SURFACE WINDS, CLIMATE VARIABILITY, AND POWER OUTAGES IN BRITISH COLUMBIA

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Abstract

Relationships among surface wind speed, North Pacific climate variability, Pacific climate variability, and tree/weather related power outages are investigated in forest rich British Columbia using almost 12 years of BC Hydro (BCH) wind and power outage data, two decades of BC weather station observations and two climate variability indices. Strong surface wind is found to be the dominate cause of power outages that are reported as being tree or weather related. The observed regional fraction of power outage days and the number of influenced customers per outage day increases quickly when the daily maximum wind speed (DMWS) exceeds 50 km/hr. These extreme winds are mostly observed during winter, with substantial interannual variability in BC coastal regions in the frequency of strong days when DMWS exceeds 50 km/hr. A simple empirical outage model is developed using monthly DMWS frequency in southern coastal BC as a predictor. Cross-validation, which is used to estimate the model's out-of-sample performance, suggests a useful level of skill in hindcasting subseasonal to interannual variations in the frequency of observed regional tree/weather outage occurrence during the 2005 to 2017 period when power outage data are available. The widespread power outage event of December 2006 can also be captured when winter windstorm information is added as an additional model input.

1 Introduction

British Columbia (BC) is situated on the west coast of Canada where it is exposed to the influence of storm activity in the northeast Pacific ocean. The province has an area of 94.5 million hectares, 64% of which is forest. BC is considered to be part of the larger Pacific Northwest (PNW) region of North America that includes BC, Washington, Oregon and Idaho. A previous study found that historically, 80% of tree mortality in Washington state is due to strong winds (Kirk and Franklin, 1992). Wind damage is the dominate natural cause for tree and weather-related power outages in PNW regions (Coder, 2007; Guggenmoos, 2011; Read 2015; Yao and Sun, 2018).

Tree/weather related power outages occur mostly in the stormy winter and spring seasons when extra-tropical cyclones (ETCs) make landfall along the PNW coast (Mass and Dotson, 2010; Read, 2015), bringing strong winds and heavy rainfall through a series of wind storm events. These are generally large-scale events affecting regions of over 1000 km in breadth and persisting over days. Severe events can have extensive impacts on electrical distribution systems and substantial economic impacts. For example, extreme wind associated with an intense ETC that hit the Pacific Northwest coast in December 2006 caused substantial electrical system damage with millions of affected customers in Washington and BC (Guggenmoos, 2011; Read, 2015).

The frequency and strength of ETC associated extreme winds has been linked with the large-scale modes of climate variability such as the warm and cold El-Nino Southern Oscillation (ENSO) phases (Wallace and Gutzler, 1981; Rasmusson and Carpenter, 1982; Mantua et al., 1997; Encloe, 2003; Read, 2015; Hamlington, et al., 2015; Mohammadi and Goudarzi, 2018) The effects of climate oscillations on variations in wind energy resource have also been investigated over the US. For example, one study found that La Niña events are associated wind speed increases through much of the US during winter and spring (Hamlington, et al, 2015). In Canada, analysis of long-term terrestrial wind speed records demonstrates that most of the low-wind events (characterized by consecutive months of negative surface wind speed anomalies) on the southern Canadian Prairies occurred during a “moderate” or “strong” El-

Niños (George and Wolfe, 2009). Also, reduced surface wind speeds and reduced ETC windstorm frequency affecting southwest BC was found during the warm phase of the Pacific Decadal Oscillation (PDO) (Abeysirigunawardena et al. 2009; Tuller, et al. 2004; Read, 2015). Atmospheric jet streams are expected to shift northward under the projected future warming scenarios, with the result that ETC related windstorm events are also expected to shift northward, leading to an increase in intensity and frequency north of 45°N (Seiler and Zwiers, 2016).

In this report, we present results derived from surface weather station observations, BC power outage reports, climate indices, and a simple outage occurrence model. Our goal is to better understand widespread connections among surface winds, North Pacific climate oscillations, and power outages so as to better predict wind impacts on tree and weather-related outage events in BC coastal regions.

Surface winds have been selected and represented in various ways to model strong wind impact on power outages in previous published studies. For example, Guggenmoos (2011) selected daily maximum wind speed data (based on 2-minute average winds) and used a Weibull distribution to fit 10 years of tree-related outage data in western Washington over the 1998-2008 period. In contrast, Zhou, et al. (2006) considered daily gust wind speed (the instantaneous peak or maximum wind speed measured every few seconds) and daily aggregate lightning frequency to fit a Poisson regression model describing yearly weather-related power outage frequency from nine Kansas substations for 1998 to 2003. Read (2015) used 2-min averaged wind speed, 5-second gust wind, peak 2-minute wind direction, storm duration and storm total precipitation and two regression models to simulate tree-related power line faults during individual ETC storm events from 2005 to 2009 in the lower mainland and Victoria region. Hirata (2011) developed a logistic regression model linking annual wind speed and high-resolution numerical weather prediction model products to outage locations over the high population lower mainland area of BC from 2004 to 2007. In addition, Wanik et al. (2018) recently used machine-learning approaches to simulate current and future Hurricane Sandy impacts on the severity and spatial distribution of power outages in Connecticut, USA. Most of these previous studies used limited power outage data and contemporaneous on-site meteorological data in modelling the association between climate factors and the occurrence of tree/weather related power outages. The timescales considered in these studies varied from that of individual windstorms (days; Hirata (2011), Read (2015), Wanik et al. (2018)) to annual or multi-annual (up to a decade; Zhou et al (2006), Guggenmoos (2011)).

Several studies have recently assessed changes in the level of risk to critical infrastructure in Europe due to climate change impacts on the frequency and severity of storms in Europe (Karagiannis et al., 2019; Fu, et al., 2017; Dunn et al., 2018; Espinoza et al., 2016; Panteli and Mancarella, 2017; Panteli et al., 2017). For example, the wind impact on the failure probability of the transmission lines and towers has been modelled and evaluated (Fu, et al., 2017; Dunn et al., 2018) using newly developed empirical fragility curves and downscaled high spatial resolution (12 km) wind gust data based on the ERA-Interim (Dee, et al., 2011) reanalysis over the United Kingdom. These studies investigated the impacts of winds exceeding the 10-, 50- and 100-year return levels on power systems (primarily considering the high-voltage transmission system) under a future climate change scenario over Great Britain (Espinoza, et al., 2016; Fu, et al., 2017) and a small region in western Europe (Karagiannis et al., 2019).

The distinction between electrical transmission systems and distribution systems is important. The former deliver power to central locations that feed lower voltage local and regional distribution systems. Failure of a transmission line or tower can affect very large numbers of people, and thus this critical infrastructure is generally designed for very high levels of reliability and is usually placed in corridors that are designed to minimize hazards from the surrounding forests and other land surface features. In contrast, the lower voltage electrical distribution systems, which are much more extensive and extend to virtually all inhabited locations, are vulnerable to such hazards as well as direct wind influences. In the forest-rich Pacific Northwest coastal region, tree-related damage to the distribution system is the primarily cause for power outages, and even moderate winds with wind speed greater than 20 km/hr can lead to tree damage. We therefore develop a new tree/weather related outage failure relationship covering all weak, moderate, and strong wind conditions for this region.

In this study, we will consider two decades of meteorological data that is representative of the broader, synoptic scale and 13-years of daily power outage data in which each event is characterized by its date, location, proximal cause and number of affected customers. The remainder of this paper is organized as follows. Section 2 describes the data; Section 3 introduces a derived wind-outage dataset that combines wind speed data with power outage data in a way that minimizes the effects of changes in the electrical distribution system over time. This dataset will form the basis for the analysis of wind-outage relationships in this paper. The outage occurrence model that is used for this purpose is described in Section 4. Observed relationships among surface wind speed, BC hydro power outage statistics, and climate variability indices are presented in Section 5. Results from the application of the outage occurrence model presented in Section 6, and finally conclusions and future research are summarized and discussed in Section 7.

2 Data

We use a power outage dataset for BC that is maintained and quality controlled by the BC Hydro emergency response team. The period covered by the dataset is June 2005 to Feb 2017. Event reports during this period are complete, whereas only incomplete quality-controlled records exist prior to June 2005. Each individual reported power outage event is recorded with the following six variables: outage ID, beginning time, ending time, location (longitude, and latitude), causes, and number of customers influenced. The variable "causes" includes environmental factors such as trees, birds, adverse weather, fire, flood/snow, and non-environmental factors such as planned outages and equipment repair. Each outage event is also classified as either a storm or a non-storm case BC Hydro defines an outage event as a storm event when the number of BC hydro emergency response staff who are deployed is greater than a fixed empirical number, which is based on its accumulated experience of deployment requirements when a wind-storm hits the region (see Table 1 for details). The occurrence of storms can result in large numbers of outage sites that are simultaneously reported as storm cases, and indeed, this classification is generally consistent with the occurrence of strong winds from a landfalling ETC. The BCH reported power outage sites are plotted as black dots shown in Figure 1.

Surface wind observations used in this study are based on Environment and Climate Change Canada (ECCC) hourly weather station surface wind speed data. Both the wind speed data and supporting technical documentation are available online for public access[1,2]. The reported hourly values indicate 5-minute mean windspeed recorded just prior to reporting time. There are 291 stations in BC that reported such hourly winds during the June 2005 to Feb 2017 study period. Among them, approximately 100 stations, shown as blue and red dots in Figure 1, are located within 0.2° latitude and longitude of the locations of reported power outage events. The red dots represent high-quality Vancouver Island and Strait of Georgia stations that will receive particular attention in this study: BALLENAS ISLAND (49.2°N, 124.1°W), COMOX A (49.4°N, 124.5°W), ENTRANCE ISLAND (49.1°N, 123.5°W), SISTERS ISLAND (49.3°N, 124.3°W), and SANDHEADS CS (49.1°N, 123.2°W). We designate the region that encompasses these stations as "Region A", which includes the developed area of eastern Vancouver Island that spans Comox, the Qualicum beach area, Parksville, Nanoose Bay, and Nanaimo plus the area surrounding Richmond and Delta in the Metro Vancouver region. The total population in Region-A was close to 0.5 million in 2019 based on BC statistics. The five stations representing this region are situated at elevations no greater than 50m above sea level, and have continuous hourly surface wind speed records from Jan. 1995 to Dec. 2017, with less than 3% missing data during 2005-2017. When missing, the daily maximum wind speed from the nearest ECCC station within 0.2° latitude and longitude is used to infill the missing value.

Two indicators of large-scale atmospheric circulation variability that are relevant for the BC region, the Southern Oscillation Index (SOI) and the Northern Oscillation Index (NOI) are also used in this study. The SOI[3], which is a standardized index based on the sea level pressure differences between Tahiti (18°S, 149°W) and Darwin, Australia (10°S, 130°E), represents large

[1] http://climate.weather.gc.ca/historical_data/search_historic_data_e.html
[2] http://climate.weather.gc.ca/about_the_data_index_e.html
[3] https://www.ncdc.noaa.gov/teleconnections/enso/indicators/soi

scale fluctuations in air pressure between the eastern and western Tropical Pacific during El Niño and La Niña episodes. The SOI influences a wide range of tropical and extratropical climate events impacting the North Pacific on intraseasonal, interannual, and decadal scales (Schwing et al., 2002; Costa-Cabral, et al., 2016), and affects observed trends and variability of surface winds in North America (Enloe, et al., 2004; Abeysirigunawardena, et al. 2009; Hamlington, et al. 2015). The NOI is defined similarly, except it is based on the seal level pressure differences between the North Pacific High (35°N, 135°W) in the northeast Pacific and Darwin. These two locations are centers of action for the North Pacific Hadley-Walker atmospheric circulation (Schwing, et al., 2002). We calculate the NOI from monthly sea level pressure anomalies at Darwin and the North Pacific High, which were obtained from the NOAA-CIRES 20th Century reanalysis V2C (Compo, et al., 2011; Cram, et al., 2015)[4].

In coastal BC, heavy snow and cold air can enhance tree damage under strong wind conditions, which further increases outage occurrence during the wind storm season. These two variables are also influenced by North Pacific climate variability that is associated with the SOI and NOI. Monthly adjusted snow data (Mekis and Vincent, 2011)[5] and monthly homogenized surface air temperature data (Vincent, et al., 2012)[5] at the COMOX station in the Region-A are therefore also used in Section 4 to better understand the NOI and SOI influence on the winter wind-outage relationship in BC.

3 Wind outage data set

A wind-outage dataset was developed by matching each outage event caused by an environmental factor (referred to as *environmental outage events*) with the highest of the daily maxima of ECCC hourly wind speeds on the day of the event at stations within a 0.2° latitude and 0.2° longitude neighbourhood of the location of the event. Instantaneous (5-second) wind gust speeds are not considered because of their much lower availability from ECCC observing stations. A station is included for a particular event only if at least 20 hourly wind values are

[4] https://www.esrl.noaa.gov/psd/data/gridded/data.20thC_ReanV2c.html.
[5] https://www.canada.ca/en/environment-climate-change/services/climate-change/science-research-data/climate-trends-variability/adjusted-homogenized-canadian-data.html.

available during that calendar day in which the event occurred. The wind-outage dataset includes seven variables: “outage event ID”, “power outage start time”, “time duration”, “outage site location (latitude and longitude)”, “cause factors”, “outage matched nearby weather station ID”, and “outage matched station daily maximum hourly wind speed”. In total, 145,865 environmental related power outage events were successfully matched with nearby ECCC station daily maximum wind speeds during the 2005 to 2017 study period. This dataset, representing 79% of environmental outage events, was subsequently used for wind-outage relationship analysis and modelling in this study.

Figure 2 illustrates the sites of environmental power outage events and the matched weather stations on two contrasting days, 10 Sept. 2005, which lies within the climatological low-wind season (April to September), and 12 Dec. 2006. Note that in Figure 2, points that appear to be over water are actually located on small islands. The figure shows that four environmental outage events (two of which were tree/weather related) occurred in southern coastal BC on 10 Sept. 2005 (blue and green points), and that a matching nearby weather station (red) providing an observed daily maximum wind speed (DMWS) was found for each event. In contrast, 330 reported environmental outage events (mostly tree/weather related) were reported on 12 Dec. 2006, with matching extreme wind speeds being provided by 18 weather stations (red). These latter outages reflect the impact of a once-in-decade extreme extratropical cyclone that affected southern BC on that date. Observed surface winds are available at only a limited number of ECCC weather station sites, with the result that many outage locations will be matched with the same station on occasions when an extreme weather event causes outages at a large number of locations, as on 12 Dec. 2006. Also, because the spatial density of ECCC stations is not uniform, the number of stations considered when identifying a matching station will vary from one outage event to the next.

One way to deal with the mismatch between the variable spatial density of outage events and the generally more constant, albeit, lower and nonuniform spatial density of weather stations, is to introduce a weather station-orientated power outage occurrence counting method with units of “station-days” (SD) based on a simple indicator function. For this purpose, for station i and day j, we set $Y(i, j) = 1$ SD if a DMWS value at station i was associated with at least one outage event of a given kind on day *j*; otherwise, Y(*i*, *j*) = 0 SD. A tally of these indicators over a region and a time period can then be obtained as the sum of Y(*i*, *j*) for all stations *i* within the region and all days *j* during the time period. In Figure 2, the regional tree/weather outage occurrence tally for 10 Sep. 2005 is 2 SD while that for 12 Dec. 2006 is 18 SD, indicating the much more extensive nature of the damage that occurred during the latter event. This indicator, while providing a less direct representation of the severity of a given event, has the benefit that it should be less strongly affected by changes in the electrical distribution system that come about over time because of ongoing local and regional development than a direct count of outage events. Development driven expansion of the electrical distribution system can cause changes in the frequency of outages since development brings about changes in the amount and type of infrastructure that is exposed to environmental hazards even if the nature of the environmental hazard (e.g., maximum sustained wind loads) does not change. This development-driven source of non-stationarity can be at least partially avoided by defining events through the occurrence (or lack of occurrence) of impacts at the station scale, thus taking advantage of the essentially fixed meteorological observing network that was in place during the period of this study.

Note, however, that it is not possible to completely isolate the analysis from development driven non-stationarity since the likelihood of occurrence of an outage within the proximity of a meteorological station will depend on the extent of the distribution system within that area. A working assumption, therefore, is that developed related distribution system changes do not substantially alter those likelihoods over the period represented by the wind-outage dataset. This represents, in effect, a classic bias-variance trade off. A longer dataset will, on the one hand, provide more information with which to estimate outage occurrence model parameters, but this happens at the cost of biases that could be introduced as a consequence of development driven non-stationarity. This station-orientated SD method will be applied in the remainder of this paper to Region A and to the whole of BC, which includes all BC area weather stations, the majority of which are located in southern coastal BC.

4 Outage occurrence model formulation

This section presents a simple empirical model that is constructed to simulate regional monthly tree/weather related power outage occurrence, based on the observed Region-A monthly DMWS distribution during the 2005 to 2017 period covered by our wind-outage dataset. The monthly distribution of Region-A DMWS varies substantially between the summer dry season and the winter windstorm season, as shown in Figure 3. DMWS has a narrow distribution varying between 10km/hr to 50 km/hr in summer whereas it varies across a much broader range, extending up to 95 km/hr, in winter. Figure 3 also shows that tree/weather related outages occur much more frequently in winter than in summer. Trees and weather are responsible for more than half of outages when the DMWS is greater than 50 km/hr (Figure 3).

Recall that in Section 2 we defined a variable $\mathrm{Y}_c(i,j)$ for station *i* and day *j* such that

$$\mathrm{Y}_c(i,j) = \begin{cases} 1, & \text{if DMWS(i, j) is associated with } \geq 1 \text{ cause c outage events on day } j \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

where $\mathrm{DMWS}(i,j)$ is the daily maximum hourly windspeed at station *i* on day *j*. $\mathrm{DMWS}(i,j)$ is a continuous random variable that takes values between 0 and ~100 km/hr in BC; there are no observations in BC of hourly mean wind speeds above 100 km/hr. As also indicated previously, $\mathrm{Y}_c(i,j)$ has units of *station-days* (SD).

The number of days with outages due to a given cause c in month m that are associated with station *i* for a given range of daily maximum winds speeds is then given by

$$O_c(i,m,k) = \sum_{j\in m} \mathrm{Y}_c(i,j) I[w_k \leq \mathrm{DMWS}(i,j) < w_{k+1}] \quad (2)$$

where m indicates the month, *k* indicates a wind-speed range $[w_k, w_{k+1})$, *j* ranges over the days that fall within month *m* for all years, and $I[.]$ is an indicator function that takes values 1 or 0 depending on whether the condition given in the argument is true or false. We use a total of 20 windspeed bins [0, 5), [5, 10), … [95, 100) km/hr.

These counts in units of SDs of outage events associated with a station by cause, station, month of the year and wind speed bin are used to define a number of other variables. The total number of cause *c* outage days in month *m* that are associated with station *i* is given by

$$O_c(i, m, .) = \sum_{k=1}^{20} \sum_{j \in m} \mathrm{Y}_c(i, j) I[w_k \leq \mathrm{DMWS}(i, j) < w_{k+1}] = \sum_{j \in m} \mathrm{Y}_c(i, j) \quad (3)$$

The total number of outage days linked to station *i* in month *m* for all causes when DMWS lies in the *k*th bin is given by

$$O_{\cdot}(i, m, k) = \sum_c O_c(i, m, k). \quad (4)$$

The total for cause *c* for all wind speeds is given by

$$O_c(i, m, \cdot) = \sum_k O_c(i, m, k), \quad (5)$$

and the total for all causes and wind speeds combined is given by

$$O_{\cdot}(i, m, \cdot) = \sum_c \sum_k O_c(i, m, k). \quad (6)$$

Note that in our notation, a “dot” in place of a subscript or argument indicates that a sum has been taken over all possible values of that subscript or argument.

We now define two further random variables – a binary variable C corresponding to outage causes (we consider essentially two causes – tree/weather combined, and all others), and a discrete variable W taking values 1-20 identifying the DMWS wind speed bin. The counts defined above can be used to estimate the joint, conditional and marginal distributions of C and W for each location and month. To this end,

$$g_{i.m}(C = c | W = k) = \frac{O_c(i,m,k)}{O_{\cdot}(i,m,k)} \quad (7)$$

estimates the conditional probability that *c* is the cause of an outage day linked to station *i* in month *m* given DMWS at that location and time of year has fallen within the *k*th wind speed range. Similarly,

$$f_{i,m}(W = k) = \frac{O_{\cdot}(i,m,k)}{O_{\cdot}(i,m,\cdot)} \quad (8)$$

provides an estimate of the marginal probability that DMWS will fall in the *k*th bin when outage days occur due to any cause. These totals can be pooled across regions prior to estimating probabilities, which we do in order to characterize BC (combining all locations *i*) and Region A (combining all Region A stations). That is, we obtain

$$g_{\cdot,m}(C = c|W = k) = \frac{O_c(\cdot,m,k)}{O_\cdot(\cdot,m,k)} \tag{9}$$

and

$$f_{\cdot,m}(W = k) = \frac{O_\cdot(\cdot,m,k)}{O_\cdot(\cdot,m,\cdot)} \tag{10}$$

where totals are taken over locations *i* either in BC or Region A.

Our primary interest is in characterizing the dependence of the conditional probability *g* on the wind speed class *k*, and thus we develop a simple parameterization to serve this purpose. We note that *g* can be written as

$$g_{\cdot,m}(C = c|W = k) = \gamma_{m,c}(k) f_{\cdot,m}(W = k) \quad \text{where} \quad \gamma_{m,c}(k) = \frac{O_c(\cdot,m,k)O_\cdot(\cdot,m,\cdot)}{O_\cdot(\cdot,m,k)^2}. \tag{11}$$

Pooling the counts further across months, we obtain $g_{\cdot,\cdot}(C = c|W = k) = O_c(\cdot,\cdot,k)/O_\cdot(\cdot,\cdot,k)$, which is the long-term fraction of outage station days due to cause *c* when DMWS falls in wind speed class *k*. This quantity is shown in Figure 4 for tree/weather caused outages and clearly illustrates the higher the observed DMWS, the greater the regional fraction of outage SDs due to tree/weather relative to all outage causes, with tree/weather becoming the predominant cause of outages for very high wind speeds. Therefore, for the tree/weather cause, since $g_{\cdot,\cdot}(C = c|W = k)$ approaches one for the upper wind speed bins, $\gamma_{m,c}(k)$ approaches $f_{\cdot,m}^{-1}(W = k)$ for those wind speed bins.

As discussed, previous studies have shown that whenever DMWS reaches a threshold (typically 50-70 km/hr), the outage ratio increases more quickly with DMWS (Guggenmoos, 2011; Read, 2015). This behavior, which is also reflected in $\gamma_{m.c}(k)$ (Figure 5), can be approximated as

$$\gamma_{m,c}(k) \approx \gamma_0 + \min\{1 - \gamma_0,\ \beta \left(\frac{k}{k_{crt}}\right)^{\alpha}\} \tag{11}$$

where γ_0, α, β and k_{crt} are parameter that are to be estimated. The maximum value for regional monthly $\gamma_{m,c}$ is 1.0 while the minimum value is γ_0, which represents the mean outage SD fraction under weak wind conditions. From previous studies, tree damage occurs when wind speed is greater than ~20 km/hr, and therefore we estimate γ_0 as the mean observed

$\gamma_{m,c}(k)$ of the first 3 bins over the period used for model fitting. The k_{crt} is chosen such that DMWS is within the previous publication suggested critical threshold range between 50-65 km/hr. We chose $k_{crt} = 12$ (55-60 km/hr) for the relatively open island Region-A (less tree damage given the same DMWS), and $k_{crt} = 11$ (50-55 km/hr) for the more forest dominated whole-BC region. Since we find $\gamma_0 < 0.1$, we have from eq. (11) that $\gamma_{m,c}(k_{crt}) \approx \gamma_0 + \beta$. We can therefore estimate β from the observed regional mean $\gamma_{m,c}(k_{crt})$ over the period used for model fitting. The remaining parameter α is estimated by fitting this model to $\gamma_{m.c}(k)$ values estimated from our wind/outage dataset via least squares.

5 Observational results

5.1 Environmental cause related power outage statistics

Trees, weather, birds, animals, fire, and flood/snow are the primary recorded causes of unplanned service interruptions to the BC Hydro electrical distribution system. There were 145,865 environmental cause related power outage events during the study period, with recorded causes including trees (36.8%), adverse weather (19.7%), birds (22.7%), animals (3.5%), fire (1.8%), flood/snow (0.2%), vibration (0.6%), and other unknown environmental causes (14.7%) as listed in Table 2. Interestingly, the number of customers affected by these events is not proportional to relative event frequency across the different event types. Irrespective of how the impact of environmental events is recorded, the top three recorded environmental factors for BC outages are trees, weather, and birds. Amongst these three causes, tree/weather related outages are wind-damage associated and account for 56% of total events and 75% of total customers influenced.

Monthly variations in tree/weather related, bird related, and other environmental factor related BC power outage events measured in station-day (SD) units are plotted in Figure 6 for 2005 to 2017. Bird and tree/weather related outage SD values have regular seasonal cycles, with a peak in summer in the case of birds and in winter or spring (mostly Nov., Dec. and Jan.) in the case of trees/weather. The tree/weather related outage annual peak varies greatly each year with the highest peak occurring in Dec. 2006, when the decade's worst ETC hit Vancouver Island and devastated Stanley Park in Vancouver, leaving more than 400,000 customers without power. The observed large variation of seasonal tree/weather related outage occurrence is primarily associated with the observed wind speed-outage relationship as will be presented in section 5.2.

5.2 Surface wind speed-outage relationship

Surface wind is the primary natural cause of tree and weather-related power outages in forest rich Pacific Northwest coastal regions (Read, 2015). The higher the wind velocity, the greater the wind pressure placed on trees, utility poles and other electrical distribution system infrastructure (wind load increases quadratically with wind speed), and thus the higher the damage to trees and power systems, which are affected both directly and by falling trees and tree branches. Coder (2007) examined wind load effects on trees over the US and found that tree branch failure (sway and/or broken) occurs under moderate winds (around 30 to 75 km/hr), tree breaking and uprooting occurs under strong winds (75-112 km/hr), and forests can be destroyed with massive tree losses occurring under violent storms when wind speed is greater than 112 km/hr.

Figure 7 displays monthly regional tree/weather related outage SD number and monthly mean daily maximum wind speed (DMWS) for the whole of BC and for Region-A during the 2005 to 2017 study period. On monthly and longer time scales, surface DMWS variations are primarily controlled by synoptic scale systems, ETCs, and storm track variations, with large spatial scales of variation. Monthly mean DMWS is therefore highly correlated not only with "whole BC" outage SD values but also with Region-A OSD values (R>95%) (Figure 7) and with SD time series for the 5 individual island stations in Region-A (Figure 8). At these monthly time scales, the entire region is affected by the same pressure system, with the result that regional tree/weather related outage SD number in both the whole-BC and the Region-A exhibit the same monthly variations as regional mean daily maximum wind speed.

The wind-outage dataset that we have developed can be used to associate a pair of variables with each SD occurrence for a given outage cause such as tree/weather: the observed DMWS and the number of customers influenced. The importance of a given cause relative to other causes can then be estimated as a function of wind speed by comparing the frequency of a given cause relative to all causes for a given wind speed range. Figure 4 displays such ratios for tree/weather related outages, calculated using 20 wind speed bins of width of 5 km/hr. For both-BC and Region-A, the ratio increases rapidly as site DMWS rises from 20km/hr to 95 km/hr. Previous studies have proposed a wind threshold of between 55 km/hour to 70 km/hour for tree/weather related power outage breakout based on individual wind storms study in western Washington (Guggenmoos, 2011) and BC (Read, 2015). Such a "break out" (abrupt increase in the relative importance of tree/weather as a cause) is not clearly evident in Figure 4, but the outage fraction does increase faster when DMWS is greater than 40 km/hr, and tree/weather becomes the dominant cause of outages, whether measure by counting station-days or affected customers when DMWS greater than ~70 km/hr.

5.3 Impact of low frequency climate variability

Observed trends and variability of surface wind speed are influenced by large-scale low frequency variations such as those associated with the El-Niño Southern Oscillation (ENSO), which strongly impacts the Pacific Northwest region (Enloe, et al., 2004; Abeysirigunawardena, et al. 2009; George and Wolfe, 2009; Hugenholtz, 2013; Read, 2015). In particular, increased wind speeds tend to occur through much of the US during winter and spring in association with La Niña events (Hamlington, et al, 2015). In Canada, strong winds known as chinooks in southern Alberta have also been found to be associated with La Niña conditions, as well as a strong polar jet stream and an increased frequency of extra tropical cyclones that sweep into the Pacific Northwest (Hugenholtz, 2013) along the North Pacific storm track. In coastal BC, local climate variables such as winds, precipitation, and temperature are also influenced by North Pacific climate variability that is associated with ENSO and the Northern Oscillation.

Figure 9 presents time series of monthly values of the southern oscillation index SOI, the northern oscillation index NOI, Region-A DMWS anomalies from the annual cycle (km/hr) and anomalies of W50 relative to its annual cycle, where W50 is the monthly total number of outage events recorded when DMWS > 50 km.hr, summed across stations in Region A. All timeseries are for the period Nov. 1995 to Jan. 2017. Monthly NOI values tend to be strongly positive during La Niña events (Dec. 1998-Feb. 1999; Dec. 2016-Jan. 2007; Dec. 2007; Dec.

2011-Jan. 2012; Nov. 2015-Dec. 2015) or during the transition from strong El-Niño to La Niña conditions (Jan.-Feb. 1998; Jan.-March 2010). Monthly DMWS and W50 values tend to peak at above normal levels during these episodes, although substantial variability can also be seen in both indices outside these periods.

While important associations between power outage occurrence and ENSO exist, variation in the NOI appear to be the dominant cause of interannual variation in W50 in BC. We therefore briefly consider the long-term interannual variation in the NDJ mean values of the NOI and its two components. Figure 10 displays time series of (a) NDJ mean NOI values, and NDJ mean sea level pressure anomalies at (b) the North Pacific High and (c) Darwin. These indices are calculated using surface pressure data extracted from the NOAA-CIRES 20th Century Reanalysis (Compo et al., 2011) for Jan. 1951 to Dec. 2014. It is evident that there is very little secular change in the NOI or either of its components, and that the interannual variability of the NOI is dominated by fluctuations in the intensity of the North Pacific High. It is also evident that there is a substantial amount of interannual to interdecadal scale variability in seasonal mean values of the NOI, which highlights some of the challenges that are faces when considering wind-outage relationships in a dataset that is only a bit more than a decade in length.

Figure 11 illustrates the challenge that is associated with quantifying and explaining the variability that occurred during the period covered by the wind-outage dataset that we have constructed. Figures 11a, 11b and 11c first present timeseries of NDJ seasonal mean tree/weather related outage statistics tabulated in station days for Region A (Figures 11a and 11b) and all of BC (Figure 11c). The variability seen in these figures exhibits some secular behaviour, although there are no significant trends, and clear evidence of low-frequency multi-year variability, whether considering all days (Figures 11b and 11c) or only days when DMWS > 50 km/hr (Figure 11a). Some clear commonality is evident when comparing the variations in the outage statistics with the seasonal DMWS variations in Region A (Figure 11d), consistent with the idea that higher daily maximum wind speeds should be associated with greater outage frequency. Some commonality between variations in the outage statistics can also be seen when comparing with seasonal variations in the NOI and SOI values (Figures 11e and 11f) that provide information about large scale circulation influences on the region, although the connection seems less direct. Finally, we also consider two other aspects of the weather as indicated by the seasonal mean surface air temperature at Comox (Figure 11g) and seasonal mean snowfall at the same station (Figure 11h). Temperature and snowfall covary, with greater snowfall when temperatures are cooler, as expected, and there is some suggestion that warmer NDJ conditions correspond to more quiescent conditions with fewer outages.

Tree/weather related power outage occurrence generally reaches its annual peak in Nov. and Dec. when the first major ETCs impact coastal BC. Figure 11e shows there are four winters when the NDJ mean NOI is greater than 3.5 mb (2006-2007, 2007-2008, 2008-2009, and 2011-2012). Strong winds and outages tend to occur more frequently, temperatures are lower, and snowfalls tend to be heavier during these four winters compared to average winters. The number of strong wind (DMWS > 50 km/hr) SD, in particular, is around 10% greater during these four strong NOI winters than during an average winter (Figure 11a). Correspondingly, seasonal tree/weather outage number is approximately 30% greater during these four winters than during an average winter in both Region A (Figure 11b) and BC as a whole (Figure 11c).

Figure 12 presents the frequency distribution of DMWS in two SOI phases in Region A during the outage period from June 2005 to February 2017 together with the distribution of monthly SD values for tree/weather caused outages. The observed total number of months, DMWS station days (SD), tree/weather caused outage SDs, the fraction of days with DMWS > 50 km/hr, and the fraction of tree/weather outage SD with DMWS > 50 km/hr are summarized in Table 3 for the same period. The highest fraction of the observed large DMWS (> 50 km/hour) SD is observed in the positive NOI phase. The tree/weather caused outage fraction with large DMWS (> 50 km/hour) is high in both the non-positive SOI and positive NOI phase, which is associated with extreme windstorm events occurred during the transition period from El Nino to La Nino (for example the once-in-a-decade extreme 2006 Dec-Jan windstorm event), in which the monthly NOI was strongly positive and the monthly SOI is non-positive as shown in Figure 9.

These findings are based on only 12 years of data and thus provide a very incomplete picture of the complex low-frequency climate variability that affect the region. Thus, many questions remain for future research. Nevertheless, there is perhaps enough information to attempt an analysis of the links between outage occurrence and the associated surface wind speed that focuses on higher-frequency, intra-seasonal variability.

6 Outage occurrence model application results

The outage occurrence model (formulated in Section 4) is trained separately for BC and Region A using the first 75% of the monthly data for the 12-year period (June 2005 to Feb. 2017), and is then evaluated using the remaining 25% of the monthly data. This gives us an opportunity to assess whether useful information about the links between winds and outages can be obtained from the intra-seasonal variability seen in relatively short records. We also perform another experiment in which we cross-validate the model, training it with the final 75% of the monthly data for the 12-year period and then evaluating it using the first 25% of the monthly data. The four model parameters and simulation performance are summarized in Table 4 for fits of the model that use several different subsets of the data for training. Depending on the choice of training and evaluation data, we find the that this simple model explains roughly 50% of the variance in monthly outage frequency as measured in station-days, with no apparent systematic difference in explained variance rates in the training and evaluation periods. Results are similar when the model is fitted only to extended winter data (October-February; not shown), while explained variance is much lower during the extended summer season (May-September; not shown) when winds tend to be weaker and other factors presumably dominate tree/weather related power outages.

As noted above, the simple empirical outage model demonstrates good skill in reproducing outage frequency measured in station-days, both within the training period and during the cross-validation period (see Table 4 and Figure 13). The model can simulate the general observed seasonal pattern of tree/weather related outage frequency and above 80% of the magnitude of most observed outage peaks from 2005 to 2016. Exceptions include the once-in-a-decade December 2006 outage peak that is substantially underestimated as shown in Fig. 11, and the subsequent minimum in outage events in summer 2007 that is also not captured, perhaps because the December 2006 storm had “harvested” distribution system infrastructure that was vulnerable due to being near its useful end-of-life. Similar “harvesting effects” are sometimes seen in heat-stress related mortality data (e.g., Kaiser et al, 2007; Arbuthnott and Hajat, 2017; and Achebak et al, 2018).

As discussed earlier, synoptic systems that occur during the cool season can produce strong winds that extend over large areas, and thus we briefly exam where the model can be improved by considering a regional DMWS maximum rather than station specific maxima. As an example, we consider Region A, which was previously defined by considering the quality of the wind observations in the region. Thus, when associating an outage event with a station within Region A, we now associate the corresponding maximum of the DMWS values for that day from the 5 stations with that event rather than the station-specific DMWS value. Using the notation established above, we simply first replace $\mathrm{DMWS}(i,j)$ with $\mathrm{DMWS}^M(j) = \max_{i' \in \mathcal{A}} \mathrm{DMWS}(i',j)$ where $\mathcal{A}$ is the list of stations *i* within Region A. Having made this change, all other details of the calculations described in Section 4 remain the same. This change leads to a better characterization of storm impacts on the BC electrical distribution system, as demonstrated in rows 5 and 6 of Table 4 and Figure 14, including a much better representation of the once-in-decade December 2006 event. Improvements can be seen irrespective of whether the model is trained using the first 75% of the observations, which includes the Dec. 2006 event, or the final 75% of the observations, which excludes that event. We note that as with the previously described models using station specific winds, the trough in outage occurrence following the Dec. 2006 event is not captured. A more complex model would evidently be required to capture the delayed influences of storm activity on the electrical distribution system.

As discussed in Section 5.3, local climate variables such as surface winds, precipitation, and temperature in coastal BC are also influenced by North Pacific climate variability that is associated with the SOI and NOI. We therefore also briefly consider models that are separately parameterized during positive and negative phases of either the SOI (Table 5) or NOI (Table 6). Results indicate that skill is generally enhanced compared to that described in Table 3 during the non-positive phase of the SOI phase and the positive phase of the NOI. It is worth noticing that the once-in-a-decadal-once 2006 Dec.-Jan. windstorm event, in which the impact of surface winds on BC hydro power lines was the strongest, occurred under non-positive SOI and positive NOI conditions.

7 Conclusions

We have described an approach for using observations from surface weather station observations to understand variations in frequency of BC power outages. In particular, we developed a simple empirical wind-outage model that exploits a new high-quality wind-outage dataset covering the period from June 2005 to February 2017 to predict surface wind impacts on tree and weather-related outage events in BC coastal regions. We also have explored impact of large-scale climate indices that are representative of the atmospheric circulation over the North Pacific Ocean on power outage occurrence. Our main conclusions are summarized as follows:

- A new wind-power outage data-set covering the period 2005 to 2017 was developed by matching individual power outage events with nearby weather station daily max surface wind speed (DMWS) observations. That is, an outage event is recorded at a meteorological station for a given day if at least one outage event occurred during that day in an area within 0.2° latitude or longitude (i.e., roughly 20-30 km) of the station. By referencing events to a fixed network of meteorological stations, we better guard against non-climate and weather-related changes in outage frequency due to distribution system changes.
- Among environmental power outage events reported in coastal BC from 2005 to 2017, 60% are classified by BC Hydro as being tree and weather related; their frequency is strongly influenced by coastal surface winds particularly during the winter and spring windstorm season.
- The proportion of outages classified as tree and weather related, as well as the number of customers affected, increases slowly with nearby station daily maximum wind speed (DMSW) under weak and moderate wind conditions but increases much more quickly with DMSW under strong wind conditions, which occur mostly during winter and spring.

- Low frequency climate variability appears to affect outage frequency. Outage frequency is approximately 30% higher than the 12-winter (2005-2017) mean during the four strong NOI (Northern Oscillation) winters. These higher numbers are consistent with 10% more observed strong wind days (DMWS > 50km/hr) during these strong NOI winter. The available 12-year wind-outage dataset is, however, not long enough to reliably quantify the impacts of low frequency climate variability.
- A simple empirical outage model that focuses on shorter time-scale intra-annual variability is developed using observed monthly DMWS in southern coastal BC as a predictor. Cross-validation, which is used to estimate the model's out-of-sample performance, suggests a useful level of skill in hind-casting sub-seasonal to inter-annual variations in the frequency of regional tree and weather-related outages during the June 2005 to February 2017 period, particularly during the non-positive SOI months or equivalently, positive NOI months. The extreme power outage occurrence event in December 2006 can also be better captured when regional maximum DMWS is considered rather than station specific DMWS values.

For future research, process studies are necessary to further understand how climate oscillations (such as ENSO, the Pacific North America pattern and the Pacific Decadal Oscillation) and North Pacific High influence the frequency of ETCs affecting coastal BC and the strength the surface winds in the winter and spring windstorm season. The empirical model should also be improved so that it can account for the delayed effects of large outage events on subsequent outage frequency. Such a delay effect can be seen following the extreme Dec. 2006 event, which was followed by a period of unusually low outage occurrence, presumably because vulnerable distribution system infrastructure had been “harvested” by the Dec. 2006 event. From a statistical perspective, the model fitting approach should be further improved to allow parameter estimation via the method of maximum likelihood. This would allow objective comparison of models of different levels of complexity, and would permit the characterization of the uncertainty of our parameter estimates.

It would also be desirable to extend our wind-outage dataset both backwards and forwards in time. Since it is unavoidable that a backward extension of the dataset would be incomplete, this would also require adaptation of the method for fitting the wind-outage model to data that are incomplete, perhaps by using a data imputation method such as the Expectation-Maximization algorithm (Dempster et al., 1977). It is worth mentioning in this context that the Dec. 20th, 2018 wind storm was the most damaging in BC Hydro's history[6,7], exceeding the impacts of the Dec. 2006 storm and affecting more than 750,000 BC customers, mainly in the lower mainland, the Fraser Valley, and on Vancouver Island. This event, with its complex circulation, would provide an interesting and useful test of the understanding that has been developed in this study.

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Data access

BC outage-daily maximum wind speed dataset, version 1. Pacific Climate Impacts Consortium, https://pacificclimate.org/~fwzwiers/Li-et-al-2020/Li-et-al_wind-outage-dataset.tar

[6] https://www.bchydro.com/news/press_centre/news_releases/2018/report--increasingly-severe-weather-lead-to-more-power-outages-i.html
[7] https://www.bchydro.com/toolbar/newsletters/connected/connected-jan-2019.html

BC hydro outage dataset, https://pacificclimate.org/~fwzwiers/Li-et-al-2020/Li-et-al_BCH-outage-data.tar

ECCC hourly wind speed data, https://pacificclimate.org/~fwzwiers/Li-et-al-2020/Li-et-al_EC-hourly-winds.tar

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Table 1: BC Hydro Storm Criteria

Storm Criteria (must meet 3/6)	
Crew dispatch	Dispatching transferred to local HQ
Peak customers out at any one time	> 10,000 customers out at one time
Overall number of nustomers impacted	> 25,000 customer outages during the storm
More than local crews utilized in the storm	More than local crews utilized on trouble
Multiple trouble orders / customers with long restoration	Multiple trouble orders or customer outages > 24 hours
Multiple districts involved	> 3 districts impacted

Table 2: Summary of environmental power outage events in BC over the period June 2005 to Feb 2017.

Recorded Cause	Trees	Weather	Birds	Animal	Fire	Flood or snow	Vibration	Others	Total
Number of Outages	53641 (36.8%)	28769 (19.7%)	33169 (22.7%)	5066 (3.5%)	2602 (1.8%)	317 (0.2%)	872 (0.6%)	21429 (14.7%)	145865
Number of customers affected	10484489 (52.6%)	4400085 (22.1%)	1552286 (7.8%)	238562 (1.2%)	237240 (1.2%)	34305 (0.2%)	67619 (0.3%)	2891707 (14.5%)	19922793

Table 3 Summary of observed number months, total DMWS station days (SD), total recorded tree/weather outage SDs, fraction of days with DMWS > 50 km/hr, and fraction of tree/weather outage SD with DMWS > 50 km/hr in different SOI and NOI phases during the period from June 2005 to February 2017.

Monthly index	Number of months	Number of DWMS SD	Number of t/w outage SD	Fraction (%) of days with DMWS > 50 km/hr	Fraction (%) of tree/weather outage SD with DMWS > 50 km/hr
SOI > 0	83	12464	1388	10.6%	27.7%
SOI <= 0	58	8815	859	10.6%	34.7%
NOI > 0	85	12717	1398	21.2%	33.0%
NOI <= 0	56	8562	849	8.5%	25.4%

Table 4: Model coefficients and simulation performance (squared correlation R^2) for two regions within the training period, during the cross-validation period, and for the entire period (June 2005-Feb. 2017). The models described in rows 5 and 6 derived identically to those described in rows 1 and 2, except that station specific daily maximum wind speeds have be replaced with Region A daily maximum wind speeds as described in the text.

Region (training period)	γ_0	K_{crt}	β	α	Training period R^2	Evaluation period R^2	Entire period R^2
Region-A (First 75%)	0.079	12	0.133	7.8	0.53	0.41	0.53
Region-A (Final 75%)	0.061	12	0.143	9.6	0.49	0.55	0.50
Whole BC (First 75%)	0.079	11	0.148	9.6	0.52	0.52	0.52
Whole BC (Final 75%)	0.061	11	0.145	9.6	0.53	0.59	0.59
Region-A $DMWS^M$ (First 75%)	0.079	12	0.133	9.6	0.59	0.44	0.56
Region-A $DMWS^M$ (Final 75%)	0.061	12	0.145	9.6	0.49	0.70	0.58

Table 5: As Table 2, except model parameters differ between the two SOI phases. The first row in each cell is based on data for the 83 positive SOI phase months while results in the second row are obtained when using data for the 58 non-positive SOI phase months only.

Region (training period)	γ_0	K_{crt}	β	α	Training period R^2	Evaluation period R^2	Entire period R^2
Region-A (First 75%)	0.085 0.063	12 12	0.143 0.136	7.8 7.8	0.41 0.74	0.16 0.51	0.43 0.67
Region-A (Final 75%)	0.070 0.047	12 12	0.145 0.140	7.8 7.8	0.46 0.58	0.41 0.63	0.43 0.56
Whole BC (First 75%)	0.084 0.063	11 11	0.146 0.144	9.6 9.6	0.45 0.62	0.39 0.66	0.48 0.62
Whole BC (Final 75%	0.070 0.047	11 11	0.152 0.139	9.6 9.6	0.53 0.52	0.59 0.48	0.49 0.52
Region-A DMWS-m (first 75%)	0.085 0.063	12 12	0.143 0.136	9.6 9.6	0.47 0.76	0.17 0.59	0.47 0.72
Region-A DMWS-m (final 75%)	0.070 0.047	12 12	0.145 0.140	9.6 9.6	0.45 0.74	0.37 0.58	0.49 0.69

Table 6. Same as Table 4 but for two monthly NOI phases

Region (training period)	γ_0	K_{crt}	β	α	Training period R^2	Evaluation period R^2	Entire period R^2
Region-A (First 75%)	0.081 0.077	12 12	0.115 0.166	7.8 7.8	0.52 0.47	0.47 0.27	0.57 0.39
Region-A (Final 75%)	0.059 0.063	12 12	0.153 0.126	7.8 7.8	0.57 0.36	0.49 0.64	0.54 0.36
Whole BC (First 75%)	0.081 0.077	11 11	0.145 0.159	9.6 9.6	0.53 0.43	0.46 0.34	0.56 0.37
Whole BC (Final 75%)	0.060 0.061	11 11	0.142 0.148	9.6 9.6	0.64 0.42	0.86 0.60	0.56 0.44
Region-A DMWS-s (First 75%)	0.081 0.076	12 12	0.116 0.166	9.6 9.6	0.62 0.42	0.46 0.36	0.63 0.39
Region-A DMWS-s (Final 75%)	0.059 0.063	12 12	0.153 0.126	9.6 9.6	0.59 0.37	0.67 0.65	0.64 0.40

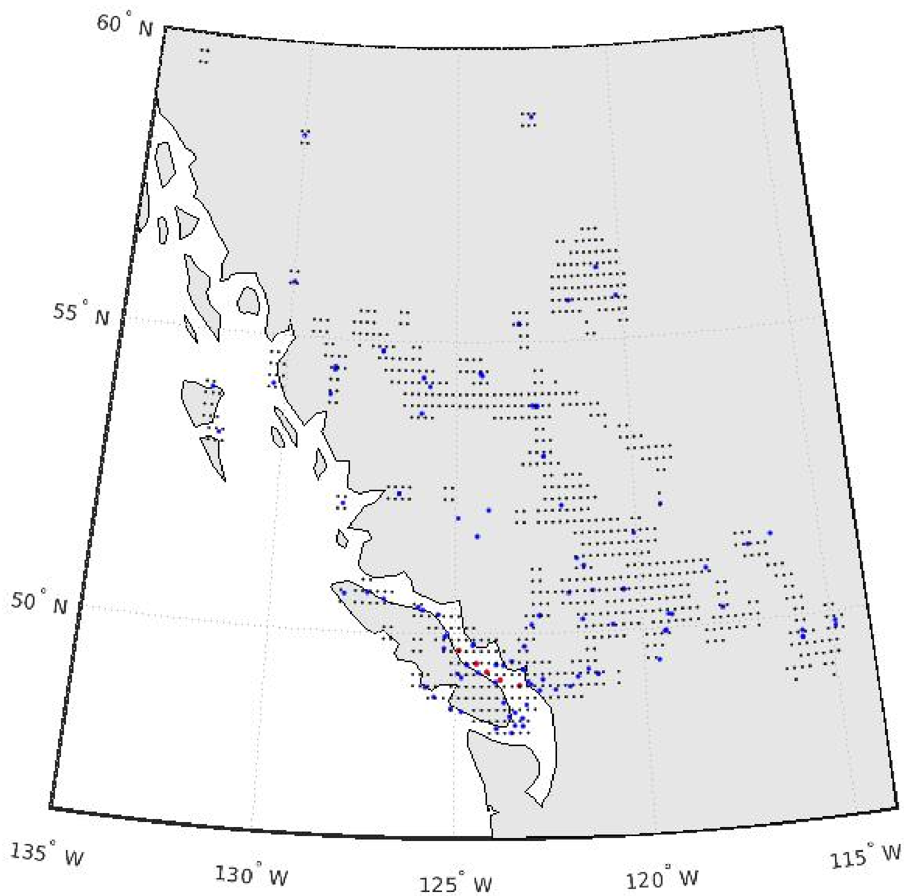

Figure 1: Environment and Climate Change Canada weather station locations and BC Hydro outage report sites. Blue and red dots represent stations within 0.2° latitude and longitude of reported power outage events during the June 2005 to Feb 2017 study period. The red dots represent “Region A” (see text), which has the 5 best quality Vancouver Island stations. The black dots represent BCH outage reported sites (resolved to 0.2° × 0.2° horizontal resolution).

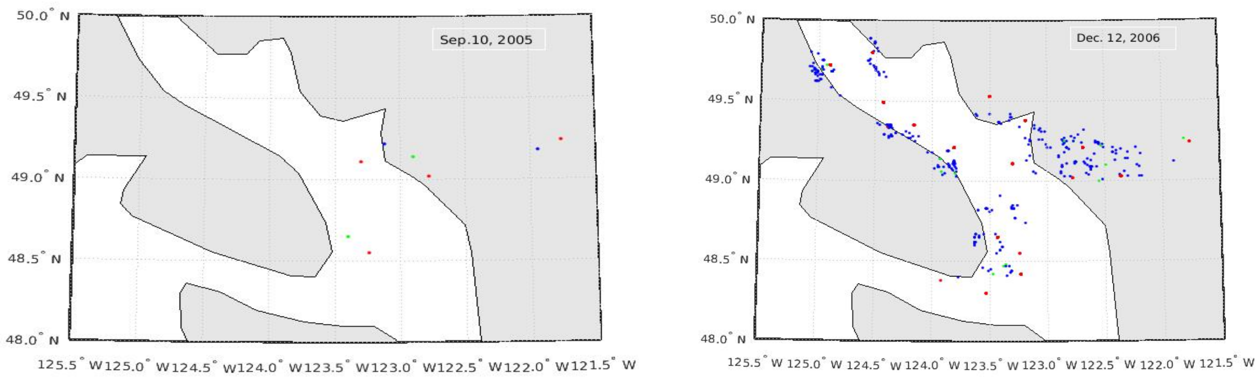

Figure 2: Environment and Climate Change Canada weather station locations (red) and power outage sites for outages caused by environmental factors (tree/weather: blue; others: green) on 10 Sept. 2005 and 12 Dec. 2006. Note that points over water represent land stations and power outage sites on small islands.

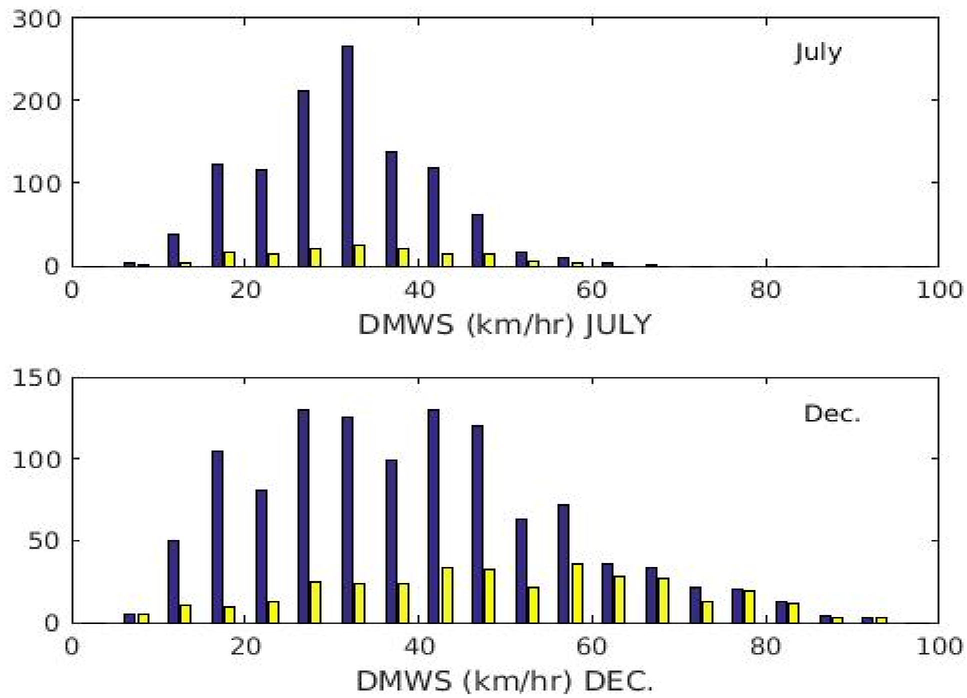

Figure 3: Comparison of the frequency distribution DMWS (blue) in July (top) and December (bottom) in Region A for the period 2005 to 2016. Also shown, in yellow, is the distribution of monthly SD values for tree/weather caused outages (yellow).

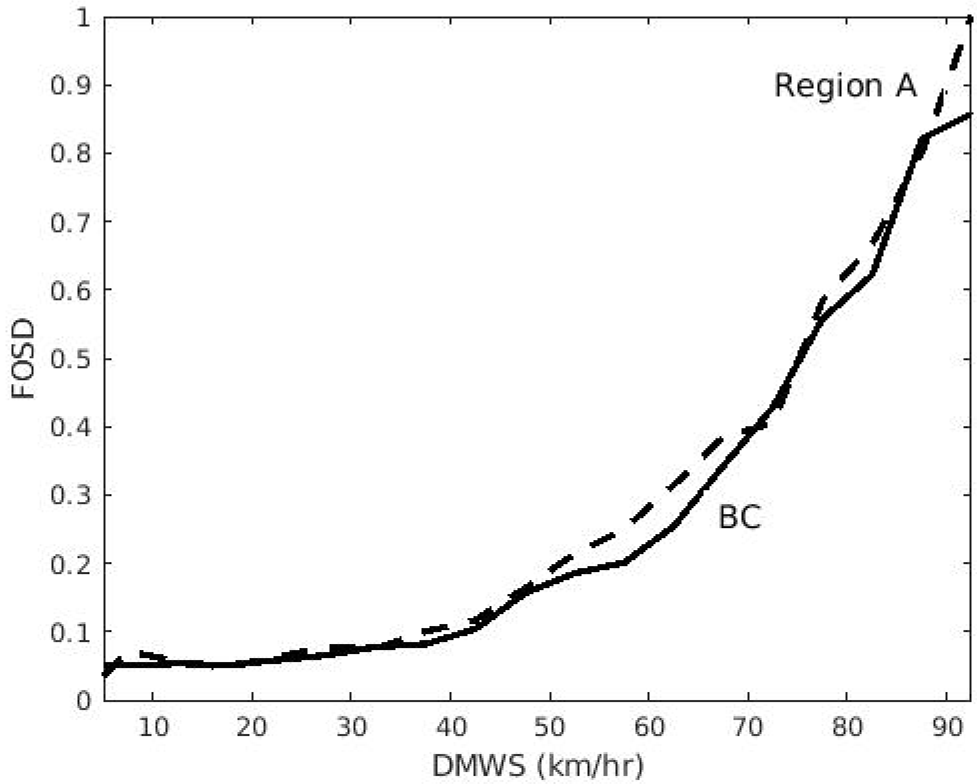

Figure 4: The fraction of outage station days (FOSD), which is given by $g_{\cdot,\cdot}(C = c|W = k) = O_c(\cdot,\cdot,k)/O.(\cdot,\cdot,k)$ due to trees/weather relative to all causes conditional on DMWS. The relative fractions are obtained for DMWS in bins of width 5 km/hr for BC (solid) and Region-A (dashed) during 2005-2017. Tree/weather is seen to be a minor cause of outages when DMWS is moderate, but becomes the dominant cause for high winds.

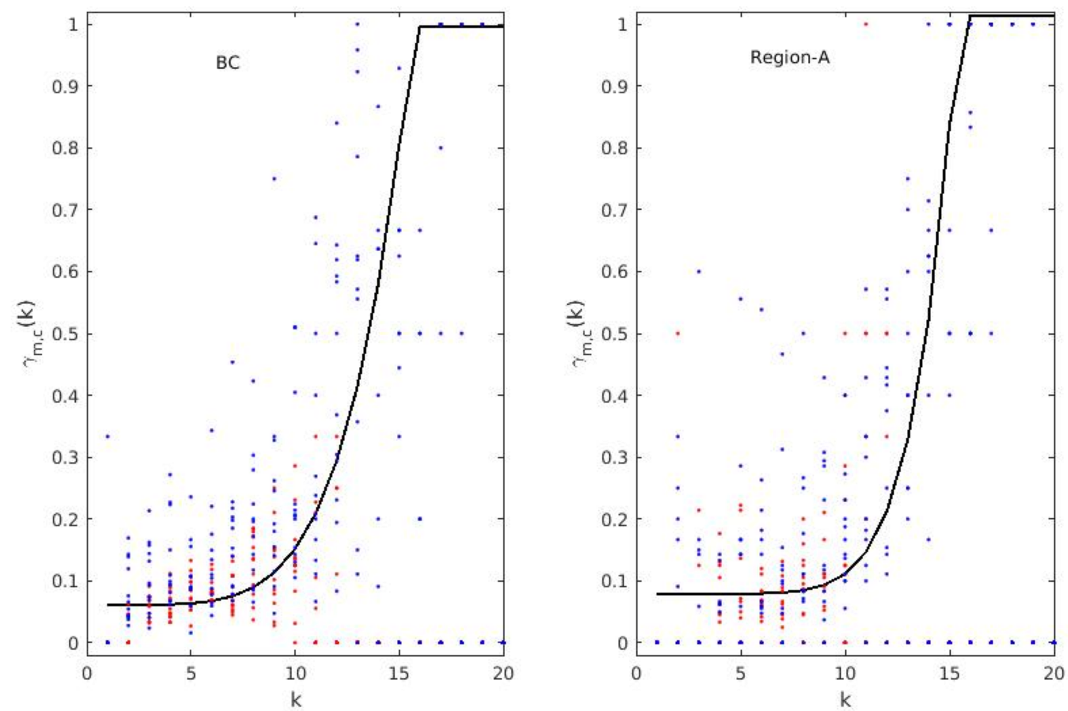

Figure 5: Plots of $\gamma_{m,c}(k)$ for July and December for BC and Region A, as estimated from individual months of observations during 2005 to 2016 (July-red, Dec.-Blue) and as fitted to all monthly data (black curve).

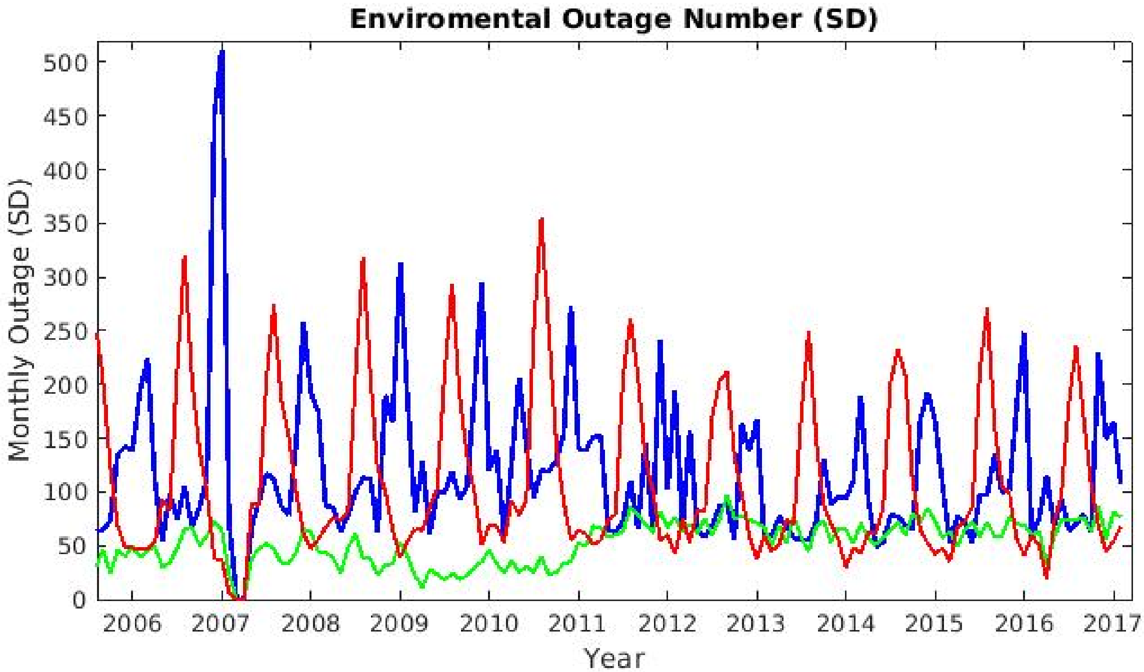

Figure 6. Observed monthly tree/weather (blue), bird/animal (red), and other (green) environmental related BC power outage station days (OSD) during the June 2005 to Feb. 2017 study period.

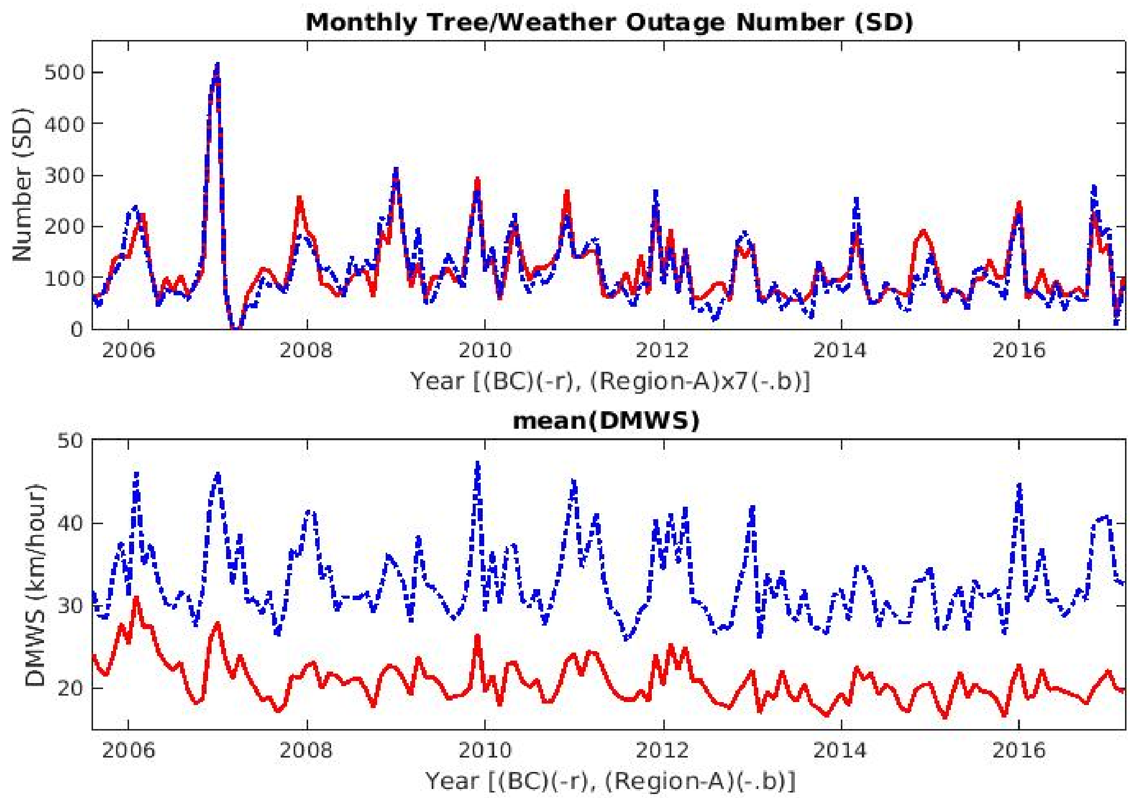

Figure 7. (a) BC hydro reported monthly tree/weather related outage SD numbers for all of BC (red) and for Region A (blue) during 2005 to 2017. Note that Region-A values are scaled by a factor of 7 to illustrate their similarity with whole-BC values. (b) Monthly regionally averaged mean daily maximum surface wind speed for whole-BC (red) and Region-A (blue).

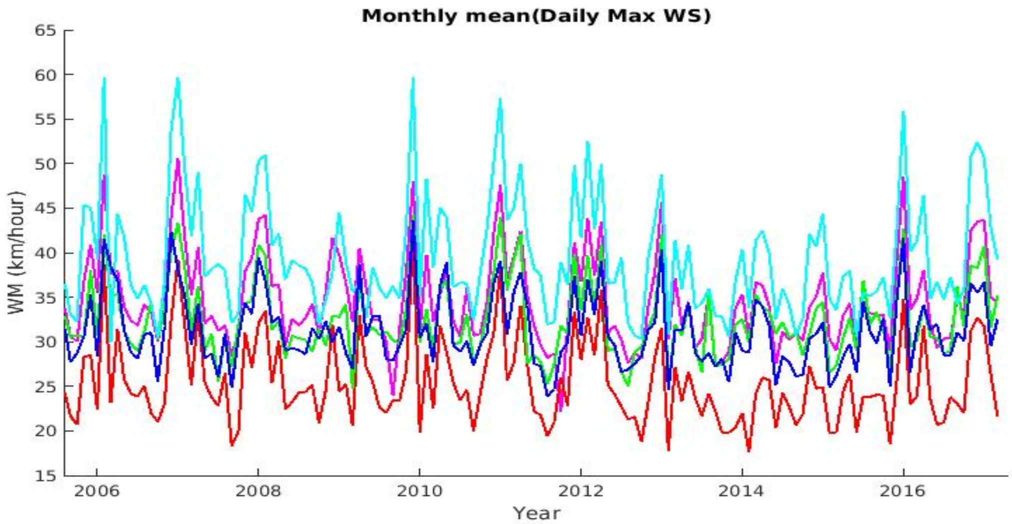

Figure 8. Observed monthly mean daily maximum wind speed in Region-A (red) and at individual stations within Region A for June 2005 to Feb. 2017.

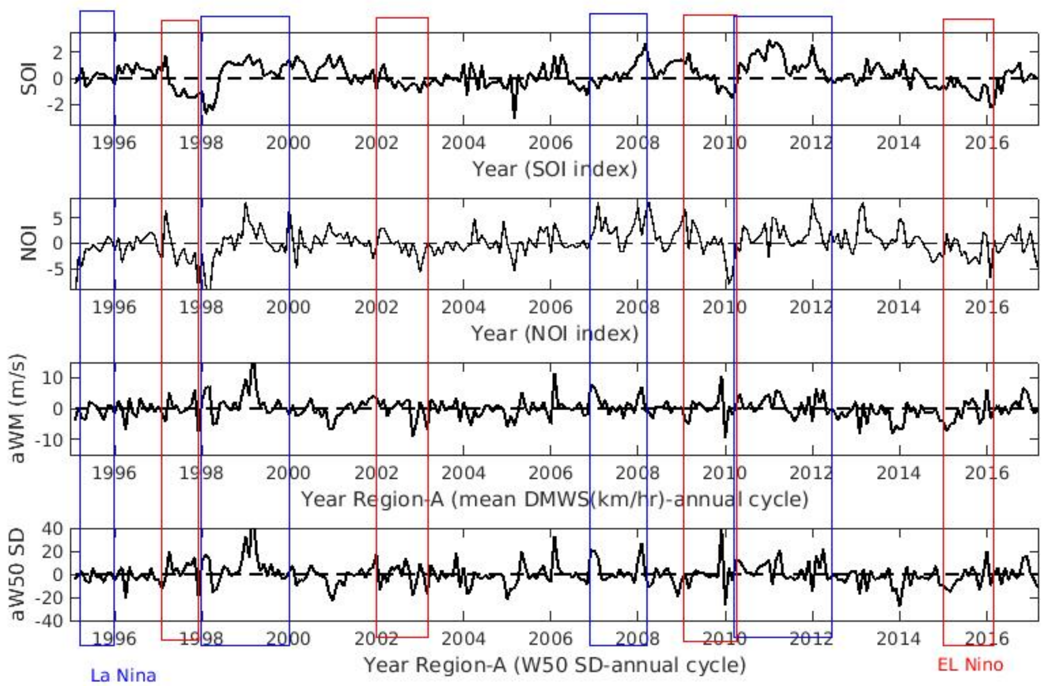

Figure 9: Time series of monthly SOI and NOI index values, Region-A monthly mean DMWS anomalies (km/hr) from the DMWS annual cycle and anomalies of W50 relative to its annual cycle, where W50 is the monthly total number of outage events recorded when DMWS > 50 km.hr, summed across stations in Region A. All timeseries are for the period Nov. 1995 to Jan. 2017. The moderate and strong El-Niño events are marked using red boxes, and moderate and strong La Niña years are marked with blue boxes.

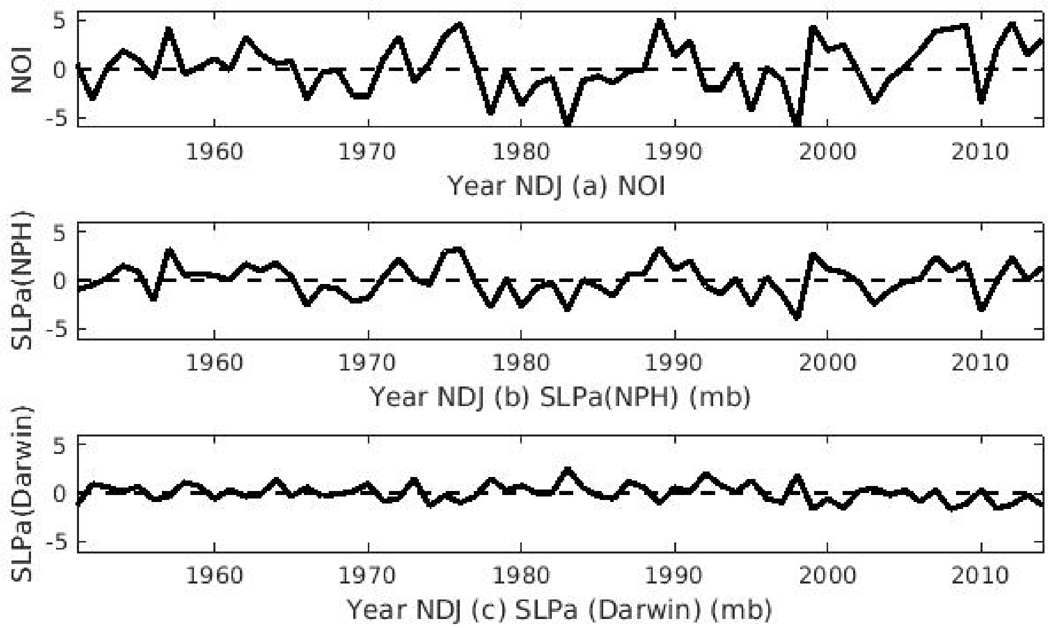

Figure 10: The time series of NDJ seasonal mean values of (a) the NOI and its components, the sea level pressure anomalies (mb) at (b) the North Pacific High (35°N, 130°W) and (c) Darwin (10°S, 130°E) based on the NOAA-CIRES 20th Century Reanalysis V2C (ensemble mean; Compo et al., 2011) Jan. 1951 to Dec. 2014.

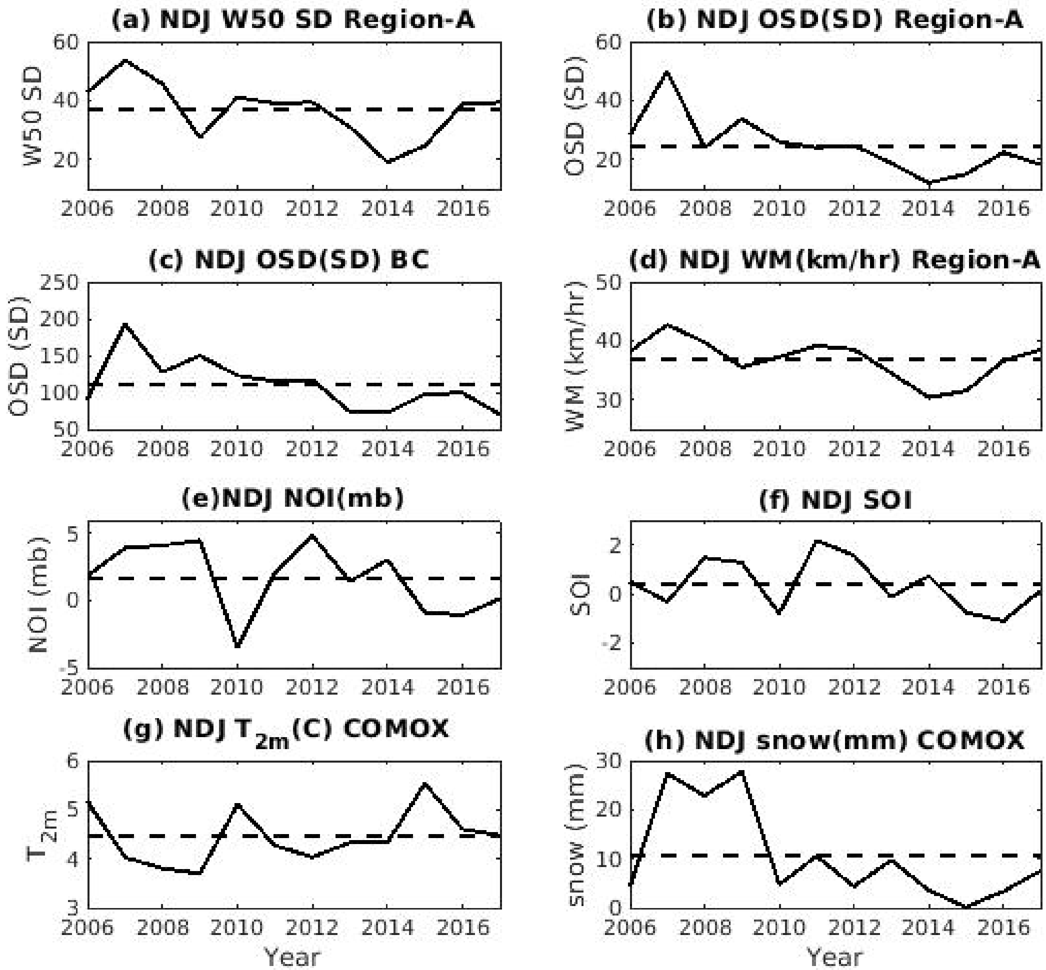

Figure 11: Timeseries of NDJ seasonal mean tree/weather related outage statistics for (a) Region-A based on monthly W50 Station-days, (b) Region-A outage SD station-days for all wind speeds and (c) whole-BC outage SD station-days for all wind speeds. Also shown are NDJ seasonal means of (d) Region-A mean DMWS (km/hr), (e) the NOI (mb), (f) the SOI (dimensionless) (f) 2m air temperature T2m at COMOX (°C) and (f) snow fall at COMOX (mm water equivalent). The dashed line in each panel indicates the 12-year NDJ mean value.

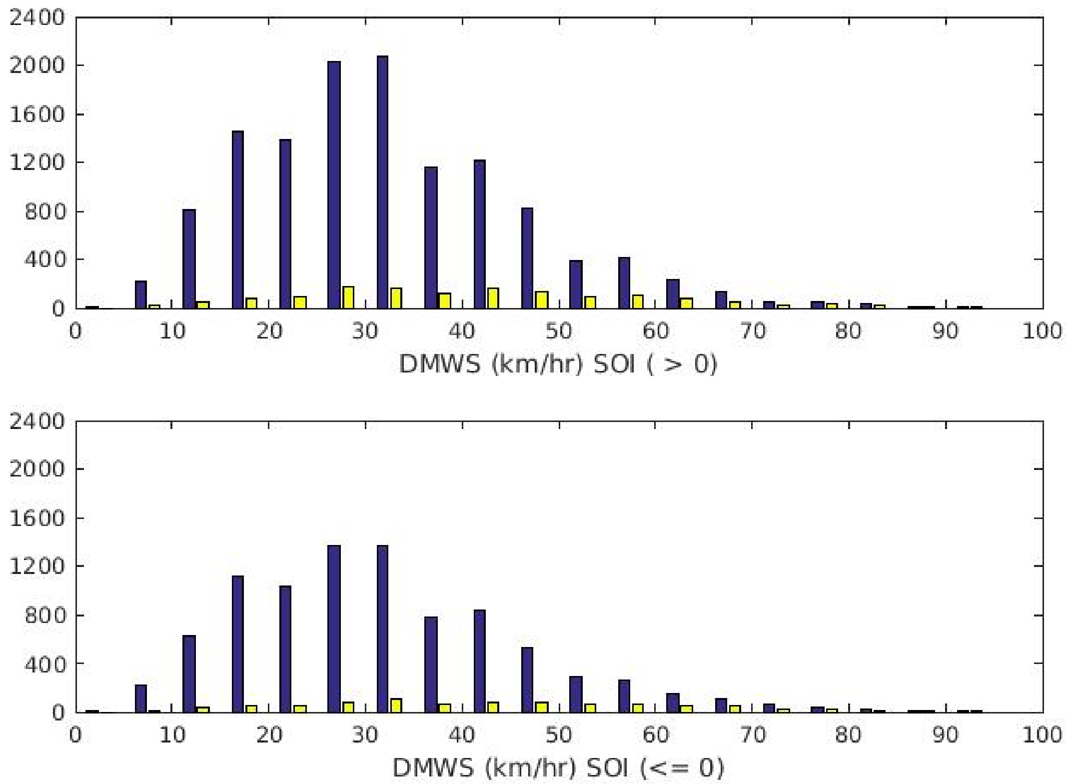

Figure 12: Comparison of the frequency distribution DMWS (blue) in SOI >0 months (top) and SOI <= 0 months (bottom) in Region A during the outage study period from June 2005 to February 2017. Also shown, in yellow, is the distribution of monthly SD values for tree/weather caused outages (yellow). There are totally 12464 DMWS samples and 1388 tree/weather related outage samples during the 83 positive SOI months in the top panel; correspondingly there are totally 8815 DMWS samples and 859 tree/weather outage samples during the 58 non-positive SOI months in the bottom panel.

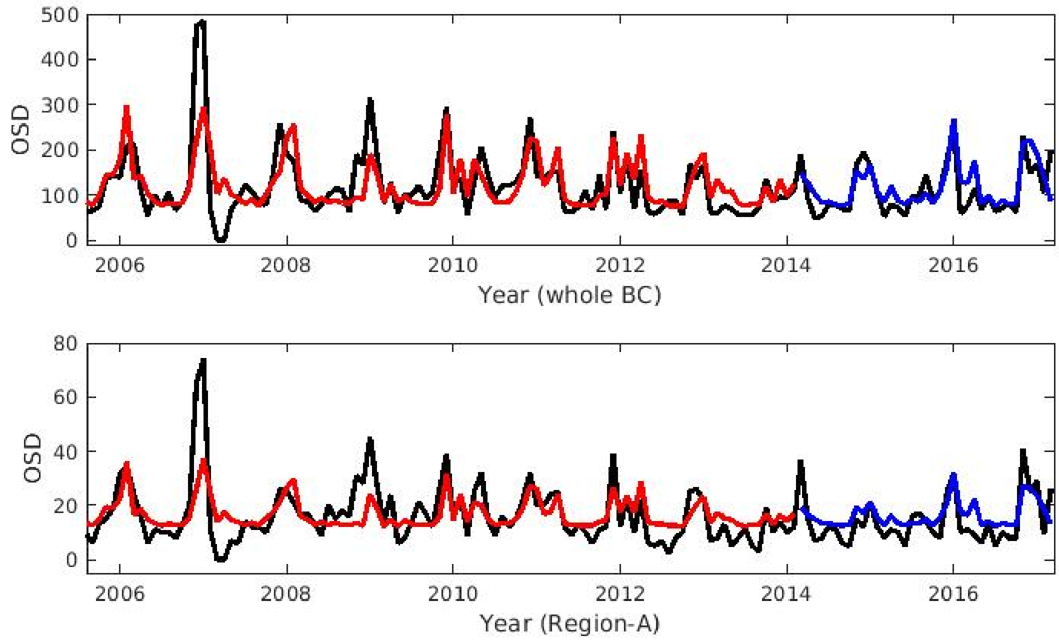

Figure 13: Monthly tree/weather related power outage SD number from observations (black) and the model for BC (upper) and Region-A (lower) during the period from June 2005 to Feb. 2017. Model values during the training period are shown in red, and those during the independent cross validation period are shown in blue. See rows 1 and 3 of Table 2 for model coefficients and performance.

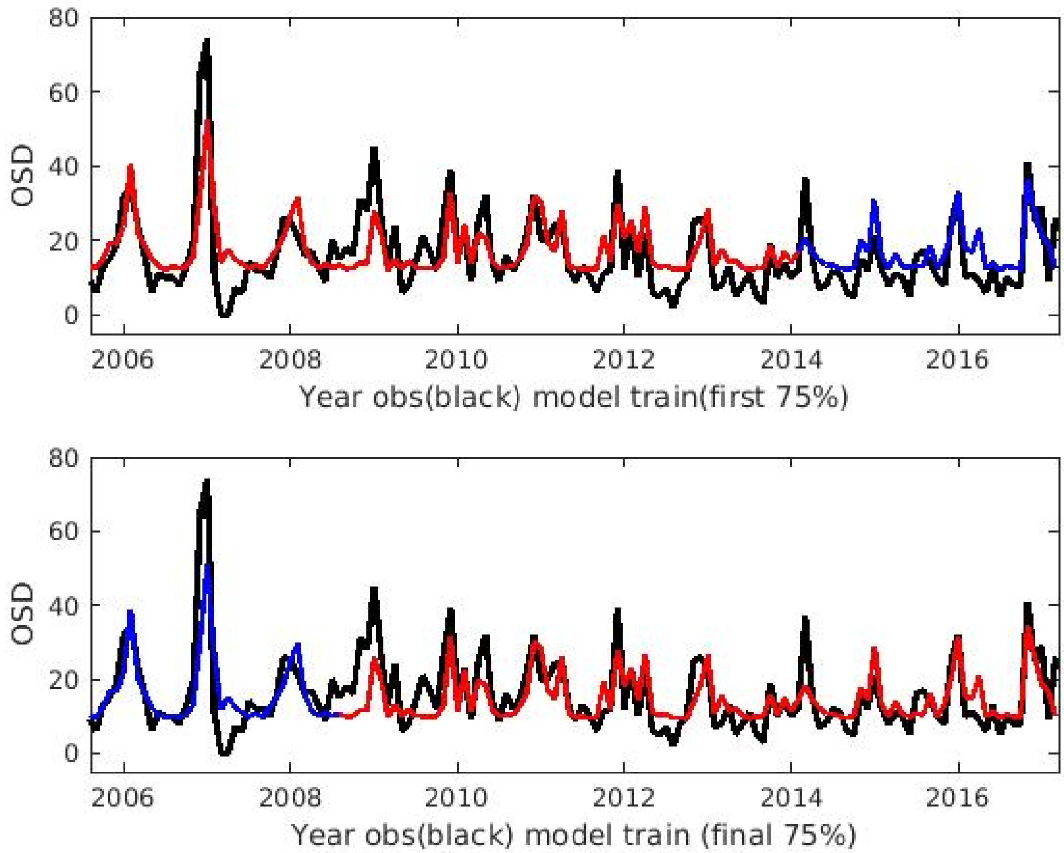

Figure 14: As the lower panel of Figure 13, except using data in which station specific DMWS has been related with Region A maximum DMSW. Upper and lower panels correspond to models trained using the first and last 75% of observations. See text for details and rows 5 and 6 of Table 2 for model coefficients and performance.

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