring that predictions from shorter datasets remain within an acceptable range of full-record values. Formulated equations for the record length coefficient, based on the data availability and return period, were developed, where fitted exponential functions were matched precisely based on the derived record length coefficient factors. As can be seen in the developed formulations, the record length coefficient increases when both the record length decreases and the return period increases.

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