WIND SPEED VARIABILITY AND ADAPTATION STRATEGIES IN COASTAL AREAS OF THE PACIFIC NORTHWEST

by

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B.A.Sc., University of British Columbia, 2004

PROJECT SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF RESOURCE MANAGEMENT

In the
School of Resource and Environmental Management

SIMON FRASER UNIVERSITY
Spring 2010

APPROVAL

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Degree:	**Master of Resource Management**
Title of Thesis:	**Wind Speed Variability and Adaptation Strategies in Coastal Areas of the Pacific Northwest**
Project No.:	**494**

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ABSTRACT

Overall, previous wind speed studies in the Pacific Northwest (PNW) present conflicting results for wind speed trends (both increasing and decreasing) in relation to climate drivers. This study fills a gap in the understanding of PNW wind behaviour by: determining if relationships exist between wind speed distributions, ocean/atmospheric climate indices, and monitoring station-specific attributes; assessing the robustness of relationships for forecasting wind speeds within the study area; and presenting adaptation strategies to wind damage. Analyzing the quantiles of the strongly skewed (non-normal) wind speed distributions reveals different behaviours for average and extreme wind speeds and significantly stronger winds at coastal locations compared with sites further inland. Coast locations appear to follow a nine-year cyclic pattern, while mainland sites have a downward wind speed trend. This finding has important implications for wind research and infrastructure or ecosystem planning in areas such as wind energy feasibility studies and timing management activities.

Keywords: Wind speed; Pacific Northwest; Quantiles; Linear mixed-effects model; Variability; Adaptation; Climate change

ACKNOWLEDGEMENTS

Thanks to all of the people who have helped and supported me throughout this work and kept me generally sane:

- Karen Kohfeld for allowing me to follow my own ideas, providing guidance, and challenging me throughout;
- Andy Cooper for being available for my many questions and translating numerous Greek letters into English;
- Tommy Rodengen, Liz Sutton, Mungandi Nasitwitwi, Brian Bylhouwer, and Christie Spry for listening as my research slowly evolved and providing invaluable thoughts and conversations;
- Caroline Sniatynski for extraordinary emotional support, not hesitating when I talked about going back to school, and listening to hours of ranting about "the model";
- Many other REM students for brilliant conversations and enthusiastic arguments about how to fix the world.

Thanks also to the National Science and Engineering Research Council, the Climate, Oceans, and Paleo-Environments research group, Michael Geller Foundation, Planning Institute of British Columbia, and Simon Fraser University for supporting this project.

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1: INTRODUCTION

In December 2006, an intense storm struck southwest BC, blowing down over 10,000 trees in Stanley Park and resulting in an estimated $9 million dollar restoration cost, as well as impacts to tourism and the local economy [Vancouver Board of Parks and Recreation, 2007; BC Hydro, 2007]. In December 2007, another severe storm hit the Pacific Northwest coast with wind gusts up to 220 km/h, bringing the first-ever hurricane warning from the U.S. National Weather Service for Washington, Oregon, and northern California [Crout et al., 2008]. Vulnerability to extreme weather events, such as these storms, increases when urbanization and infrastructure development do not consider changing weather patterns. The resulting damages can reach into the millions of dollars, with costs being borne by society through government aid, taxes, or insurance fees. Non-monetary costs can be even greater with irreplaceable cultural or natural places damaged or lives lost [Costanza and Farley, 2007].

How does a changing climate affect the Pacific Northwest's (PNW) regional weather patterns, and therefore the frequency and magnitude of extreme wind events? A great deal of uncertainty still surrounds wind behaviour and its consequent impacts, such as storm surge, tree blow-down, and infrastructure damage. Studies looking at the PNW, and the North American continent as a whole, show inconsistent results that seem to depend on the type of data used for analysis. Further, few studies have yet tried to conduct a comprehensive investigation examining all available observed wind speed data for a particular area. Nevertheless, despite the lack of understanding, scientists must make forecasts that are as dependable as possible to inform future planning and development. Society carries the costs of replacing or repairing damaged public goods, and therefore, public managers and policy makers have a duty to plan effectively for future wind conditions. Researchers have the opportunity to translate scientific information into understandable and accessible language for policy makers and managers, who may not have extensive experience with climate science. It is especially important that scientists and managers both play roles in forming adaptation policies that correctly assess physical system dynamics and are also politically and socially acceptable [Bray et al., 1997].

Historical wind data are limited for many areas and any resulting forecasts often have large uncertainties associated with them [National Research Council, 2006]. However, this limitation is not a rationale to avoid forecasting wind speeds and storm behaviour. Rather, it is a reason to better identify the most uncertain elements in order to focus future research. In the short term, we must still make management decisions. We should base those decisions on the best forecasts possible, with the inherent uncertainties explicitly stated, in an open and transparent process. Methods like quantitative decision analysis are well suited to incorporate uncertain information into management action choices.

My research examines the variability of historical wind speeds for the PNW and establishes relationships with several climate-related, Pacific Ocean indices of sea surface temperature and sea level pressure using a linear mixed-effects (LME) model. LME models use available meteorological data better than standard linear regression when determining regional patterns [Zuur et al., 2007; Zuur et al., 2009]. Meteorological station data often include short and intermittent time-series records with different variance across observations and possibly correlated measurements. Linear regression cannot adequately handle these complications, while LME models offer much more flexibility to incorporate lower quality data using adaptable variance and correlation structures. Throughout this analysis, I use a range of quantiles (50th to 95th) for wind speed data, rather than the usual mean or max/min values, to explore the highly skewed and non-normal distribution of wind speeds. Also, quantiles help smooth the inherently spiky nature of wind speed data (i.e., sudden large changes in wind speed) to elicit more meaningful results than traditional summary measures [Cade and Noon, 2003; Koenker, 2005].

1.1 Study Objectives

My research aims to explore the variability and trends of historical wind behaviour in coastal areas of the Pacific Northwest and improve future policy decisions regarding adaptation to severe windstorms. Accordingly, three specific research objectives guide the course of this study:

1. Determine if relationships exist between wind speed distributions (i.e., quantiles), ocean/atmospheric climate indices, and monitoring station-specific attributes (e.g., elevation, geographic location, data source);
2. Assess the robustness of relationships for forecasting wind speeds within the study area; and
3. Convey forecast results and potential adaptation actions in a manner easily understandable by a wide (potentially non-technical) audience.

1.2 Background

1.2.1 Disaster Planning

Scientists' inability to forecast extreme wind speeds reliably has consequences for resource and urban management along coastlines. As coastal communities urbanize and develop resources, they may expose themselves to increasing risks from extreme weather events (e.g., damage from severe winds or storm surge). For instance, Hurricane Katrina's impact on New Orleans, USA, a well-developed coastal city, showed that infrastructure is often poorly located in risk-prone areas and impairs the functioning of natural capital (e.g., building in floodplains and removing wetlands that might mitigate storm surge). These natural defences could otherwise provide adequate protection and mitigate physical and financial losses [Costanza and Farley, 2007]. Planning and risk analysis for future infrastructure decisions will necessarily require accurate forecasts of weather conditions. To this end, Natural Resources Canada produced a report documenting changes in vulnerability with changing frequencies and magnitudes of natural hazards [Walker and Sydneysmith, 2008]. They note that possible wind impacts include storm surge damage (potentially combined with sea level rise), tree wind-throw, and infrastructure impairment. While the authors do not provide a future scenario of wind conditions and the possibly changing consequences, the report does highlight that management decisions in the future must incorporate changing risks from extreme weather events. Incorporating risks will be especially important for coastal urban areas with aging infrastructure that was developed based on the assumption of stable average and extreme conditions.

1.2.2 Influential Climate Behaviour in the Pacific Northwest

Our atmosphere and weather patterns are largely governed by air pressure and temperature. These variables are in turn, driven by solar and terrestrial/ocean radiation. Differences in pressure and temperature create vertical air currents that cause rising and falling of air masses in the troposphere (the portion of the atmosphere we experience). Unequal heating and cooling of water and different areas of land create horizontal air flows. For example, air in a city grows hotter during the day compared to surrounding areas due to heat absorbed and emitted from concrete and roads, becomes less dense (due to thermal expansion), and rises in an updraft. Cooler, denser air over the countryside or ocean flows into the city in the form of surface wind to fill the low-pressure area. As the cooler incoming air heats up, it also rises and continues to create a low-pressure area over the city. This cycle is reversed at night as the city cools faster than the surrounding areas. Local surface responses of wind, like the city example above, may differ from regional weather regimes that are predominantly dictated by upper air currents [Reynolds, 2005].

Observational evidence suggests surface expressions of weather regimes (e.g., wind, temperature, and precipitation) are driven by regional and global climate oscillations [Reynolds, 2005; Mantua and Hare, 2002; Ropelewski and Halpert, 1986; Schwing et al., 2002]. Oceanic and atmospheric circulation patterns occur at various temporal scales, lasting years to decades. Many patterns are centred on either the Pacific or Atlantic Oceans [Abeysirigunawardena et al., 2009].

Indices of climate circulation patterns are often generated using anomalies (residuals) of averages of sea-level pressure (SLP) or sea-surface temperature (SST). Climate variability indices based on anomalies of observed or calculated variables are independent of normal seasonal cyclic patterns and therefore do not exhibit seasonality. Most indices are also de-trended to remove any pattern associated with secular (i.e., anthropogenic) influences. The climate-related, Pacific Ocean indices used in this study are detailed below and summarized in Table 3 (see Appendix A for index time series plots). These indices represent the major, currently theorized, climate oscillations that are likely to influence Pacific Northwest (PNW) wind speeds.

Pacific Decadal Oscillation

The Pacific Decadal Oscillation (PDO) has been described as a long-lived (decadal-scale rather than yearly-scale) Pacific Ocean version of the better-known El-Niño climate variability pattern [Ropelewski and Halpert, 1986]. Phases of the PDO occur at the scale of 15-25 years and include varying strength "warm" and "cool" phases. Typical characteristics of the warm (cool) phase for the PNW include increased (decreased) ocean and surface temperatures and decreased (increased) precipitation and wind speeds (Figure 1). Warm phases of the PDO (positive index values) are not uniformly warm across the Pacific Ocean, but rather follow the spatial pattern shown in Figure 1, with cool phases (negative index values) following the reverse pattern.

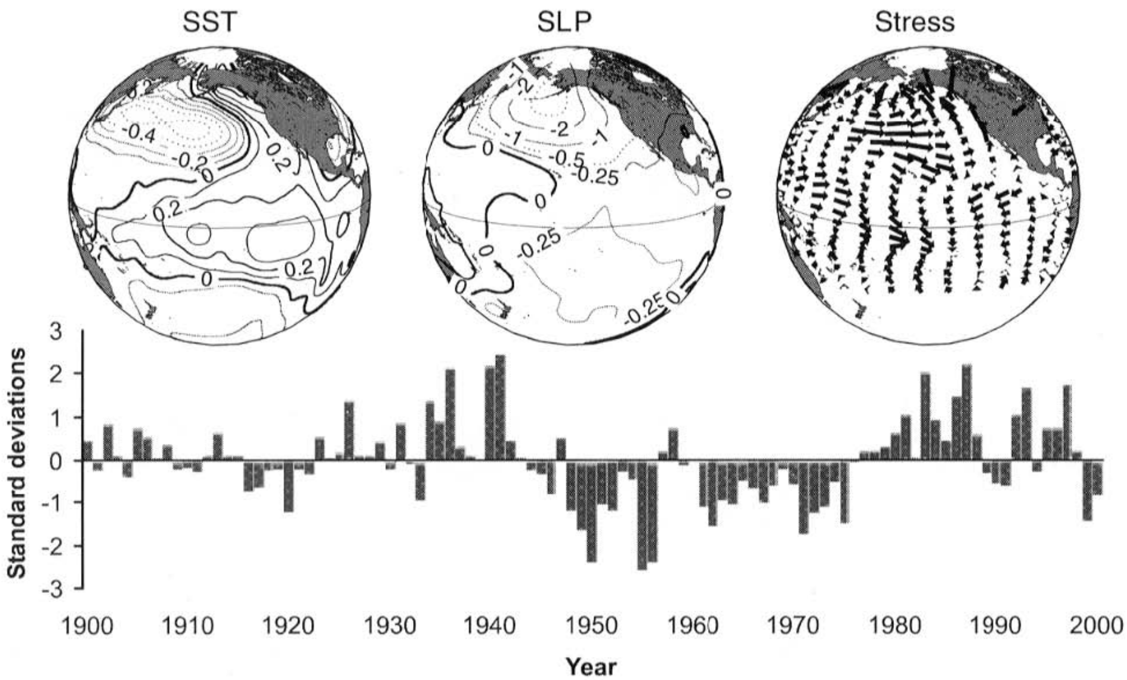

Figure 1: PDO Warm Phase Characteristics

Anomalous climate conditions associated with warm phases of the Pacific Decadal Oscillation (PDO) (top), and November–March average values of the PDO index (bottom). Values shown are °C for sea surface temperature (SST), millibars for sea level pressure (SLP) and direction and intensity of surface wind stress. The longest wind vectors represent a pseudostress of 10 m^2/s^2. Actual anomaly values for a given year at a given location are obtained by multiplying the climate anomaly by the associated index value. Adapted from [Mantua and Hare, 2002].

The PDO is calculated as the leading principal component of an empirical orthogonal function (EOF) of monthly SST residuals relative to long-term averages (1900-1993). Residuals are defined as the difference between observed North Pacific (poleward of 20 N) SST anomalies and the monthly mean global-average SST anomaly [Mantua and Hare, 2002].

El Niño-Southern Oscillation

The Global-SST El Niño-Southern Oscillation index (ENSO) has been directly linked to average and extreme directional wind regime variations in the Pacific

[Abeysirigunawardena et al., 2009]. This ENSO index captures the low-frequency part of the phenomenon, which is associated with both tropical Pacific SST and SLP. In the PNW, warm (positive or El Niño), phases of ENSO are related to above-average temperature winters with below-average precipitation and stronger mid-latitude westerlies (for the PNW, winds originating from the Pacific Ocean). Cool (negative or La Niña), phases result in the opposite atmospheric expression of below-average temperature and above-average precipitation winters [Ropelewski and Halpert, 1986; Ware and McFarlane, 1989]. ENSO is a considerably shorter-lived phenomenon compared to climate oscillations like the PDO, with phases typically lasting for 1-3 years before changing sign. ENSO is calculated as the average SST anomaly equatorward of 20N & 20S latitude minus the average SST poleward of 20N & 20S [Rasmusson and Wallace, 1983]. Anomalies are determined with respect to the period 1950-1979.

Arctic Oscillation

The Arctic Oscillation (AO) represents the dominant pattern of non-seasonal sea-level pressure variations poleward of 20N, with anomalies of opposite sign to that in the Arctic centred at about 37-45N (adjacent to the study area latitude). During the positive (warm) phase of the AO, this pattern describes below normal Arctic SLP, strong westerly winds, and warmer than average winter temperatures over the PNW. The negative (cool) phase has above average Arctic SLP, with weak westerly winds allowing colder than normal PNW winter conditions. Phases of the Arctic Oscillation typically persist for periods of 1-2 years. The AO index is calculated as the variable (from an EOF) describing the most variability of monthly atmospheric pressure anomalies relative to long-term means (1979-2000), poleward of 20N [Thompson and Wallace, 1998].

Northern Oscillation Index

The Northern Oscillation Index (NOI) relates variability in atmospheric forcing of climate regimes in the mid-latitudes of the northern hemisphere. By measuring the NOI as the SLP anomaly difference between the North Pacific High (NPH) (35N, 135W) and Darwin, Australia (10S, 130E), this index introduces a proxy for the atmospheric circulation link between the tropics and northeast Pacific Ocean. While the NOI is roughly the north Pacific equivalent of the Southern Oscillation Index (SOI), it seems to provide a more direct indication of how global-scale climate events affect the north Pacific and North America, and describes environmental and atmospheric changes in the PNW better than SOI [Schwing et al., 2002].

The Northern Oscillation appears to follow a cycle of positive and negative phases lasting approximately 14 years. Positive phases of the NOI are associated with high SLP and SSTs in the northeast Pacific Ocean and anti-cyclonic surface wind stress (i.e., north-westerly winds in PNW). The negative phase of the NOI provides a strong reversal of the pattern with low SLP and SSTs and southerly winds over the PNW. Wind speeds change prevailing direction, but do not appear to change magnitude significantly.

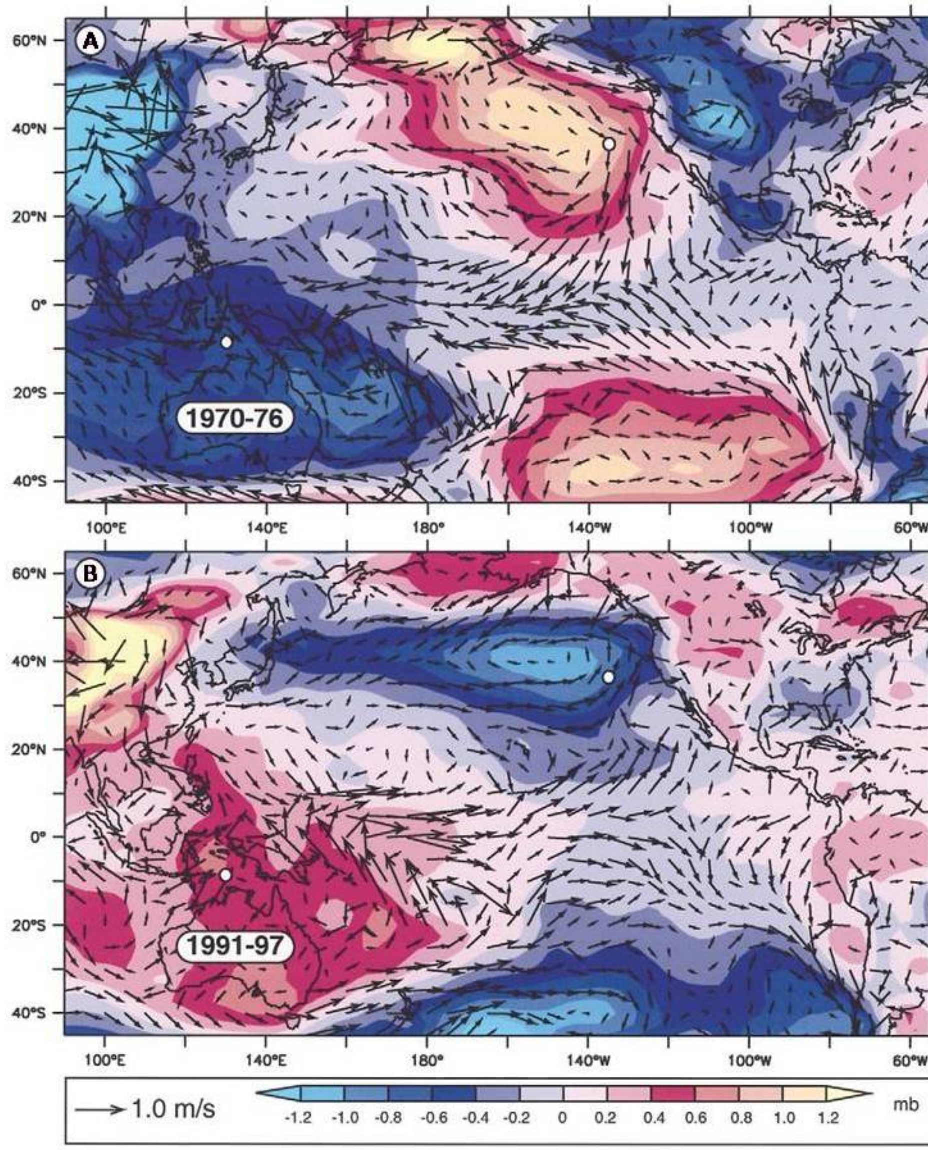

Figure 2: Anomalies of SLP and Surface Wind Associated with NOI

Anomalies of SLP (colours) and surface wind (arrows) over the Pacific during (a) 1970–1976, a period of predominantly positive NOI values, and (b) 1991–1997, a period of predominantly negative NOI values. Yellow–red (blue) shades denote positive (negative) SLP anomalies. Contour interval is 0.2 mb; scaling arrow shown in lower left. White circles mark the climatological annual mean positions of the NPH (35N, 130W) and Darwin, Australia (10S, 130E). Adapted from [Schwing et al., 2002].

Pacific/North American Pattern

One of the most prominent modes of low-frequency climate variability in the northern hemisphere extratropics is the Pacific/North American Pattern (PNA). The PNA pattern is a natural internal mode of climate variability, but the El Niño/ Southern Oscillation (ENSO) phenomenon also strongly influences it. The positive phase of the PNA pattern tends to be associated with Pacific Ocean warm SST episodes (as in El Niño), and the negative phase tends to be associated with cold SST episodes (as in La Niña) [NCEP, 2006]. For surface conditions, positive phases of the PNA are associated with above-average temperatures over western Canada and U.S. and below-average temperatures over the southern portion of North America. The positive phase is also associated with above-average precipitation over the PNW. Phases typically persist for 1-5 years before changing sign. The PNA index is calculated as the variable (from an EOF) describing the most variability of monthly atmospheric pressure anomalies relative to long-term means (1950-2000), for the region 20N-90N [Wallace and Gutzler, 1981].

1.2.3 Models of Wind Behaviour in Pacific Northwest

Several studies assess the trends and variability of wind speeds, including time series and extremes analyses, for areas along the Pacific coast of North America [Abeysirigunawardena et al., 2009; Enloe et al., 2004; Gower, 2002; Pryor et al., 2009; Tuller, 2004]. However, wind speed trend and covariate findings are inconsistent. The limited number of locations, differing scales of the analyses, and the variability of statistical methods used constrain interpretation of these results.

In particular, only two studies specifically address developed urban areas [Abeysirigunawardena et al., 2009; Tuller, 2004]. Abeysirigunawardena et al. [2009] construct return periods for wind speeds (interval time between extreme wind events) at three monitoring stations near Delta, BC. They fit Generalized Pareto Distributions (GPD) to extreme wind speed distributions using climate-related, Pacific Ocean indices as covariates for equation parameters and estimate wind speed return periods. Only the most extreme events observed form the basis for statistical distributions of this nature, and the required assumption of independence between events further limits the number of measurements that can be included for analysis. Small or incomplete data sets, which are often encountered in environmental modelling, can therefore bias results when using this type of method [Mcinnes et al., 2003]. The researchers find significantly different extreme wind speed responses to warm and cold ENSO modes, with higher extreme wind events occurring in Delta, BC during cold (i.e., La Niña) phases.

Alternatively, Tuller [2004] correlates mean annual and seasonal wind speeds with climate indices (PNA and PDO). He uses data from four atmospheric monitoring stations with long, relatively complete wind speed records representing southern BC (Vancouver Int. Airport, Victoria Int. Airport, Comox Airport, and Cape St James, Haida Gwaii). This straightforward method provides easy-to-interpret correlation values between surface wind speeds, air pressure gradient triangles, and PNA and PDO indices. Overall, he finds a general declining trend, but notes that temporal periods have very different trends (both negative and positive). He also finds moderate negative correlation values between wind speeds and PDO and, to a lesser extent, PNA. However, mean annual and winter wind speeds for Comox Airport deviate significantly from the decreasing trends and correlations determined for the other three stations. Tuller [2004] cannot explain the difference in wind behaviour without additional time series data. While he is unable to determine if this station is an anomaly or following a separate pattern, he suggests differences may be due to changes in surrounding surface roughness.

A further study examining wind behaviour over the contiguous United States shows that wind speeds determined from direct observations, re-analysis[1] data from several organizations, and Regional Climate Models (RCMs) exhibit very different trends [Pryor et al., 2009]. Observational data sets exhibit consistent negative temporal trends, for the 50th and 90th quantiles and annual mean wind speeds, across the entire U.S. Another study of continental U.S. wind speeds supports a declining max/min trend found in observation data [Klink, 1999]. Pryor et al. [2009] point out though, that time series of in-situ wind speed measurements are typically highly fractured and exhibit large heterogeneities, which makes analysis difficult. Other data sources (such as, NARR, ERA-40, & RSM) demonstrate a converse trend and do not agree with the observational data sets. These discrepancies imply that wind speed analysis should use several data sets and methods and that some of the assumptions currently applied to re-analysis data products and RCMs may need to be re-evaluated in future modelling efforts. Further research should pursue the inter-annual variability in wind speeds and reconcile the discrepancies between in-situ measurements, re-analysis products, and forecast models [Pryor et al., 2009].

Enloe et al. [2004] compare peak wind gusts over the contiguous United States and phases of the El Niño-Southern Oscillation (ENSO) using a non-parametric Kolmogorov-Smirnov (K-S) test. They classify years as ENSO warm, neutral, or cold-phase and generate monthly peak wind gust distributions for all monitoring stations across each phase. A K-S test compares monthly distributions for extreme ENSO phases

[1] Various techniques exist to generate multiple climate variables (re-analysis data) from observed data, which are interpolated onto regular geographical grid formats. A forecasting model is initialized and continually tuned with observed data to produce simulated output of unobserved climate variables.

(warm and cold) with the neutral phase to determine if changes in peak wind gust distributions are significant. The researchers find a dominant ENSO cold phase signal. During the winter months from November to March in cold phase years, the Pacific Northwest, Southwest, Great Plains, and the region extending from the Great Lakes through the Ohio River valley experience an overall increase in the gustiness of winds, as compared to neutral phase years. The Pacific Northwest experiences decreased gustiness during winter months in warm phase years. Fewer stations exhibit significant changes during warm phase years than in the cold phase and the changes are smaller in magnitude. Forecasts of climate variability patterns, like ENSO and PDO, have some reliability on multi-year time scales [National Research Council, 2006; Mantua and Hare, 2002][National Research Council, 2006; Mantua and Hare, 2002], and Enloe et al. [2004]note that further improvements in forecasting ability of climate indices can only improve predictions using this type of method.

Finally, a study of the northeast Pacific Ocean demonstrated that wind speeds recorded from most of 25 ocean buoys experience an apparent increasing trend [Gower, 2002]. However, some buoys also indicate negative trends. Of the buoys with longer than 20-year records, three show positive and three indicate negative trends, though the positive trends are larger and more are statistically significant.

These studies illustrate the difficulty in obtaining consistent results for wind speed trends and variability in the Pacific Northwest (Table 1). For example, Pryor et al. [2009] suggest a declining trend for observed wind speeds, while Gower [2002] indicates both increasing and decreasing wind speeds measured at ocean buoys. Due to the diverse study locations, climate indicators, and markedly different methods used it is difficult to compare the results and generalize.

Table 1: Summary of Wind Behaviour Studies with Spatial Coverage of the Pacific Northwest

Study	Location	Number of Sites	Time Period	Resolution	Result
Abeysirigunawardena et al., 2009	Delta, B.C.	3 Monitoring stations	1953-2006	Hourly wind speed	Significantly different extreme wind responses to warm and cold ENSO modes; higher winds occur during cold (i.e., La Niña) phases
Enloe et al., 2004	Continental USA	169 Monitoring stations	1948-1998	Daily peak gust	Overall increase wind gustiness during winter months (in cold phase years; for some areas) A lesser signal is associated with decreased gustiness for PNW in warm phase ENSO years during winter months
Gower, 2002	Northeast Pacific Ocean	26 Ocean buoys	1972-1999	Monthly mean wind speed	Wind speed trends from most buoys show an apparent increasing trend; however, some buoys also indicate negative trends
Klink, 1999	Continental USA	187 Monitoring stations	1961-1990	Mean monthly max/min wind speed	General decreasing (increasing) pattern for minimum (maximum) wind speeds averaged across U.S. PNW shows decreases for both max/min.
Pryor et al., 2009	Continental USA	336 & 193 Monitoring stations (2 data sets) 4 Re-analysis products 2 RCMs	1948-2006 (shorter record lengths are included within this time period)	Daily wind Speed (0000 UTC & 1200 UTC only)	Observational data sets, MM5, & NCEP-2 indicate declining wind speed trends NARR, ERA-40, & RSM indicate increasing (lesser magnitude), or absent, trends
Tuller, 2004	Southern B.C.	4 Monitoring stations	1947-1995	Hourly Wind Speed (annual and seasonal means)	Decreasing mean annual and winter wind speed trends (three of four stations)

1.2.4 General Circulation Models and Transfer Functions as a Means of Forecasting Wind Speeds

While most recent research on forecasting wind speeds addresses empirically based techniques (i.e., using observed or re-analysis data), a growing alternative field is dynamic or process-based techniques. These methods use General Circulation Models (GCMs) to generate forecasts of climate variables (temperature, precipitation, pressure). GCMs by themselves are often inadequate for local forecasting because of large grid cells (usually ~300 km per side) with subsequently poor resolution of predicted variables [Environment Canada, 2007a]. Downscaling methods, which can include dynamic, statistical, and stochastic approaches, provide a solution.

Regional Climate Models (RCMs) are the process-based means to provide increased resolution for dynamic GCM models. A particular region of interest is covered by both the high-resolution RCM and lower-resolution GCM. Downscaling uses the output from a few large grid cells of the global model as driving conditions for the many smaller cells of the regional model. RCMs trade off increased resolution of the local atmospheric processes at the expense of additional computational time and large increases in data needs. These models are evolving quickly, but are still unwieldy for routine forecasting [Environment Canada, 2010].

While process-based techniques, with their ability to include changing future conditions, are likely to be central downscaling methods in future, empirical techniques are available now. Empirical techniques use statistical methods to generate relationships between local- or regional-scale climate variables and larger-scale atmospheric forcing mechanisms. The relationships, often termed transfer functions, can translate large-scale

GCM output into locally meaningful information. Transfer functions offer a quickly available and less computation-intensive method than RCMs for scientists to downscale GCM data [Hewitson and Crane, 1996]. One caveat, though, is empirical downscaling bases results only on observational data. Past relationships are therefore assumed to hold into the future [Environment Canada, 2007a]. This assumption may not remain valid if atmospheric processes change due to natural or anthropogenic forcing. Despite that, GCMs themselves do not simulate surface winds very well and RCMs may not be available for all regions. Managers need to plan in some way for future wind conditions to help preserve built-infrastructure, and development of transfer functions offers a legitimate comprise for current planning needs.

This study investigates the relationship between climate-related, Pacific Ocean indices and wind speeds, and begins to define a potential method for statistical downscaling in the PNW. While I do not apply the relationships determined in this research as a transfer function for downscaling, future studies could attempt to do so.

2: METHODS

In this study of regional wind patterns, I collected available historical meteorological data from Environment Canada and the U.S. National Climatic Data Center (Dr. Gerhard Boenisch, Max Planck Institute for Biogeochemistry provided data from NCDC's Integrated Surface Hourly Database). Because of different data standards and conventions for each of these organizations, extensive data processing was necessary to convert information to a common and useable format. I used the statistical software package “R” to manipulate and analyse data throughout the analyses [R Development Core Team, 2009].

The study area encompasses the Pacific Northwest of North America (45-52° N, 129-122° W). Initially, no controls were placed on which stations were included in the analyses (unless clear discrepancies were detected through visual inspection of station measurements) and all available data were incorporated for the years 1950 to 1999. Many monitoring stations did not have detailed secondary data, such as specific location relative to other structures, local topographic features, or height above ground. Including many stations in the study helped compensate for any anomalous records, which I could not adjust without secondary data. To reduce sampling bias, at each monitoring station a day, month, or year was only included in the study if it met the following completeness criteria:

1. Day – at least 90% of 3-hourly measurement frequency (i.e., 7.2 measurements per day);

2. Month – at least 90% of days in month (e.g., January – 27.9 measurements); and
3. Year – at least 3 years with valid months and days.

Using these criteria, I reduced the initial 186 stations down to 146 locations considered valid for the study. Additional standardizing was necessary due to varying monitoring frequencies (e.g., 1-hourly vs. 3-hourly) over time, within and across stations. Consequently, for each day of valid data, I retained only the maximum daily wind speed.

Data deseasonalizing required a minimum number of data points in each time series when generating monthly averages for missing values (see Section 2.2 below). This further reduced the study sample to 114 valid stations (Figure 3). Collectively, the criteria listed above reduced the number of data points to a manageable level for available computer processing capabilities[2], while still including a large number of monitoring stations across time and space.

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[2] Even with the reduced number of stations, the long length of many of the data records meant LME models took hours to process. To evaluate complicated fixed and random structures in the LME model required lower resolution response data (i.e., max daily wind speeds rather than hourly measurements).

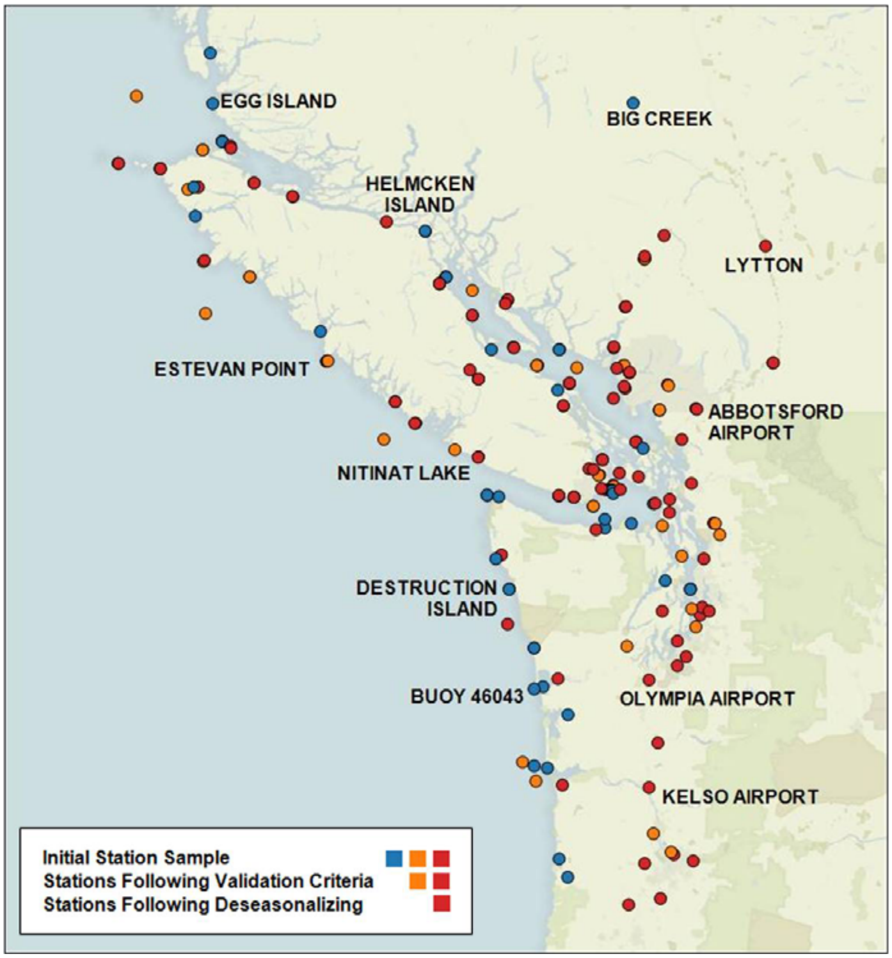


Figure 3: Study Area and Sample Location Selection Process

Applying completeness and validation criteria to data records reduced an initial 186 monitoring station sample (red, orange, blue) to 146 locations (red, orange) considered valid for the study. Further sample reduction occurred to ensure a sufficient minimum number of data points in each time series for deseasonalizing data records. This left a final sample of 114 wind speed monitoring locations (red).

2.1 Quantiles

Focusing solely on mean values may underestimate, overestimate, or fail to distinguish real nonzero changes in response-explanatory relationships [Cade and Noon, 2003]. This is especially true for distributions, such as those typical of wind speeds, which display strong skew or exhibit unequal variance across the magnitudes of observations (Figure 4). Frequently, measures other than the mean (or maximum/minimum), such as skewness, boxplots, or histograms are used to gain further insight into non-normal distributions. Summary quantiles (equivalent to percentiles in this study) can succinctly state these types of information and provide a much more robust statistical starting point than a single value such as the mean [Koenker, 2005].

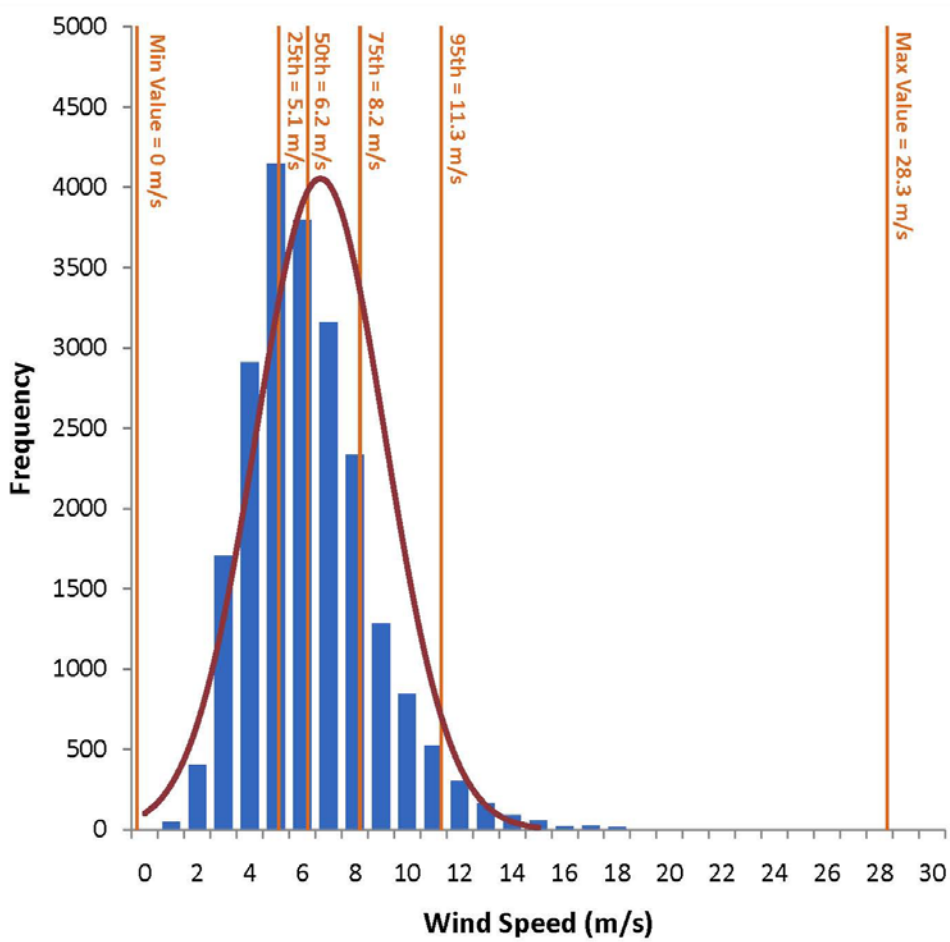


Figure 4: Typical PNW Wind Speeds and Idealized Normal Distribution

Wind speed distribution (bars) generated from 50 years of observation data for Portland International Airport (726980) and is representative of wind speeds in the PNW. The idealized normal distribution (line) has the same mean and variance as the original data. However, because the wind speed data is strongly skewed, the true median (50^{th} quantile = 6.2 m/s) does not line up with the idealized median (peak of the idealized normal = 6.7 m/s).

Strong skew (non-normal distribution) or heterogeneous variance can create problems for many statistical methods, which assume that input data have normally distributed observations with homogeneous variance. Regression models are particularly problematic to fit for processes with heterogeneous variance, such as wind speeds, as the response-explanatory relationship may change across the range of observed values. To investigate processes more fully, several quantiles may provide a better alternative to a single mean for regression of responses.

Koenker [2005] and Cade and Noon [2003] discuss quantile regression to determine relationships between explanatory and response variables when data are non-normally distributed. Quantile regression is a relatively recent development in statistical applications and as such, methods other than linear regression are still emerging or may not yet be developed (e.g., linear mixed-effects models). However, the notion of exploring various parts of a probability distribution separately is still extremely valuable and I have accordingly used several quantiles throughout this study. To explore the responses of average and extreme wind speeds, I calculated the 50^{th}, 75^{th}, and 95^{th} monthly quantile values from the maximum daily wind speeds (Table 2).

Table 2: Typical Wind Speeds Observed in the PNW with Beaufort Wind Scale

The range of wind speed values typically observed in the Pacific Northwest (values from data used in this study) is shown with corresponding categories of the Beaufort Wind Scale (often used by government agencies with jurisdiction in coastal areas for characterizing wind speeds). Adapted from [Environment Canada, 2007b].

Wind Speeds Typically Observed in PNW			**Beaufort Wind Scale**					
Quantiles			**Value**	**Limits of Wind Speed**			**Description**	**Effects Observed on Land**
50th	**75th**	**95th**		**Knots**	**m/s**	**km/h**		
			0	<1	0-0.2	<1	Calm	Smoke rises vertically
			1	1-3	0.3-1.5	1-5	Light Air	Smoke drift
			2	4-6	1.6-3.3	6-11	Light Breeze	Leaves rustle
			3	7-10	3.4-5.4	12-19	Gentle Breeze	Leaves and small twigs move constantly
			4	11-16	5.5-7.9	20-28	Moderate Breeze	Small branches move
			5	17-21	8.0-10.7	29-38	Fresh Breeze	Small trees in leaf sway
			6	22-27	10.8-13.8	39-49	Strong Breeze	Large branches move
			7	28-33	13.9-17.1	50-61	Near Gale	Whole trees move
			8	34-40	17.2-20.7	62-74	Gale	Twigs broken off trees
			9	41-47	20.8-24.4	75-88	Strong Gale	Slight structural damage (e.g., roof shingles)
			10	48-55	24.5-28.4	89-102	Storm	Trees uprooted; Considerable structural damage
			11	56-63	28.5-32.6	103-117	Violent Storm	Widespread damage
			12	64+	32.7+	118+	Hurricane	Rare

These quantiles cover the portions of wind speed distributions most meaningful for resource managers. The 50^{th} quantile (median values) represents typical wind speeds (i.e., close to average values) and can be expected to occur relatively frequently. Stronger wind speeds, represented by the 75^{th} and 95^{th} quantiles, will be less frequent but may have much more important impacts for managers (e.g., cause damage to infrastructure or ecosystem features). Using various parts of the wind speed distribution for analysis may allow the observation of trends for extreme values that are not apparent for the mean.

2.2 Deseasonalizing

For this study, I removed the seasonal component from the monitoring station time series to investigate changes in the variability and trends of wind speeds. Seasonal data may induce spurious correlations across stations due to regional seasonality rather than climate patterns. I used the R function *stl*, Seasonal Decomposition of Time Series by Loess, to deseasonalize quantile data [R Development Core Team, 2009]. This algorithm iteratively used loess (locally weighted scatterplot smoothing) to identify the seasonal pattern, long-term trend, and residuals of a time series (Figure 5), but needed a complete time series with no missing values. Consequently, monthly averages filled any missing quantile values (e.g., the average across all March values for a monitoring station time series filled any missing March values for the respective station). To ensure data points were present in each month for generating averages, a station record could not contain more than 90% missing values over the study period (1950 to 1999). Following deseasonalizing, the added-in monthly average values were removed, leaving the missing values as they were in the original time series. Most analyses, except hierarchical clustering, used the time series data with the seasonal component removed (i.e., only trend plus residuals). Hierarchical clustering could not correctly compare sample data if values were missing.

This data-augmentation method imparted as little extraneous information as possible to the non-seasonal components of the data while still accomplishing the deseasonalizing, though I could not test the extent to which the added monthly average values altered the outcome of the deseasonalizing algorithm. However, because the sections of the time series that were filled-in show information mostly in the seasonal component and very little in the trend or residual components (e.g., months between January, 1965 and December, 1972 in Figure 5), I feel confident that the algorithm is interpreting the additional data as seasonal-only information.

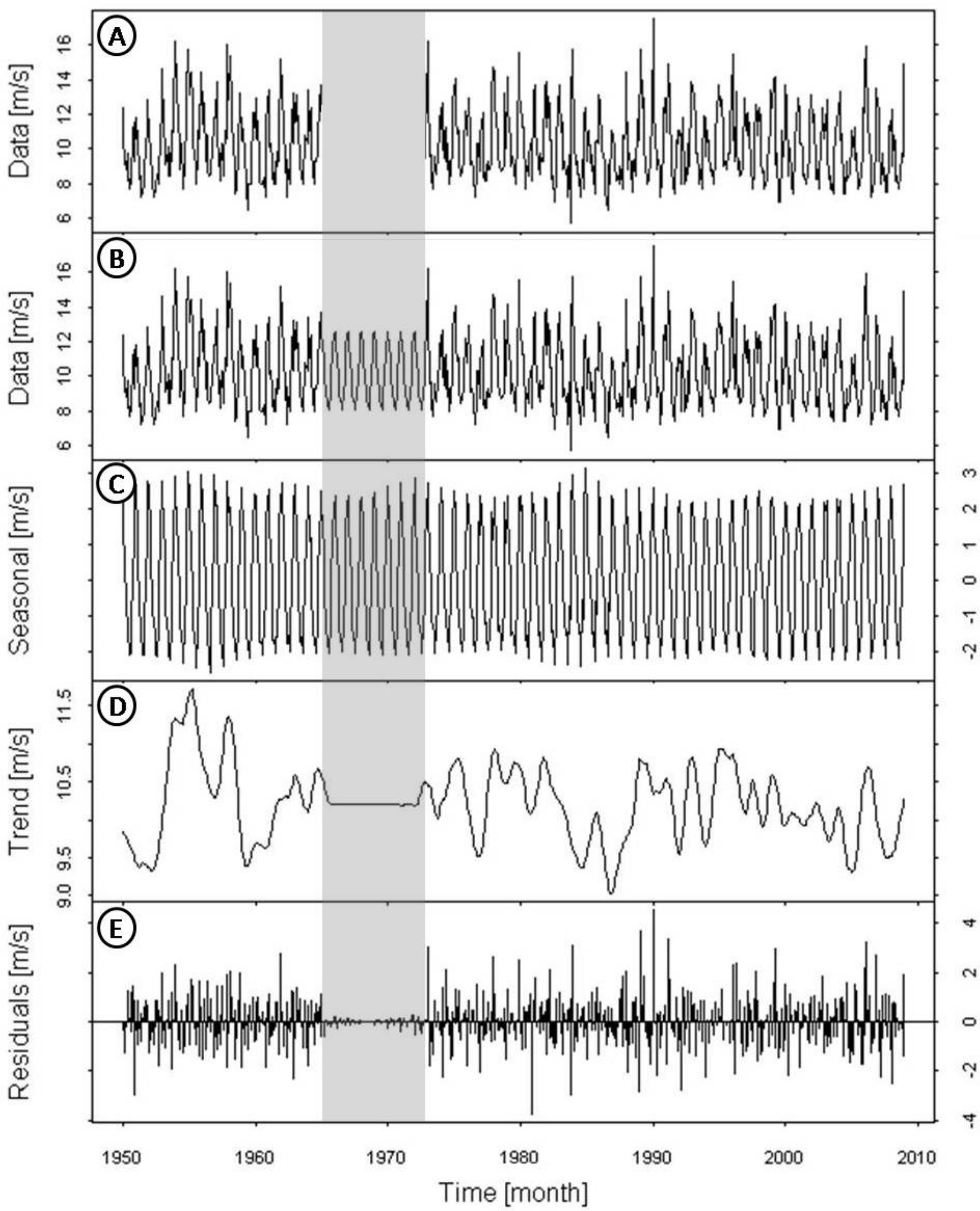


Figure 5: Wind Speed Data with Deseasonalized Components

Typical wind speed observations (shown: Portland International Airport – 726980), including (a) original data and (b) filled-in monthly average values, for January 1965 to December 1972 (shaded area). The *stl* algorithm decomposed data into (c) seasonal component, (d) trend, and (e) residuals (unexplained information). Flat sections in trend and residual components are a result of the added-in monthly average values reflecting predominantly seasonality. Further analyses used the trend plus residual components.

Allowing the seasonal component of the *stl* algorithm to vary over time accounted for yearly changes in seasonal wind speed patterns. If I did not include this liberty and constrained the seasonal pattern to be the same across all years (an unrealistic assumption), some variability may have been inappropriately shifted to the long-term trend and residual components. In some stations, the maximum seasonal amplitude (for a given month) in Figure 5 can be more than twice as large as the minimum seasonal amplitude (of the same month).

2.3 Hierarchical Clustering

Hierarchical clustering looks for commonalities among time series and groups them according to the shared features. Features common to many time series create the upper branches of the dendrogram (tree diagram, Figure 6), whereas features specific to only a few series create the lower branches [R Development Core Team, 2009]. But, while hierarchical clustering is a useful exploratory tool for identifying stations with co-varying patterns, it does not provide explanations for any of the identified groupings. Researchers must determine physical process explanations of commonalities.

I used the R function *hclust* to perform the hierarchical clustering of the 114 stations with sufficient valid data. Because this analysis does not allow missing values, I used the deseasonalized time series with missing values filled by monthly averages.

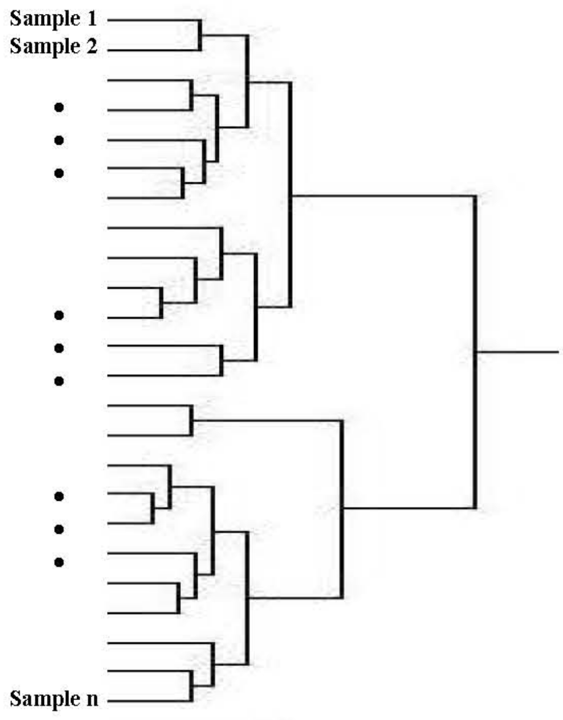


Figure 6: Typical Dendrogram (Tree) Diagram

2.4 Linear Mixed-Effects Models

Correctly representing physical processes with statistical models is a complicated and time-consuming process. Available data and the research questions asked should dictate model selection, not a favoured or common modelling procedure. Investigations should always use the simplest statistical technique that adequately represents the data. Unfortunately, standard linear regression often fails to be appropriate for physical processes because they violate many of the underlying assumptions, such as normality, homogeneity, and independence, and therefore more complicated methods should be used [Zuur et al., 2007; Zuur et al., 2009].

This study looks at multiple monitoring stations across a large region, with each station repeatedly measuring the local wind speed. Phenomena such as the PDO may have an overall effect (population level) on wind speed, but the relationship between these phenomena (e.g., PDO) and wind speed may differ at individual stations. Linear mixed-effects (LME) models are ideally suited to investigate this type of repeated-measures data due to their use of both fixed (population) and random (individual) effects [Pinheiro and Bates, 2000]. In addition to this, LMEs can accommodate heterogeneous variance such as that observed in the frequency distribution of wind speeds, and they can deal with correlated residuals, as in time series data, where a measurement in one period is related to the value in a previous period. Finally, mixed-effects models can incorporate multiple levels of data grouping, which may exist when sampling locations are "clumped"; meaning locations within a group are more related to each other than to locations in other groups. Linear regression cannot offer these types of flexibility [Zuur et al., 2009; Pinheiro and Bates, 2000].

2.4.1 Model Assumptions

Wind speed data violates the assumptions of standard linear regression, namely normality, homogeneity, and independence of regression residuals. These violations do not occur with LMEs because the assumption of normality and homogeneity apply to the residuals within groups and the assumption of independence applies to the residuals between groups. Each of these conditions in relation to the wind speed data available for the Pacific Northwest is discussed below.

LMEs assume normality of residuals after model fitting, for any given individual or within a group. Zuur et al. [2009] suggest looking for normality of the pooled residuals after model fitting. Though not a rigorous check, it does provide some reassurance. For this study, residuals represent the information that is unexplained by the influence of the explanatory variables. I checked pooled values with a Quantile-Quantile plot and performed a visual inspection (Appendix C). For example, in a typical QQ-Plot for wind speeds, the reader can see violation of normality by the deviation of residuals from the reference line (Figure 7), due to the strongly skewed distribution of wind speed values (Figure 4). Some authors argue that violation of normality is not a serious problem with large enough sample sizes [Zuur et al., 2009].

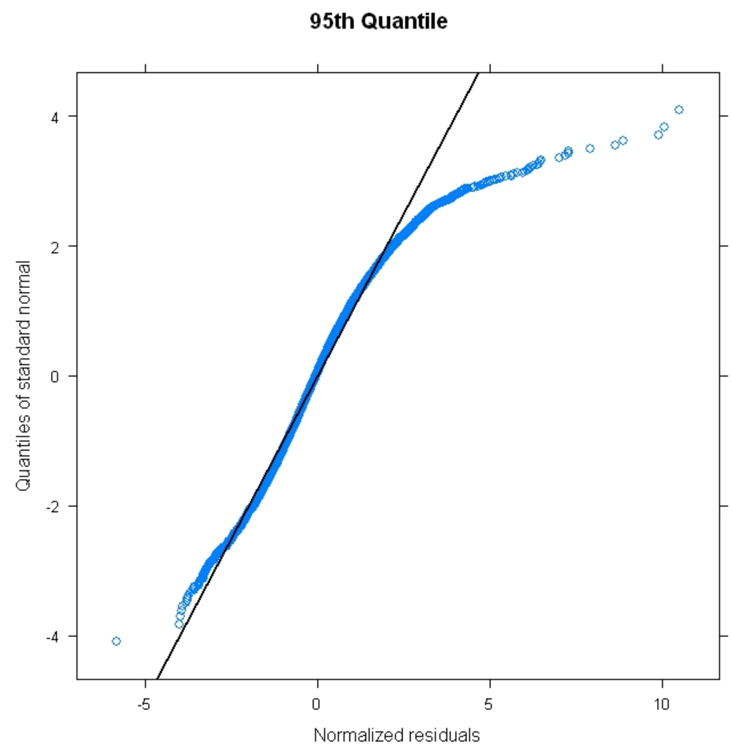


Figure 7: Quantile-Quantile Plot for Wind Speeds

Typical residuals for wind speeds show violation of normality by strongly non-linear pattern (i.e., deviation from x = y line).

Violation of the homogeneous variance assumption (often referred to as variance heterogeneity or heteroscedasticy) occurs when the variance is not the same at each fitted (wind speed) value. I assessed the validity of the homogeneous variance assumption using a visual check of the residuals plotted against fitted values (Figure 7).

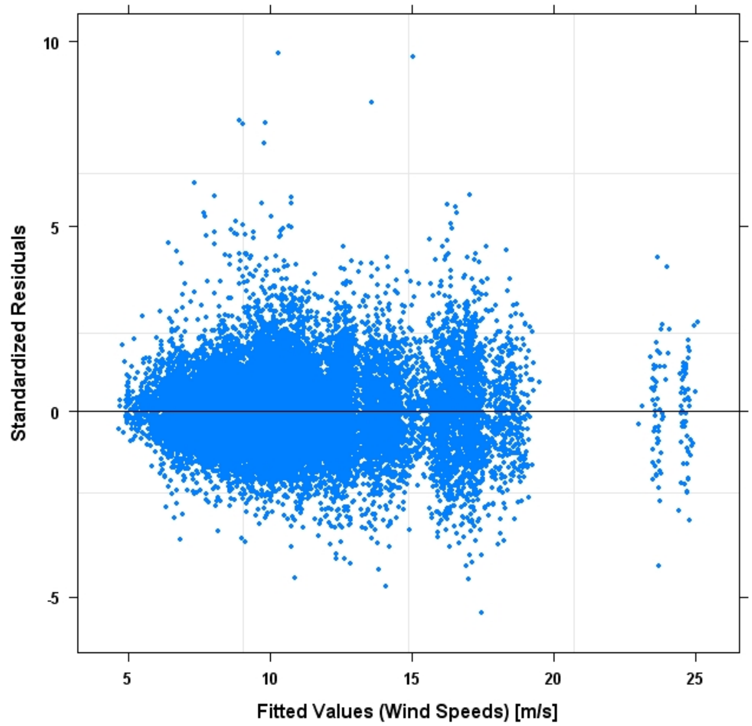


Figure 8: Standardized Residuals Plot for Wind Speeds

Typical residuals pattern shows violation of homogeneous variance assumption (changing spread of residuals as fitted values increase).

An increasing (or decreasing) spread of residuals as the fitted values (wind speeds) increase demonstrates a violation of the homogeneity assumption. Zuur et al. [2009] note that a visual inspection method is often more appropriate than a statistical test because of the test's assumption of normality (which may or may not hold). When variance appeared to be heterogeneous, I explored a range of structures that allow variance to change with fitted value (e.g., the variance at each wind speed is equal to that particular wind speed raised to a common power).

Independence of model residuals is an important assumption for the LMEs. This assumption is violated when the residual of $Y_{i,t}$ (in this case, wind speed at time, t) is correlated with the residual of $Y_{i,t-1}$ (that is, wind speed at some prior time, t-1). Some physical processes or data types (e.g., time series) inherently contravene the independence assumption. Auto-correlation of wind speed residuals can exist due to seasonality (removed in this case) or other driving variables (e.g., PNA or long-term trends). If the auto-correlation function indicates the independence assumption is invalid (Figure 9), tests such as the *F*-test and *t*-test cannot be used to determine the significance of the independent variables [Zuur et al., 2009]. LMEs can incorporate temporal correlation structures so that the significance of independent variables can be properly assessed despite the presence of correlated residuals (Figures 9 & 10). The y-axes of the figures show auto-correlation as a function of lag in the residuals. A greater Auto-Correlation Function (ACF) value indicates greater correlation between residuals at different lags.

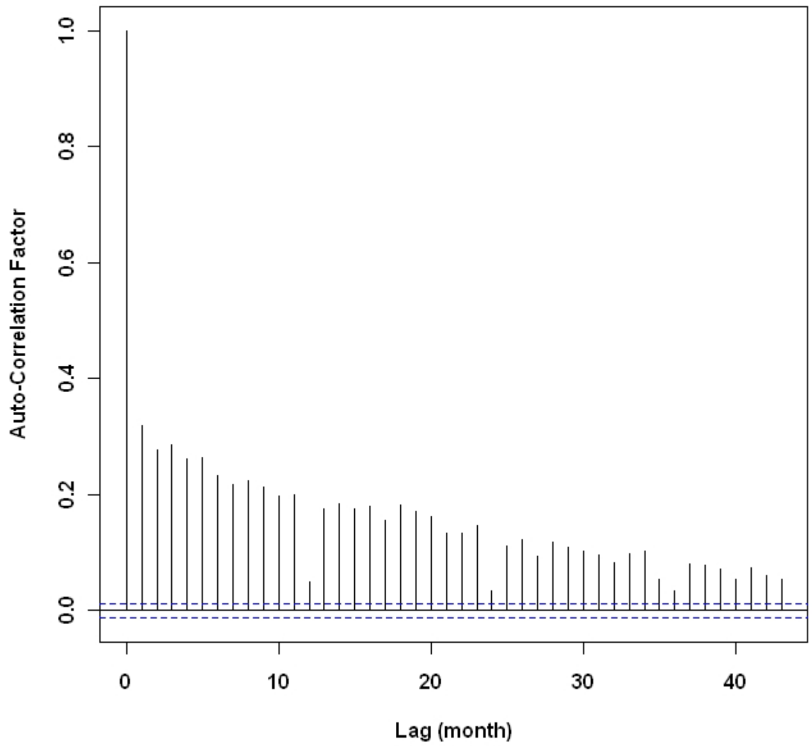


Figure 9: High Auto-Correlation of Residuals

A typical auto-correlation function for wind speeds, calculated for the normalized residuals before incorporating a correlation structure. Spikes at early time lags (1 to 3 months) indicate that residuals for a particular month relate to measurements in previous periods (the height of the spike shows the degree of correlation). Auto-correlation variables of less than ~0.2 are generally considered uncorrelated.

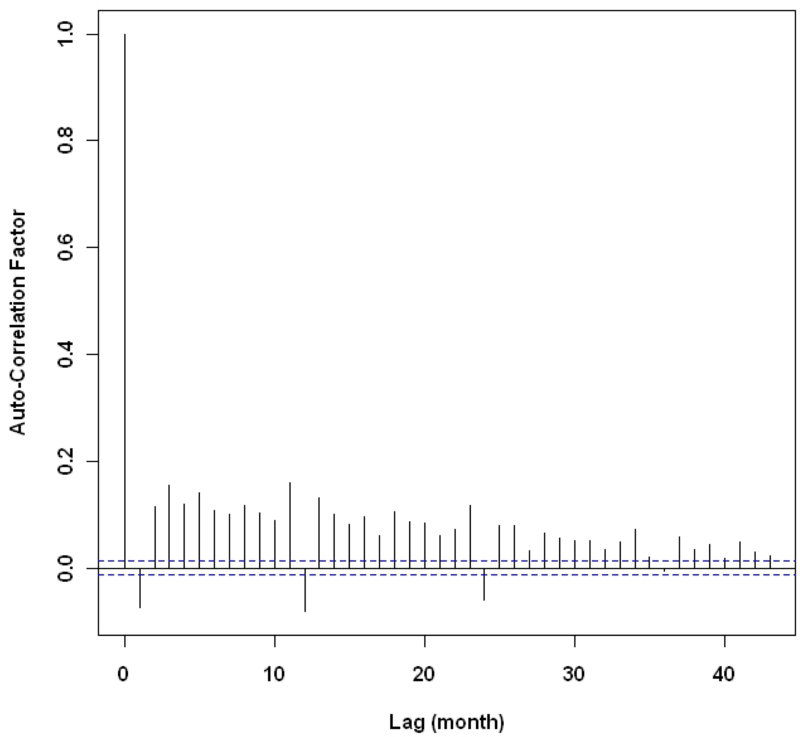


Figure 10: Low Auto-Correlation of Residuals

A typical auto-correlation function for wind speeds, calculated for the normalized residuals after incorporating an AR(1) structure. Including an auto-regressive structure into the LME model reduces unexplained correlation between residuals to acceptable levels.

2.4.2 Model Structure

A linear mixed-effects model contains two components for explanatory variables: fixed and random variables. Equation 1 shows the notation for a general version of the LME model. Each of the variables included in the LME equation represents a matrix of values.

$$Y_{t,i} = X_{t,i} * \beta_t + Z_{t,i} * b_{t,i} + \varepsilon_{t,i} \qquad \text{Equation 1}$$

Where:

$\mathbf{Y_{t,i}}$ = observations of response variable (wind speeds)

$\mathbf{X_{t,i}}$ = fixed term explanatory variables

$\boldsymbol{\beta_t}$ = fixed term coefficients

$\mathbf{Z_{t,i}}$ = random term explanatory variables

$\mathbf{b_{t,i}}$ = random term coefficients

$\boldsymbol{\varepsilon_{t,i}}$ = errors

The fixed term components ($X_i * \beta$) provided the population level effects, such as the regional influence of PDO or Elevation. Random term components ($Z_i * b_i$) gave the individual effects, like the unique station-specific responses to PNA. In this model, each individual (monitoring station) was allowed to have a different relationship with the explanatory variable (included in Z_i) and coefficients for these variables were included in b_i (the subscripts denote that each individual "i" had a separate relationship). The explanatory variables included in the fixed term X_i describe the overall pattern across individuals (note the lack of subscript for the fixed effects coefficients matrix β). The coefficients b_i and errors ε_i were assumed normally distributed and independent (excepting the caveats listed above in Section 2.4.1).

I assumed the monitoring stations sampled were representative of the entire population of potential monitoring stations within the study region. Treating some explanatory effects as fixed implied that those relationships (between response and fixed explanatory variables) hold for all individuals, not just those sampled. In other words, I am observing the weather at several monitoring locations (where observations may be similar, but unique) and then extrapolating to a common regional weather description. Including both population and individual effects allows great flexibility in LME models. This method recognizes that individual stations may differ, but still contribute information to finding regional or population level relationships. Explanatory variables (such as, Year, Elevation, PDO, or PNA) may appear as both fixed and random terms in the LME model (i.e., while the overarching population relationship affects all individuals, they each exhibit unique responses as well) allowing further flexibility when modelling. For example, all monitoring locations at the same elevation should respond similarly to pressure patterns. However, despite being at the same elevation, due to unique topographic features each station will have somewhat different responses to the regional pressure patterns. Including fixed and random effects in the LME model derives a more valid relationship between the explanatory variables and regional physical processes than if all observations were treated as fixed (as in linear regression). Forecasting generally uses the regional relationship, rather than each individual relationship. Therefore, the fixed term should include as many relevant variables as can be accommodated by computing capacity, as this relationship is most pertinent to understanding regional wind speed dynamics. LME models can also include interactions between explanatory variables to represent modifying behaviour of one variable on another. For example, the effect of PDO may change with elevation and affect low and high elevation sites differently.

In this study, I fit LME models using various quantiles of the wind speed distributions for the study area. The response variables included the 50th, 75th, and 95th monthly quantile wind speeds for each station to represent the prevailing conditions and extreme wind speeds. For resource managers, the 50th quantile wind speeds are most likely to characterize wind speeds encountered on average, or “normal” conditions. The 75th and 95th quantile wind speeds are those most likely to cause damage.

Many variables, ranging from elevation to climate behaviour, are likely to influence wind speeds in the PNW (Table 3). I used the variables listed as potential explanatory variables (included in the LME model) to determine relationships between these variables and observed wind speeds. This list of influencing variables was not exhaustive, in part due to data constraints. For instance, SSTs in the north Pacific Ocean may influence PNW wind speeds, but were not included in the study because I could not obtain SST observation data for relevant locations.

Proposed fixed effect variables included PDO, PNA, Global-SST ENSO, NOI, AO, Year, Elevation, Coast/Mainland, and Data Source. Coefficients for the Coast/Mainland and Data Source variables were relative to a reference state (Mainland sites and NOAA data, respectively). I allowed interactions between all variables except Data Source. The LME models included Data Source to determine if a bias was present between the Environment Canada and NOAA data, not to test its effects with other variables. Interactions between Data Source and other variables were therefore not appropriate. I imposed a limit of two-way interactions on fixed effect variables to help with interpretation. Interactions between more than two variables (i.e., three-way or greater) could be difficult to understand, especially if those variables were involved in other sets of interactions.

Potential random effects included Year, Elevation, Coast/Mainland, and Data Source. Random effects did not include Pacific Ocean climate indices because of computing limitations. For each random effect that I included, the LME model had to fit an additional 114 variables (i.e., number of monitoring stations), which could quickly make the time needed to fit each model iteration overly cumbersome.

I placed little restriction on the atmospheric indices included in the LME model other than the requirement that an index was theorized to explain some climate variability in the Pacific Ocean (see Section 1.2.2). I selected these particular indices in an attempt to cover the observed teleconnections (causal link between weather patterns in different locations) between climate drivers (i.e., sea surface temperatures and sea level pressure) and atmospheric response (wind speed).

While, some of the indices listed correlated with each other (up to a coefficient of 0.6), none of them did so exceptionally. Accordingly, all indices were initially included in the fixed effect term of the LME model to elicit the explanatory power of even the small, uncorrelated portions.

Table 3: Explanatory Variables Included in Wind Speed LME Model

Variable	Data Source	Definition
Pacific Decadal Oscillation (PDO)	JISAO	Long-lived cyclical pattern of Pacific climate variability based on sea surface temperatures (SST) [JISAO, 2008]
Arctic Oscillation (AO)	NCEP	Dominant pattern of non-seasonal sea-level pressure (SLP) variations north of 20N, with anomalies of opposite sign to that in the Arctic centred about 37-45N [NCEP, 2006]
Pacific/North American Pattern (PNA)	NCEP	One of the most prominent modes of low-frequency variability in the northern hemisphere extratropics [NCEP, 2006]
Global-SST El Niño-Southern Oscillation (ENSO)	JISAO	Low frequency portion of ENSO phenomenon measured as the average SST anomaly equatorward of 20N & S, minus the average SST poleward of 20N & S [JISAO, 2008]
Northern Oscillation Index (NOI)	PFEL	Based on SLP differences between the pressure high in the northeast Pacific Ocean and the pressure low near Darwin, Australia. Provides an indication of how global-scale climate events affect the north Pacific Ocean [PFEL]
Year	N/a	Each year of data is modelled separately to allow long-term trends to be identified
Coast/Mainland (CM)	N/a	Highest level of grouping from the hierarchical clustering; potential differences in coastal versus inland behaviour
Elevation	EnvCan & NOAA	Potential differences in valley/coastal versus higher elevation sites
Data Source	EnvCan & NOAA	Environment Canada/National Oceanic and Atmospheric Administration; detect systematic bias in data source

I considered fitted values raised to a power or exponentiated as variance structures for the LME model. When evaluating if changing variance allowed a better model fit, I also considered grouping fitted values by Coast/Mainland and Data Source. For example, if the variance was equal to the fitted values raised to a power term and grouped by

Coast/Mainland, a separate power coefficient was calculated for each of the Coast and Mainland groups.

Finally, an auto-regressive order one (AR(1)) correlation structure was considered. This structure assumed that a wind speed residual in a given month related to the residual of the previous month. The LME model determined one coefficient value (between zero and one) to best fit the AR(1) process for the total wind speed data.

2.4.3 Fitting Procedure

Various authors suggest different methods for fitting LME models, mostly relating to the order for adjusting fixed and random effects [Zuur et al., 2007; Pinheiro and Bates, 2000; Venables and Ripley, 2002][Zuur et al., 2007; Pinheiro and Bates, 2000; Venables and Ripley, 2002]. I have chosen to generally follow the procedure outlined in Zuur et al. [2009] and use the R function *lme,* from the nlme library [Pinheiro et al., 2009], to fit linear mixed-effects models. The steps involved in this method for fitting a LME model are as follows:

1. **Find the optimal Random Structure**

   The initial step to fit a LME model involved determining the random (individual) variables (Z_i), within-group variation, and correlation structure. Each of these components relates to the basic model assumptions (Section 2.4.1).

   a. *Use Restricted Maximum Likelihood (REML) when fitting the initial LME models*

      Mixed-effects models were fit using maximum likelihood (ML), rather than ordinary least squares (OLS). However, ML gives biased variance estimates compared with OLS. To correct for this bias, standard model fitting procedure uses REML. I followed this method when comparing the random structure of competing models and fitting the final full model.

b. *Include all proposed fixed variables*

To allocate as much explanatory power as possible to the fixed (population) component (X_i) and not to the random (individual) component (Z_i), all potential variables and interactions were included as fixed effects at this stage. The "beyond optimal" model contained more fixed variables than would likely be in the final model [Zuur et al., 2009].

c. *Test alternative random variables*

In order to select which random variables (e.g., Year or Elevation) best explained the observed wind speeds, given the presence of all of the fixed-effect variables, each model fit was compared using the Akaike Information Criterion (AIC) and p-value of the likelihood ratio test. I used AIC because of its wide application in modelling, its ability to measure goodness of fit and model complexity, its use in comparing non-nested models, and R's automatic tools for evaluating it for large models. AIC rewards competing models (lower AIC value) for higher likelihood values, but penalizes them (higher AIC value) for including additional parameters. It is a measure of the relative fit between competing models – the absolute AIC value in itself is meaningless. This method recognizes that additional model parameters will always increase the goodness of fit, but discourages over-fitting and tries to find the optimal and most parsimonious model structure. However, AIC is conservative when evaluating competing models so the likelihood ratio test p-value was also used when comparing models. I compared alternative random variables using homogeneous within-group variation and no within-group correlation, as is standard modelling practice [Pinheiro and Bates, 2000].

d. *Determine the optimal variance structure*

If heterogeneity (i.e., changing variance of residuals by fitted values) was present, then I compared alternative error structures using AIC and p-values as was done when testing various random variables (1c). Examples of variance structures available in R include fixed variance, changing with the power or exponential of a covariate (random or fixed variable, fitted value), or changing variance patterns by group.

e. *Assess the correlation structure*

Potential correlation structures were considered in the same manner as alternative descriptions of variance (1d). To assess the presence of auto-correlation, the R function *acf* plotted the correlation of model residuals at various time lags. I only considered an auto-regressive order one (AR1) correlation structure due to computing limitations.

Once the individual variables and variance and correlation structures were determined, the next step was to find the optimal fixed structure relating the population level variables (e.g., Elevation, PDO, or PNA) and wind speeds.

2. **Find the optimal Fixed Structure**

   a. *Use Maximum Likelihood (ML) as fitting method*

      REML is inappropriate for comparing models with nested fixed structures (i.e., the fixed variables of the nested model were a subset of the fixed variables of the competing model) because of its treatment of regression coefficients when correcting for bias in variance estimates. Standard model fitting practice uses ML for comparing the fixed effects of alternative models [Pinheiro and Bates, 2000].

   b. *Use the same random structure for all competing fixed structure models*

      Each of the alternative models compared had to use the random structure established in Step 1 to ensure that only the effect of changes to the fixed structure was evaluated.

   c. *Fit fixed variables*

      The fixed variables of potential models were nested so that the AIC and likelihood ratio test could compare marginal differences. Model building was conducted both forward and backward. Forward model building begins with only an intercept and iteratively adds variables to the fixed structure (recommended by Pinheiro and Bates [2000]). Backward model building starts with the largest fixed structure considered (i.e., that used in Step 1) and iteratively removes variables (recommended by Zuur et al. [2009]). Forward and backward building do not always arrive at the same final model structure, especially for complicated fixed structures. I used both methods in this study to compare final structures and determine the set of optimal fixed variables. The final model (forward or backward) with the lowest AIC value was selected as the optimal model. In each case, this criterion chose the backward model.

3. **Fit the final LME model**

   A final model was fit to check that violation of the underlying model assumptions (i.e., homogeneity and independence) had not occurred. The model was fit using Restricted Maximum Likelihood (REML) to estimate unbiased variance terms. Visual inspection of the diagnostic plots (see Section 2.4.1) ensured agreement with the assumptions.

Sensitivity analyses assessed the robustness of the LME model to changes in structure and parameter values.

2.4.4 Forecasting

Users should always test the forecasting accuracy of a final LME model. The proper way to test a model's forecasting ability is to apply it to a new set of data that was not used to generate that model. The validating wind speed and explanatory variable dataset for this study included measurements from 2000 to 2008. Correlations between the forecast and observed values indicated the forecasting ability. For example, if the 95^{th} quantile wind speeds were highly correlated with model forecasts, then my model would likely provide accurate predictions, at least in the short to medium-term (one to several years). The farther into the future the model forecasts, the lower the probability that established wind speed-explanatory relationships will continue to be valid [National

Research Council, 2006]. In future, the LME model can be re-fit with increasing numbers of observations to refine response-explanatory relationships and increase forecasting ability.

2.5 Adaptation Actions

Forecasts of wind speeds for the Pacific Northwest should help decision makers and resource managers plan more effectively for future conditions. When considering future wind conditions, many managers may be aware that they should take some kind of action to prevent negative outcomes, but they may not have a clear idea of what type of action to initiate or even of the range of actions possible. Forecasts for decision makers may be much more informative if accompanied by potential actions to help adapt to the predicted conditions.

I chose three interview respondents from the disaster response, large electric utility, and environmental management fields. These fields are often more prone to wind damage than other sectors and may be at increasing risk in the future from changing wind hazards. The goal of these informal interviews was to elicit a range of potential actions to adapt to changing wind conditions in the future. A series of questions (included in Appendix D) guided the conversations with decision makers and academics about the types of information needed for forecasts, lead-times, and representativeness for a given area. In this study, I aggregated responses to interview questions and did not include any attribution of answers or quotes.

3: RESULTS

In this chapter, I present the major results of my Pacific Northwest wind speed study. I begin by looking at the patterns observed during data exploration (hierarchical clustering and data visualization). Next, I detail the final statistical models that I generated to relate the 50th, 75th, and 95th quantile wind speeds to various explanatory variables and the subsequent forecasts. Finally, I consider potential adaptation actions suggested during the informal interviews with decision makers and academics.

3.1 Exploration of Wind Speeds

Early investigation steps in the wind speed study included variable analysis, hierarchical clustering, frequency plots, and data visualization. Each of these methods helped explore the nature of wind speeds in the PNW. Only hierarchical clustering and data visualization produced results that were significant and distinct.

3.1.1 Hierarchical Clustering

Grouping monitoring stations together by similarities in wind speed observations provides a way to look for previously unidentified associations. Hierarchical clustering of the 95th quantile wind speeds produced the groupings shown in Figure 11. The broadest level of grouping (i.e., furthest from the branch tips) separates the coast monitoring locations (lower cluster) from the mainland locations (upper cluster). The physical interpretation of this grouping level was inferred by plotting the locations of the monitoring stations by groups (i.e., Coast and Mainland) and by elevation (Figure 12).

With few exceptions (e.g., Lytton and Holberg), the Coast monitoring sites are near to the ocean and at relatively low elevation, usually less than 30 m. The coast/mainland groups are included in the LME model as potential fixed and random variables.

Hierarchical clustering was also performed for the 50th and 75th quantile wind speeds. The grouping observed for these quantiles is similar to that for the 95th quantile, but not as pronounced. Generally, the analysis sorted monitoring stations into coast and mainland locations for the lower quantiles as well, but not at the broadest grouping level; for this reason I am unable to identify the physical meaning of the grouping levels for the 50th and 75th quantile wind speeds. However, because the coast/mainland grouping is generally present for the 50th and 75th quantiles, although not well defined, I use the station grouping from the 95th quantile wind speeds for the LME models of lower quantiles.

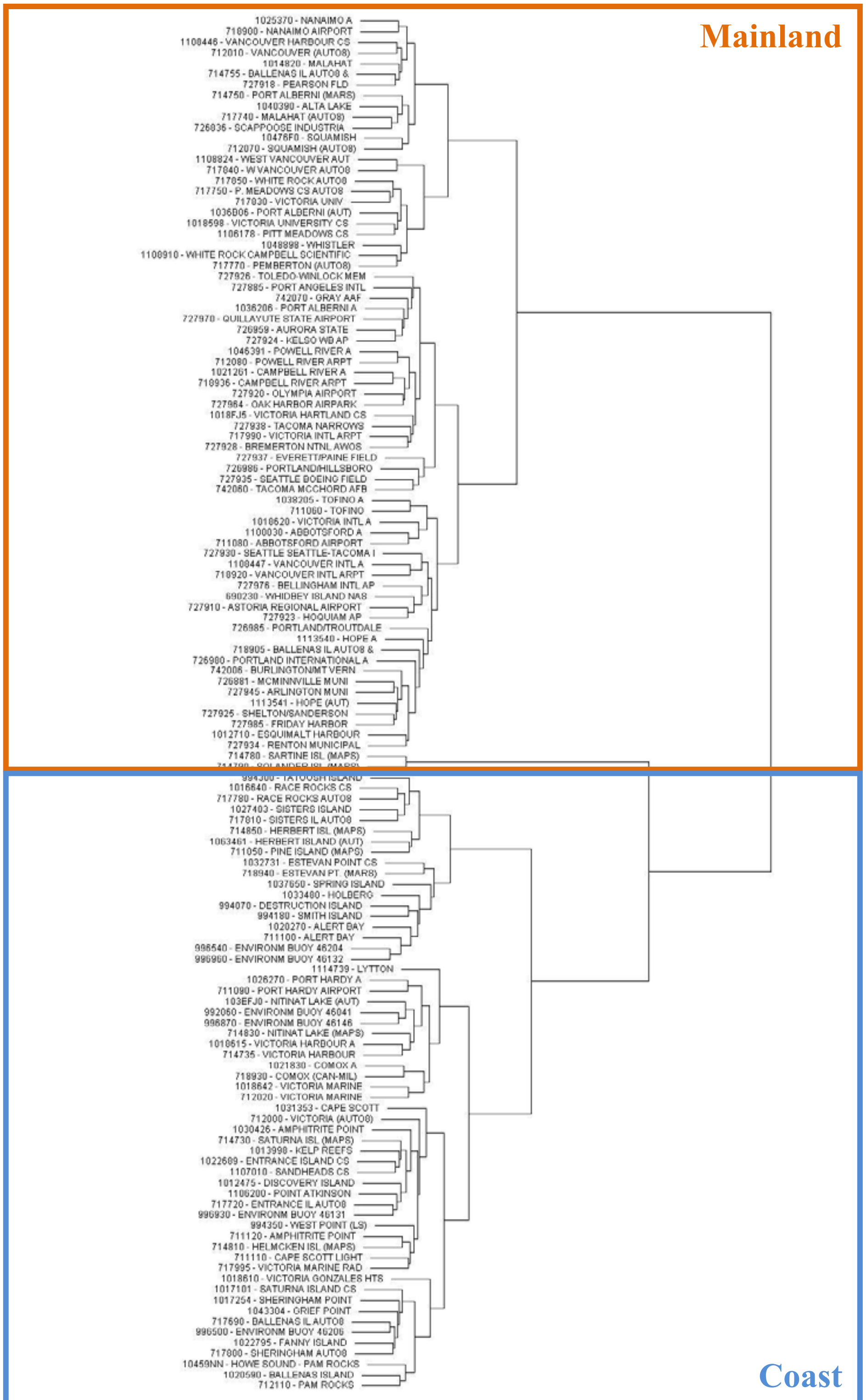


Figure 11: Hierarchical Clustering for the 95th Quantile Wind Speeds

Mainland group contains 69 locations and Coast group has 60 locations. Note that every station within the study area, from both the validation dataset and the fitting data, was included in the cluster analysis to characterize all locations in anticipation of forecasting (coast/mainland designation is required for the LME model).

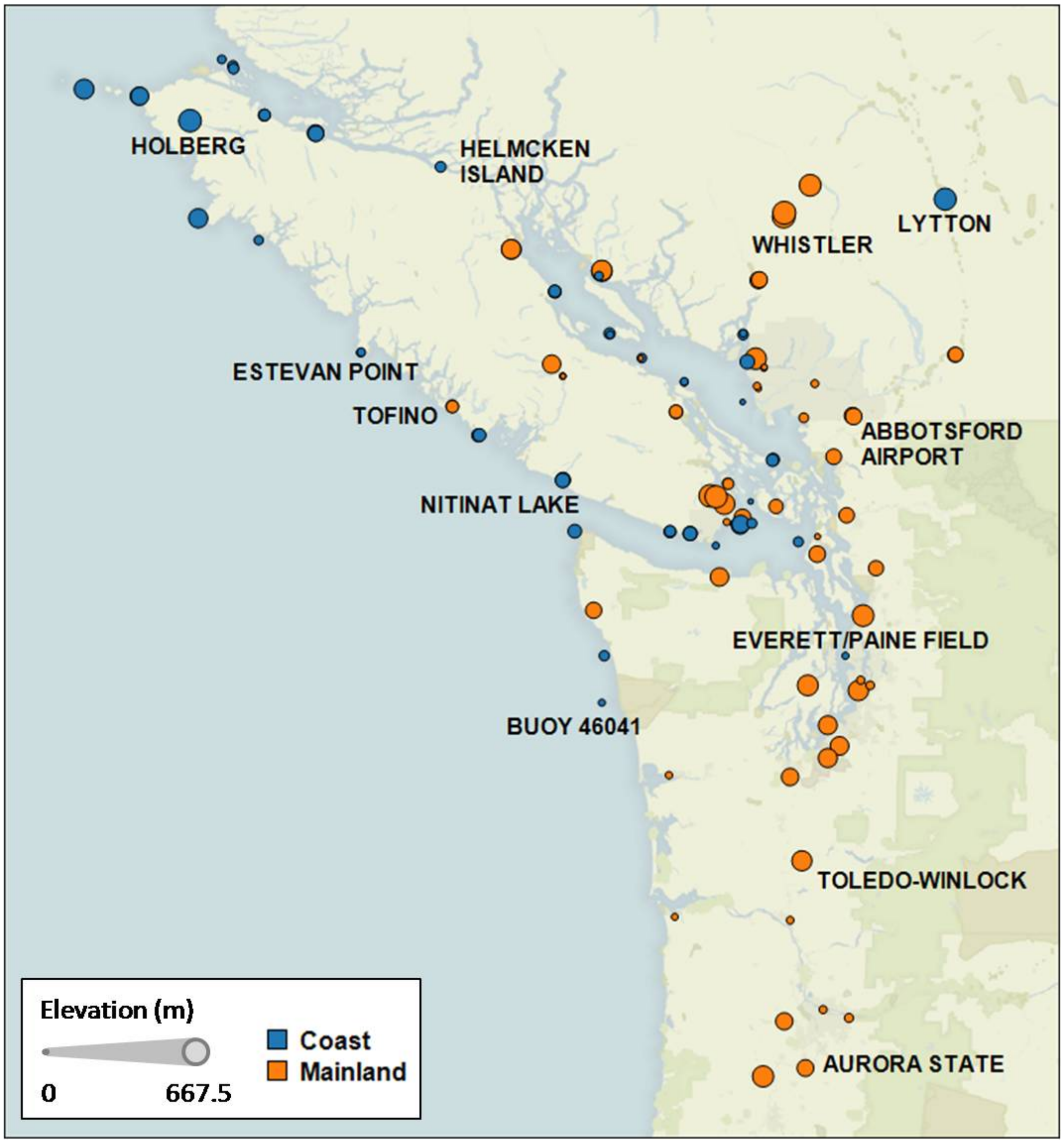


Figure 12: Coast and Mainland Monitoring Station Locations

Monitoring locations are scaled (size of circle) with elevation. With few exceptions (e.g., Lytton and Holberg), Coast monitoring sites are near to the ocean and at relatively low elevation, usually less than 30 m. Mainland sites are generally further inland and many are at higher elevations.

3.1.2 Data Trends

Plotting the average 50th, 75th, and 95th quantile wind speeds across each of the Coast and Mainland groups further explored the PNW wind speed data. Each of the quantiles show generally higher speeds and increased variability for coast relative to mainland sites (Figure 13). While mainland monitoring locations appear to have a downward wind speed trend (approximately -0.03 m/s/year for the 50th quantile to -0.04 m/s/year for the 95th quantile) , it is unclear if the coast sites have an upward trend or are essentially stationary around a fixed mean. Coast locations appear to follow a cyclic pattern with an approximate period of nine years (most apparent in the 95th quantile with up to a ~3 m/s difference between cycle peaks and troughs). The periodogram (not included) of the 95th quantile coast time series supports an approximate nine-year cycle with a peak at ~9.3 years. I evaluate potential time trends in PNW wind speeds using the Year fixed and random effect terms in the LME models.

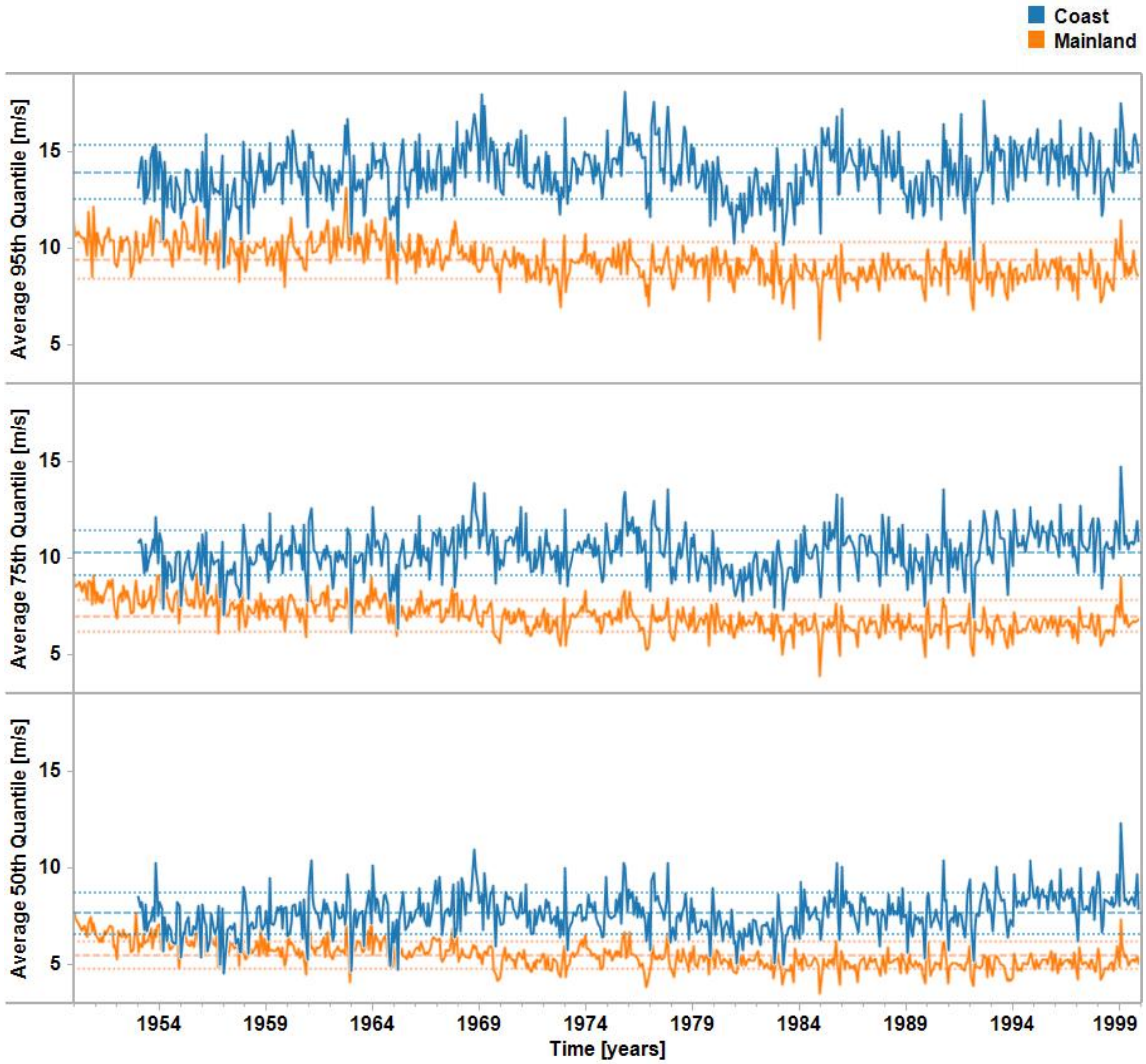


Figure 13: Variability of Coast and Mainland Monitoring Stations (1950-1999)

Time series represent wind speed quantiles averaged across all stations within the respective group. Average (dashed lines) and one standard deviation (dotted lines) shown for each time series. Mainland monitoring locations appear to have a downward trend, while coast locations follow a roughly cyclic pattern with a frequency of ~9 years.

3.2 Linear Mixed-Effects Models

LME models fit for each of the 50th, 75th, and 95th quantile wind speeds are not restricted to the same fixed and random effects or variance and correlation structures. As this study used a very large sample size (~23,000 data points), slight violations of the normality assumption were allowed without adjustment.

Tables 4, 5, and 6 below, present the details of the final models. All of the fixed and random variables included in each model are presented in the tables.

3.2.1 50th Quantile

The final LME model for the 50th quantile of PNW wind speeds includes all of the proposed fixed effects, along with most of the available fixed effect interaction terms (Table 4). Notable among the interaction terms is that the effect of all fixed variables changes over time (i.e., Year is involved in interaction terms with all other fixed variables). The effect of time on other variables is possibly due to the downward sloping trend in the Mainland group (Figure 13).

Based on parameter coefficients, fixed effect terms with constant (i.e., Coast/Mainland) or slowly varying (i.e., Year) variables have larger effects on fitted wind speeds than monthly varying variables (e.g., PDO), and much larger than interaction terms. Interpretation of coefficients depends on the scale of the associated variable. Each of the coefficients is multiplied by the value of the respective fixed effect term (e.g., the effect of Year in 1980 is equal to -0.00865 * 1980 = -17.127). Similar contributions come from PDO, PNA, ENSO, AO, and NOI. The best fitting random effects term groups each station by Coast/Mainland.

For the case of PNW wind speeds, including a variance structure that changed by fitted (wind speed) value and a correlation structure was important because wind speeds have larger variance for higher values (heteroscedasticy) and were auto-correlated through time. Variance equal to the fitted (wind speed) values raised to a power term best fits the LME by allowing a separate variance power term for Coast and Mainland groups of 0.6186 and 0.4256, respectively. The correlation structure takes the form of an auto-regressive order one function (AR(1)), with a phi value of 0.4330. Including power variance and auto-regressive order one structures greatly improves the fit for the 50th quantile (and the 75th and 95th) wind speed LME models, as measured by the AIC model building criterion.

This LME model appears to have a strong correlation between observed and fitted values with a squared correlation value of 0.71. However, most of this correlation is based on slower wind speeds within the quantile, and not the extreme speeds I am most interested in (Figure 14). Observed wind speeds are generally underestimated by the LME model, particularly above ~12 m/s.

Table 4: 50th Quantile Wind Speeds Linear Mixed-Effects Model

Fixed Effects[3]

Q50 ~ Year + Elevation + Coast/Mainland + Data Source +
PDO + PNA + NOI + ENSO + AO +
Year : (Elev + C/M + PDO + PNA + NOI + ENSO + AO) +
Elevation : (C/M + PDO + PNA + AO) +
C/M : (PNA + NOI + AO) +
PDO : (PNA + NOI + ENSO + AO) +
PNA : (NOI + AO) + ENSO : (NOI + AO)

Fixed Effect Coefficients[4]

	Value	Std. Error		Value	Std. Error
(Intercept)	22.18497	2.808576	Year:AO	-0.00329	0.000555
Year	-0.00865	0.001410	Elev:C/M	0.00704	0.003372
Elevation	-0.07152	0.029366	Elev:PDO	0.00016	0.000079
Coast/Mainland	-32.46480	6.118964	Elev:PNA	-0.00014	0.000058
Data Source	0.35138	0.254088	Elev:AO	0.00011	0.000060
PDO	-3.46906	1.508112	C/M:PNA	0.04342	0.017168
PNA	8.99593	1.111255	C/M:NOI	0.02625	0.006541
NOI	2.58666	0.385861	C/M:AO	0.03341	0.018290
ENSO	0.31550	0.080807	PDO:PNA	0.02765	0.005429
AO	6.51667	1.099007	PDO:NOI	0.02029	0.002837
Year:Elev	0.00003	0.000015	PDO:ENSO	0.00073	0.000359
Year:C/M	0.01787	0.003070	PDO:AO	-0.02180	0.007748
Year:PDO	0.00171	0.000761	PNA:NOI	-0.04187	0.002586
Year:PNA	-0.00460	0.000561	PNA:AO	0.03221	0.006440
Year:NOI	-0.00129	0.000195	ENSO:NOI	-0.00013	0.000110
Year:ENSO	-0.00016	0.000041	ENSO:AO	0.00068	0.000350

Random Effects

Q50 ~ Coast/Mainland | Station

Variance Structure

Variance ~ $(\text{Fitted Wind Speed Value})^{\text{Power}}$ | Coast/Mainland

Power = 0.6186 (Coast) 0.4256 (Mainland)

Correlation Structure

AR(1) ~ 1 | Station $\varphi = 0.4330$

Observed v. Fitted Values Squared Correlation

$\text{Corr}^2 = 0.71$

[3] **:** indicates "interacts with"
| indicates "grouped by"
φ is the degree of correlation parameter

[4] All single-term fixed effect variables are included in the LME model. Two-way interactions included are detailed, while interactions not included in the model are not present in the table.

3.2.2 75th Quantile

The final LME model for the 75th quantile wind speeds includes all of the proposed fixed effects, along with most of the fixed effects interaction terms (Table 5). The fixed effect terms for the 75th quantile are similar to the 50th quantile LME model terms, with the terms having the same relative dominance. Fewer interactions are included in the 75th quantile model.

Based on parameter coefficients, fixed effect terms with constant (i.e., Coast/Mainland) or slowly varying (i.e., Year) variables have larger effects on fitted wind speeds than monthly varying variables (e.g., PDO), and much larger than interaction terms. Smaller contributions come from Elevation, PDO, PNA, ENSO, AO, and NOI. The best fitting random effects term groups each station by Coast/Mainland.

Variance equals the fitted wind speed values raised to a power term. Again, this is best fit by allowing a separate variance power term for Coast and Mainland groups of 0.6210 and 0.4886, respectively. The correlation structure takes the form of an AR(1) function, with a phi value of 0.4311. The 50th and 75th quantile LME models are very similar in structure and the values of the coefficient terms. The 75th quantile model appears to have a good fit with an observed and fitted value squared correlation of 0.75.

Table 5: 75th Quantile Wind Speeds Linear Mixed-Effects Model

The ":" symbol indicates, "interacts with" and the "|" symbol indicates, "grouped by".

Fixed Effects

Q75 ~ Year + Elevation + Coast/Mainland + Data Source +
PDO + PNA + NOI + ENSO + AO +
Year : (Elevation + C/M + PDO + PNA + NOI + ENSO + AO) +
Elevation : (C/M + PDO + AO) +
C/M : (PNA + NOI) +
PDO : (PNA + NOI + ENSO) +
PNA : (NOI + ENSO + AO)

Fixed Effect Coefficients

	Value	Std. Error		Value	Std. Error
(Intercept)	31.57011	3.302047	Year:NOI	-0.00147	0.000226
Year	-0.01268	0.001658	Year:ENSO	-0.00014	0.000048
Elevation	-0.11441	0.034158	Year:AO	-0.00380	0.000612
Coast/Mainland	-33.49665	6.986238	Elev:C/M	0.00861	0.004023
Data Source	0.46584	0.289280	Elev:PDO	0.00026	0.000090
PDO	-2.62999	1.738874	Elev:AO	0.00014	0.000068
PNA	8.14015	1.312215	C/M:PNA	0.06961	0.019282
NOI	2.96115	0.448637	C/M:NOI	0.02835	0.007380
ENSO	0.27065	0.094188	PDO:PNA	0.02945	0.007419
AO	7.53193	1.212078	PDO:NOI	0.01958	0.002837
Year:Elev	0.00006	0.000017	PDO:ENSO	0.00134	0.000426
Year:C/M	0.01899	0.003505	PNA:NOI	-0.04790	0.003079
Year:PDO	0.00129	0.000877	PNA:ENSO	-0.00070	0.000428
Year:PNA	-0.00418	0.000662	PNA:AO	0.02567	0.006571

Random Effects

Q75 ~ Coast/Mainland | Station

Variance Structure

Variance ~ (Fitted Wind Speed Value)^{Power} | Coast/Mainland

Power = 0.6210 (Coast) 0.4886 (Mainland)

Correlation Structure

AR(1) ~ 1 | Station $\varphi = 0.4311$

Observed v. Fitted Values Squared Correlation

$Corr^2 = 0.75$

3.2.3 95th Quantile

The final LME model for the 95th quantile wind speeds includes all of the proposed fixed effects, along with many of the fixed effects interaction terms, but fewer than both the 50th and 75th quantile models (Table 6).

Based on parameter coefficients, fixed effect terms with constant (i.e., Coast/Mainland) or slowly varying (i.e., Year) variables have larger effects on fitted wind speeds than monthly varying variables (e.g., PDO), and much larger than interaction terms. However, smaller contributions are only given by Elevation, PNA, ENSO, NOI, and AO (PDO no longer contributes significantly). The best fitting random effects term groups each station by Coast/Mainland.

Variance equals the fitted wind speed values raised to a power term. The variance structure may again be best fit by allowing a separate power term for the Coast and Mainland groups. However, during the model building process, a solution could not be found for this model without raising the convergence tolerance level (i.e., the computer could not come to a singular solution). While raising the tolerance level to fit one model during the building process is acceptable, doing so early in the process causes the convergence problem to propagate onwards (i.e., the tolerance level for most subsequent models must be raised too). A higher tolerance level may cause the LME algorithm to arrive at an incorrect solution for variable coefficients. Therefore, I reject grouping the variance terms by Coast and Mainland and include only one variance power term of 0.7819.

Table 6: 95th Quantile Wind Speeds Linear Mixed-Effects Model

The ":" symbol indicates, "interacts with" and the "|" symbol indicates, "grouped by".

Fixed Effects

Q95 ~ Year + Elevation + Coast/Mainland + Data Source +
PDO + PNA + NOI + ENSO + AO +
Year : (Elevation + C/M + PNA + NOI + ENSO + AO) +
Elevation : (C/M + PDO + ENSO) +
C/M : (PNA + NOI) +
PDO : (ENSO + AO) +
PNA : (NOI + ENSO) +
NOI : ENSO

Fixed Effect Coefficients

	Value	Std. Error		Value	Std. Error
(Intercept)	46.73389	4.159065	Year:NOI	-0.00218	0.000326
Year	-0.01919	0.002089	Year:ENSO	-0.00021	0.000058
Elevation	-0.16803	0.040815	Year:AO	-0.00569	0.000930
Coast/Mainland	-31.95206	7.693313	Elev:C/M	0.01092	0.004794
Data Source	0.60290	0.340208	Elev:PDO	0.00018	0.000128
PDO	-0.09249	0.018980	Elev:ENSO	0.00001	0.000006
PNA	10.35312	1.823909	C/M:PNA	0.06046	0.025286
NOI	4.36135	0.646747	C/M:NOI	0.02216	0.009408
ENSO	0.40808	0.115407	PDO:ENSO	0.00200	0.000568
AO	11.30787	1.842655	PDO:AO	0.04913	0.010127
Year:Elev	0.00008	0.000021	PNA:NOI	-0.04073	0.004067
Year:C/M	0.01898	0.003859	PNA:ENSO	-0.00070	0.000500
Year:PNA	-0.00529	0.000921	NOI:ENSO	0.00060	0.000100

Random Effects

Q95 ~ Coast/Mainland | Station

Variance Structure

Variance ~ $(\text{Fitted Wind Speed Value})^{\text{Power}}$

Power = 0.7819

Correlation Structure

AR(1) ~ 1 | Station $\varphi = 0.3436$

Observed v. Fitted Values Squared Correlation

$\text{Corr}^2 = 0.75$

The correlation structure takes the form of an AR(1) function, with a phi value of 0.3436. The 95th quantile LME model appears more distinct from the 50th and 75th

quantile models than the lower wind speed models are from each other. Potentially, higher wind speeds are more independent from each other and following a different governing process.

Again, the observed versus fitted squared correlation value is quite high at 0.75. All of the LME models' squared correlation values appear to be largely based on slower wind speeds within each quantile. High wind speeds are consistently fit poorly and specifically, they tend to be underestimated.

Review of the diagnostic plots for each of the final LME models does not show violation of the underlying assumptions (Appendix C). To assess the variation explained by a linear regression an R^2 statistic would normally be calculated. However, because LME models are fit using maximum likelihood (ML) instead of ordinary least squares (OLS), an R^2 value cannot be easily calculated. While I use the squared correlations for observed versus fitted values reported above as a substitute for the R^2 value, wind speed quantiles are dominated by many low values and the single squared correlation value does not give an adequate impression of the fit of a given model. Therefore, I also plot the observed versus fitted values for each quantile for visual inspection (Figure 14).

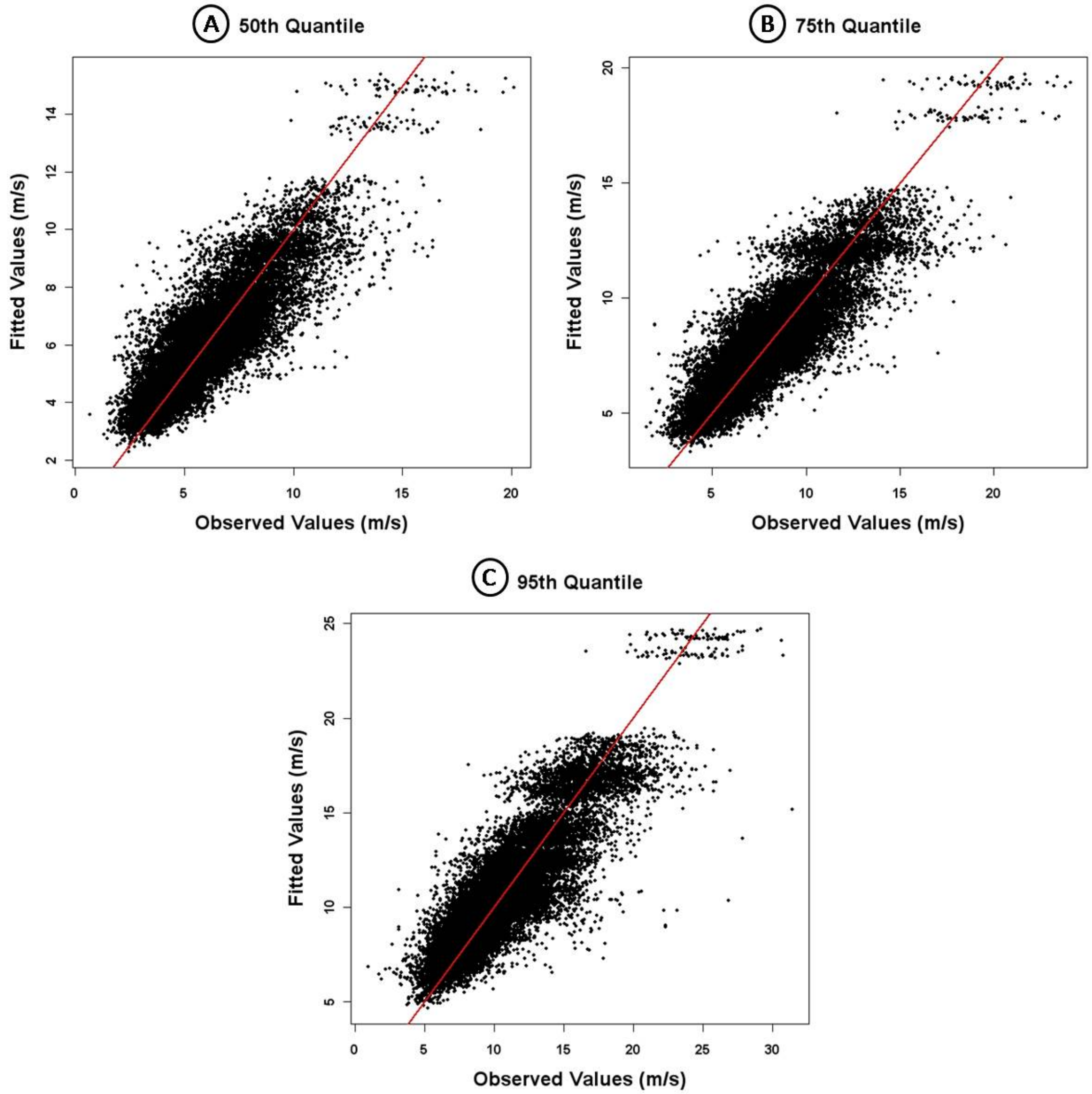


Figure 14: Fitted v. Observed Values for LME Models

Red line shows $x = y$ (i.e., ideal correlation of fitted and observed values).

Each of the LME models fits the majority of the observed data relatively well. The spread of data points appear to be symmetrically distributed around the $x = y$ line. The extreme values (very low and very high) in each quantile are fit poorly. Observed low/high values are over/under-estimated, with very high observed values being fit the worst.

3.3 Forecasts

To assess the accuracy of the fitted LME relationships when forecasting future wind speeds, I make comparisons between observations and model output for years 2000 through 2008. LME models are based on data from 1950 to 1999. The forecast validation data set contains wind speed quantile values (50^{th}, 75^{th}, and 95^{th}) for 105 monitoring stations and the Pacific Ocean climate index values from 2000 to 2008. This information generates forecasts at each of the monitoring stations (i.e., using the station's particular elevation, coast/mainland, year, and data source values along with the indices) and compares with the observed wind speed. Plots of the 95^{th} quantile wind speed observed data (black dots) and three categories of forecasted wind speeds (representative monitoring stations used as examples) over the validation period (upper panel in Figure 15). Categories of forecasts include within (pink), above (blue), and below (grey) one standard deviation of the observation mean. Forecasts made for monitoring locations that were not included in the LME model fitting process (15 stations) are distributed relatively evenly within, above, and below one standard deviation of the observations (lower left panel). However, if the LME model has included the monitoring location during fitting (90 stations), even if only a few years, forecasts are dramatically improved (lower right panel). The expected value of forecasts within one standard deviation of observations improves from 33% to 87% by including data in the fitting stage. Bias in forecasting ability does not seem to exist for stations with very few years in the fitting dataset. This indicates that if enough data is present to include a station in the fitting data, given the validation criteria (Section 2), then a relatively reliable forecast of expected value can be made.

Spatial or temporal patterns are not apparent in the plots of forecast category and observation locations. The number of locations in each category and geographic distribution are similar for the 50th and 75th quantile forecasts.

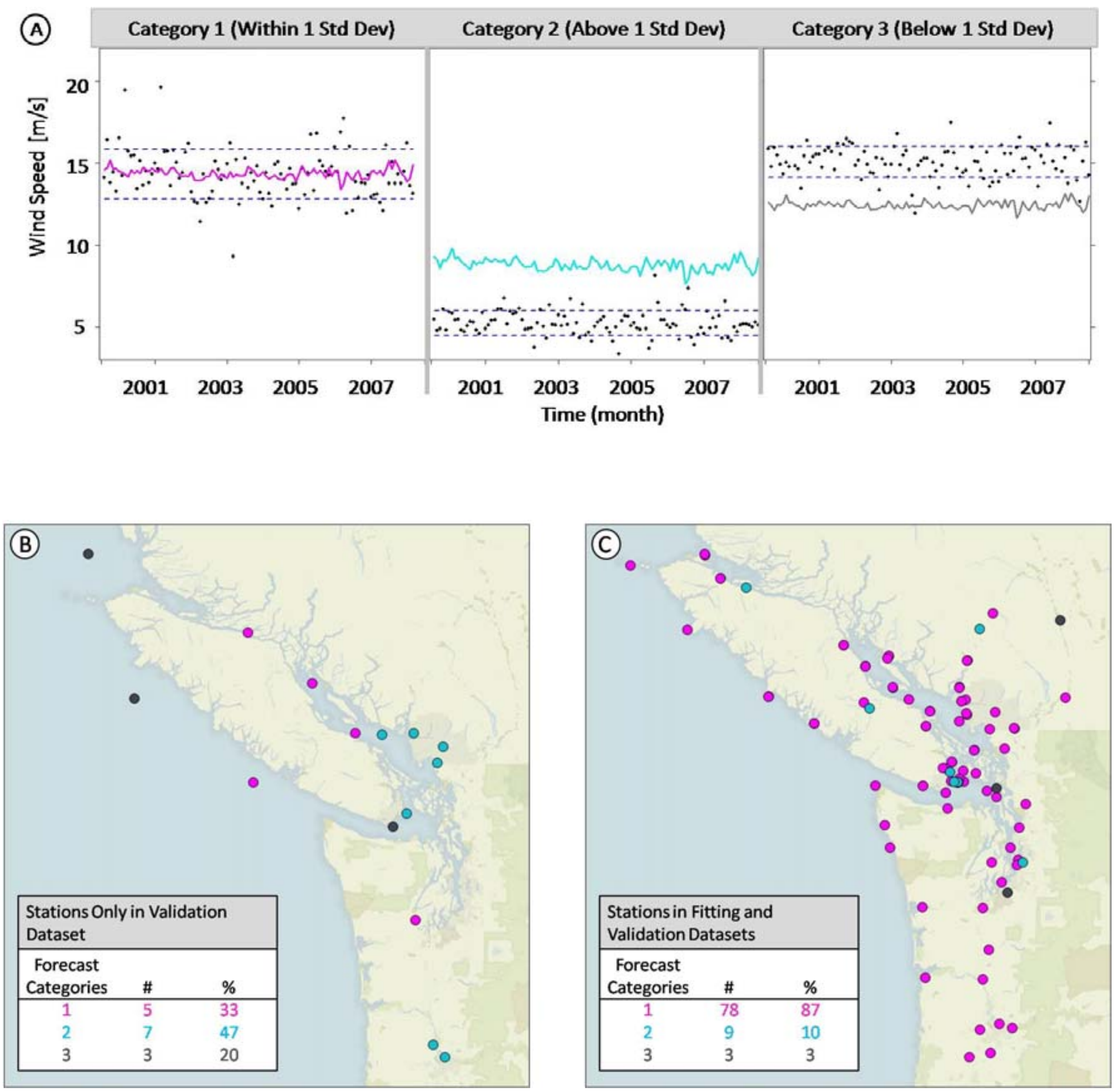


Figure 15: Representative 95th Quantile Wind Speed Forecasts (2000-2008)

Forecast locations separated into three broad categories: within (pink), above (blue), and below (grey) one standard deviation of the observation mean (a). Representative stations shown for the 95th quantile forecasts (1022795, 717750, and 1114739). The spatial distribution of each category is reasonably even across the study area if monitoring location is not included in the LME model fitting data (b). Forecasting ability is greatly improved by including the location in the fitting dataset (c). The number of locations in each category and geographic distribution are similar for the 50th and 75th quantile forecasts.

Despite predicting expected value well, forecasted wind speeds do not correlate well with the observed values (Figure 16). Correlation values are approximately normally distributed (skewed towards negative correlations for the 95th quantile) around very low correlation values and are relatively low. To have high forecasting ability, correlation values should be positive and as high as possible. Low correlation values are due to LME model forecasts not capturing enough of the observed wind speed variability (upper panel in Figure 15).

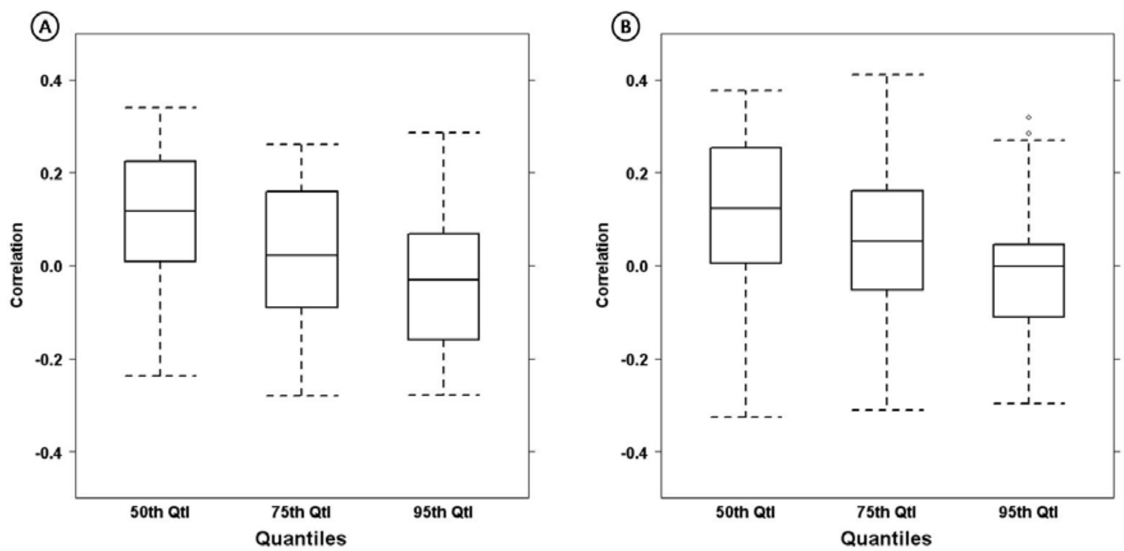


Figure 16: Summary of Correlations between Forecast and Observed Wind Speeds (2000 - 2008)

Boxplots based on the distribution of correlations between observation time series and their respective forecasts for stations only in validation dataset (a) and stations included in both fitting and validation datasets (b). Validation-only boxplots based on 15 stations. Validation-and-fitting-boxplots based on 90 stations. Including random effect terms for forecasts (b) does not significantly improve the correlation between forecast and observations.

3.4 Adaptation Actions

Semi-structured interviews revealed the attitudes of decision makers and academics towards wind speeds and the consequent impact mechanisms (e.g., tree blow-down, storm surge, and infrastructure damage). Responses have been aggregated so that generalizations can be made. Responses are unattributed and remain anonymous.

All of the organizations questioned are aware of damage mechanisms related to wind. Respondents place focus on damages though, and not on the causal mechanism of wind itself. For example, one respondent indicated that ecosystem values, such as bird nesting sites or riparian areas, are the focus of conservation and preservation actions. Guidelines, policies, or regulations are in place to maintain these values, but often do not explicitly address wind damage. They indicated that adaptation, which occurs related to wind damage is generally incidental, and that often, liability concerns regarding public spaces prompt mitigation or adaptation activities. One exception to the general disregard for wind is the B.C. Provincial Emergency Program, which mandates Extreme Weather Response Plans for B.C. communities. This program details many aspects of severe weather, including windstorms, and how to prepare for it. It does not strongly address any future changes in frequency or severity of storms, though.

Respondents thought that strong winds do impart positive outcomes in some settings. Coastal areas with windy sections, and the associated large waves, create tourism revenue for many areas like Tofino, B.C where people come to surf or recreate. Tree blow-down can result in coarse woody debris, an important component of some properly functioning ecosystems. They also noted, however, each of these positive results of wind might be tempered by increased public hazards (e.g., risky access during surfing season or added fuel for future wild fires, which strong winds may exacerbate).

Few studies have been conducted by these organizations to quantify the extent of damage suffered due to wind. Respondents generally agreed that most of the knowledge related to wind damage is derived from experience gained through the organizations' institutional memories (i.e., the collective memory of employees and recorded information). However, as was suggested by respondents, people generally remember only 10-15 years of experiences at any given time and probably can only recall particularly severe or well-publicized weather events.

Respondents felt a more variable wind regime would increase organizations' difficulty when planning future management activities. For example, contractor costs may be increased if they are required to be on-call more often. If parks or roads were closed more frequently due to public harm concerns, this would reduce the inherent value of those services.

A tool for estimating future wind conditions would be useful to most of the respondents and their organizations. If probabilistic forecasting can provide a reasonable level of accuracy, it would help them to plan upcoming management actions, identify areas vulnerable to wind damage, and set infrastructure standards. Examples of management planning include when and where to schedule ecosystem restoration activities (such as rip-rapping shorelines), mapping areas with danger-trees at risk of blow-down, planning fire season activities, preparing contractors for building or ecosystem management, or budgeting revenues from park attendance. To illustrate, knowing that coming winter winds were forecast to be above average, managers might decide to invest in proactive ecosystem restoration. Taking action now may create a higher value in terms of protecting habitat and the public, than if the cost was delayed, but would later protect a degraded environment.

4: DISCUSSION

Wind speed behaviour in the Pacific Northwest appears to differ strongly by proximity to the coast. Hierarchical clustering identified a cyclic pattern for coastal areas and slowly declining trend for locations further inland. My linear mixed-effects model supports this conclusion with large coefficient values for the Coast/Mainland parameters in each quantile model (and therefore large importance in the model and subsequent forecasts). This relationship between wind and geographic location reconciles apparently conflicting results from previous wind studies in the PNW and continental U.S. Several studies have found declining trends for wind speeds over mainland areas [Pryor et al., 2009; Klink, 1999; Klink, 2002], while others appear to see contradictory declining and increasing patterns near coastlines [Gower, 2002; Tuller, 2004]. By separating wind regimes into coast-cyclic (both increasing and decreasing periods) and mainland-declining, discrepancies between studies can be resolved. Section 4.1 discusses this behaviour in more detail.

Despite finding a significant pattern in wind behaviour, my LME model forecasts under-represent wind variability in the PNW. LMEs offer great advantages for modeling physical systems because of their flexibility to incorporate phenomena measured repeatedly over time, grouped monitoring locations, and heterogeneous or correlated data residuals (Section 4.2). Therefore, improving the variability captured by model forecasts is an important goal if this model is to be used as a decision tool for managers; especially given the small number of years that a station must observe wind to correctly predict the expected value of future wind speeds. Sections 4.3 and 4.4 consider potential methods for improving forecasts and incorporating long-term trends (e.g., potential climate change effects).

Finally, I discuss the limitations I faced attempting to model a physical system. I also make recommendations for wind study directions in the future and how my results may be applied to the challenges faced by resource managers (Section 4.5).

4.1 Changing Wind Speed Trends and Variability

Observed trends and variability behaviour (Figure 13) differ significantly between coast and mainland locations, as well as between the 50^{th}, 75^{th}, and 95^{th} quantiles. Coast locations are much more variable than mainland sites across all of the quantiles explored. They also appear to be relatively stationary around some fixed mean for each quantile (although stationary trends are unclear from Figure 13). The very small coefficients for Year and Year:Coast/Mainland lend support for stationary time series in each quantile (Tables 4, 5, and 6). When the coefficients are multiplied by their respective variable values, the coast time series in each quantile is essentially non-trending. Mainland locations are downward trending and less variable for all quantiles. Again, coefficient values for relevant variables support this idea.

Coast wind speeds, especially for the 95^{th} quantile, appear to follow a roughly decadal (~ 9-year period) cyclic pattern. Peaks in average wind speed across sites can be seen in Figure 13 at roughly 1969, 1977, 1986, and 1995, with troughs visible between each peak. A similar, but less distinct, pattern is apparent in the lower wind speed quantiles as well. This cyclic pattern is not well represented by any of the Pacific Ocean climate indices that are included in this study. However, these indices (PDO, PNA, ENSO, NOI, and AO) represent the major, currently hypothesized proxies for climate drivers in the Pacific Ocean. The cyclic pattern in observed wind speeds in the PNW may be the result of an unidentified climate oscillation or an interaction (modifying behaviour) between current indices, that was not included in this study (e.g., three-way interaction).

The apparently conflicting results from previous wind studies looking at the PNW, and the continental U.S., can be resolved by the differing patterns for coast and mainland locations. Pryor et al. [2009] and Klink [1999] identified predominantly declining trends of 0.5-1.0% per year for the PNW. These results appear confined to mainland monitoring locations (it is unclear if coastal stations are represented). My result of a declining mainland trend of 0.4-0.6% per year agrees well with their findings. A slowly declining trend also corresponds with results focusing specifically on the PNW [Tuller, 2004]. Interestingly, my results appear to reconcile a problem from Tuller [2004]. In his study, Vancouver and Victoria International Airports (mainland locations in my study) exhibit declining trends, while Comox Airport (a coast site) seems to follow both increasing and declining trends. A cyclic pattern for Comox Airport could explain that monitoring location's deviating behaviour. Gower [2002] reports a similar pattern of contradictory trends for observation buoys off the Washington, U.S. coast. Again, my study would consider these stations as coast sites that follow a cyclic pattern.

Parameter values from the LME model indicate that geographic location (i.e., coast or mainland) and time have strong influences on wind. Regional climate drivers also play significant roles in determining wind speeds. The coefficients in the LME models have the signs I would expect from previous studies (Section 1.2.2). My positive relationship between wind and ENSO differs from the negative one (i.e., a correlation between La Niña (cold/negative phase) and increased wind speed or gustiness) found in Abeysirigunawardena et al. [2009] and Enloe et al. [2004]. However, all of the parameter values in my LME model are conditional on the other included variables. Alternative LME models with similar climate variable specifications to those in the other studies would be necessary to determine if this apparent disagreement actually exists. Of the Pacific Ocean climate indices, the Arctic Oscillation (AO) and Pacific/North American Pattern (PNA) influence winds the most. These indices are calculated using pressure differences near, or over, the Pacific Ocean, while PDO and ENSO are determined using SSTs and NOI uses pressure differences over a much larger region. Because pressure differences create winds, they may be a better predictor than temperature, which creates pressure (and indirectly creates wind).

All of the variations in wind speed distributions: decreasing trend for mainland locations and greater variability and cyclic pattern for coast sites, make planning ecosystem, infrastructure, and emergency response activities more difficult. I examine several examples briefly to highlight some of these challenges.

In urban settings, managers must provide minimum distances for set-backs around ecosystem features that wind damage may harm (e.g., wind throw, downed power lines, or direct impact). If cities, like Vancouver, Victoria, or Seattle, are situated near coastlines, they may have difficulty imposing set-back limits. During times of higher variability (peaks of cyclic pattern), set-backs may be inadequate because of stronger wind events. When variability is lower (troughs of cyclic pattern) and less severe wind events occur, managers may face pressure to reduce the limits because they are seen as unduly strict. Forestry areas near to the coast might encounter similar problems with requirements for trees to be left standing for ecosystem values.

Studies relating air quality measurements to wind trends may need to re-evaluate the monitoring locations used to represent regions because of differing patterns for Coast (cyclic) and Mainland (declining trend) sites. Vancouver and the Fraser Valley are an example of an urban/rural area where light winds can lead to build up of ground-level ozone. Future land use and public health decisions will need to consider weaker winds, and airborne pollutant studies should be careful when choosing representative locations for air quality studies [Vingarzan and Thomson, 2004].

Fluctuations in electricity generation and demand for emergency response services will impact power utilities. Wind power generation is increasing throughout the PNW with projects proposed for both coast and mainland areas. Each of these areas may face problems. Coast wind power projects will have greater variability in the range of wind speeds observed with an oscillating average over time. The cyclic pattern is most apparent in the 95th quantile wind speeds, however strong winds are what generate the most power. Electricity generated by wind turbines is proportional to the cube of wind speed. If power providers conduct feasibility studies during peak times of the decadal cycle, the amount of power generated over the lifetime of a project may not meet the expectations of owners or utilities requiring electricity. For example, a 3 m/s decrease in the 95th quantile wind speed for coast stations (the change from peak to trough of the cyclic cycle) would result in a ~49% decrease in power produced from strong winds. A decrease of 0.9 m/s (mainland declining trend multiplied by 30 years) in the 75th quantile wind speed for mainland stations would result in ~15% less power produced by a turbine at the end of its 30 year lifespan.

Damages from emergencies (e.g., power outages) can result in large losses to productivity and necessary restoration costs when power is not available to the society dependent on it (see Section 3.4). Emergency planners face similar problems to resource managers when trying to allocate scarce resources (in this case, monetary budgets and person-hours) to adapt or cope with inherently variable conditions like those observed at coast locations.

Whether the observed cyclic pattern or the current scale of trends and variability will continue into the future is unknown. Anthropogenic climate change is likely to alter existing weather patterns by reducing the gradient in average temperature and pressure between the poles and tropics [Reynolds, 2005]. A reduced gradient may decrease wind speeds in the Pacific basin and those observed in the PNW because of warmer SSTs and lower pressure differences. Changes to future weather patterns dictated by climate change are still very uncertain though. Regardless of changes to climate patterns, resource managers must try to adapt to future wind conditions when making planning decisions. Future conditions may be similar to those experienced in the past or may present new uncertain challenges. Quantitative decision analysis offers an excellent tool to incorporate future uncertainties (from the unknown atmospheric conditions or the probabilistic output from the LME model) when making important decisions with long-term consequences, such as infrastructure choices or ecosystem alterations [National Research Council, 2006].

4.2 Application of Linear Mixed-Effects Model

Using LME models to relate wind speed quantiles to Pacific Ocean climate indices and local variables represents only one of many possible applications of mixed-effects modelling for physical systems. LME models were developed, and have been primarily used, for econometric problems and until recently have not been widely considered for use in other disciplines [Zuur et al., 2007; Cade and Noon, 2003].

The great flexibility of LME models makes them excellent candidates for representing relationships in physical systems. Often, studies for these types of systems rely on historical data collected over many years. Data may be discontinuous or have varying measurement errors associated with them. However, LME models can successfully help with interpretation of system dynamics by intentionally or retroactively considering sampling programs to be repeatedly measured at stationary monitoring locations. Including individual (random) and population (fixed) effects in LME models allows for a more realistic representation of sampling programs than linear regression. Linear regression attributes all observations to the population level regardless of how inappropriate this might be. Despite potential violations of independence or homogeneity of residuals, linear regression is often used due to its ease of application and interpretation of results. These results should be highly suspect though, because of the assumption violations [Zuur et al., 2009]. While LME is more complicated to apply than linear regression, it is not as involved as many other methods such as dynamic systems modelling. It offers a good balance between appropriate treatment of data and the ability to abide by method assumptions and straightforward results and interpretability.

I have chosen to combine a LME model with quantiles of wind speed data for a more comprehensive depiction of the available data. Physical data are often normally distributed, but many forms may violate this common assumption. Wind speeds, precipitation, and exceedances measurements are all types of data that are zero-bounded. These data may be represented by non-normal distributions such as the Poisson or Weibull and may have properties like strong skew or heteroscedasticy. Quantiles present a more robust method to look at these distributions and extract meaningful information (or alternatively not miss important information) than the often standard mean or max/min [Koenker, 2005].

4.3 Model Forecasting Ability

This study began by hypothesizing that surface wind speeds in the PNW relate to regional climate drivers, such as sea-surface temperature and sea-level pressure. These variables have previously been shown to influence precipitation and surface temperature in the PNW [Reynolds, 2005; Mantua and Hare, 2002; Ropelewski and Halpert, 1986]. The LME model includes Pacific Ocean climate drivers through indices based on SST and SLP anomalies. Some variables related to local effects, such as elevation and coast/mainland, are also included. Using both regional and local variables allows a comparison of their relative influence on wind speeds. The coefficients from the final LME models (Tables 4, 5, and 6) weight their respective variables and determine regional and local importance.

Based on parameter coefficients, fixed effect terms with constant (i.e., Coast/Mainland) or slowly varying (i.e., Year) variables have larger effects on fitted wind speeds than monthly varying variables (e.g., PDO), and much larger than interaction terms. While the expected value of future wind speeds is predicted fairly well (when including random effects), forecasts have relatively small variations around some fixed mean compared to the observations (Figure 15). Forecasts consequently have low correlations with the much more variable observed wind speed data (Figure 16).

A possible reason for the low correlation values is that one or more variables are missing from the LME model specifications. The current explanatory variables are generating forecasts that are within the range of observed values (Figure 15), but are not able to capture all of the wind variability. Pacific Ocean climate indices have been shown to describe other surface phenomena in the PNW with some accuracy, such as temperature, precipitation, snowfall, and fish stock and plankton productivity [Mantua and Hare, 2002; Schwing et al., 2002; Rasmusson and Wallace, 1983]. Given this descriptive ability, it follows that climate indices could summarize the regional driving forces for winds. However, the indices may not do so accurately enough because of the processing needed to calculate them (Section 1.2.2). Including SST and SLP directly as monthly-fluctuating variables, instead of as the basis for the climate indices, may offer better forecasts of surface wind speeds. Including either the climate indices or the temperature and pressure variables as random effects would also help capture more variability. I did not do this during my study due to computing restraints, but a reduction in the number of wind speed time series could accommodate these random effects.

Further complication in forecasting may be added because the PNW is located in a transition zone between ocean domains (Figure 17). The transition zone divides two coherent ocean circulation patterns, the north-flowing Alaska Current and the south-flowing California Current [Ware and McFarlane, 1989]. The formation of these currents is not abrupt. It occurs, due to a divergence in the prevailing wind pattern, in a disorganized manner between 45-50°N, and 130-150°W, in close proximity to the study area. An upwelling zone exists off coastal California during summer when northwesterly winds dominate. During winter, southerly winds take over and downwelling occurs over the region. The opposite phenomenon is largely present throughout the year for the area covered by the Alaska Current. This transition zone also creates very different responses in other climate variables, such as snow pack, precipitation, and fisheries productivity, in response to regional climate shifts such as the PDO. For example, warm PDO phases favour enhanced ocean biological productivity in Alaskan waters and inhibited productivity off the west coast of the continental U.S. The opposite north-south pattern exists during cold phases [Mantua and Hare, 2002].

The location of the transition zone, and associated wind currents, moves throughout the year with seasonal cycles and with atmospheric circulation patterns like ENSO or PDO. Though the major drivers of the transition zone location have been accounted for in my model (seasonality removed and circulation patterns as explanatory variables), small variations due to other climatic influences may not be included. Because of the PNW's close proximity to the transition zone, including the zone's location over time may explain some of the unidentified variation in the LME model. Alternatively, wind speeds from Alaska and California may indicate if the LME method can achieve more accurate results for locations distanced from the transition zone.

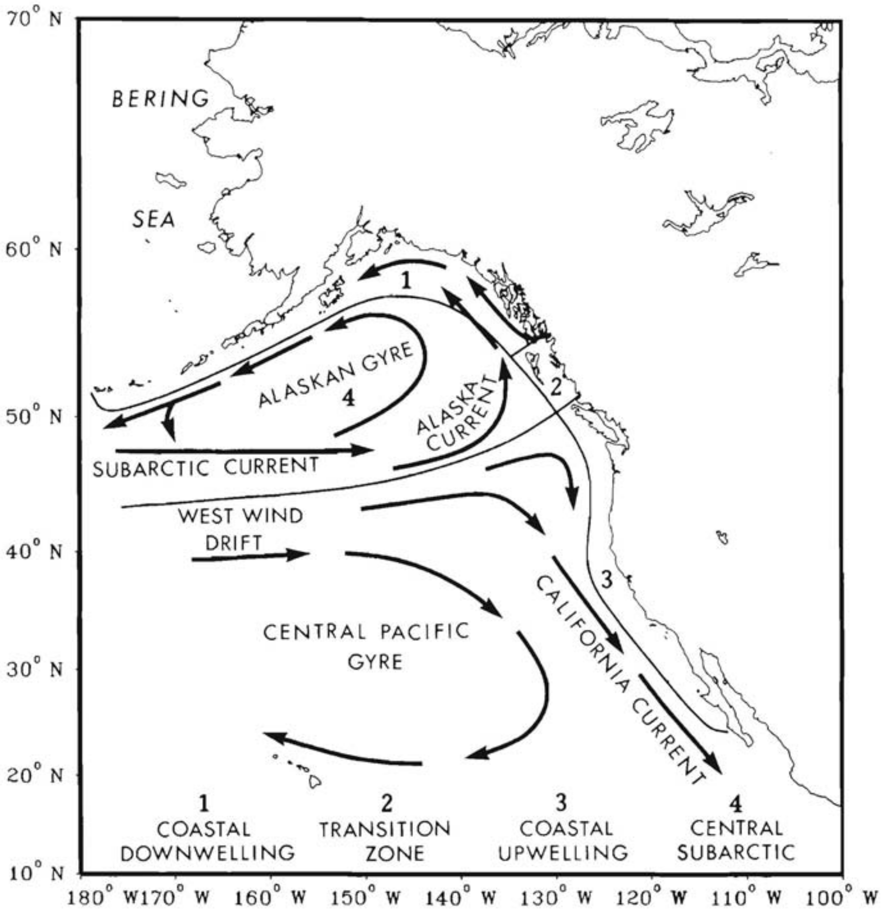


Figure 17: Prevailing Current Directions in the Northeast Pacific Ocean

Approximate ocean domains listed in the bottom of the figure and located by number. The location of the transition zone moves throughout the year and is coincident with the PNW study location. Adapted from [Ware and McFarlane, 1989].

Other information sources that could provide an informative link between regional climate drivers and surface wind include upper air wind speed measurements, and SST and SLP re-analysis data. These sources are in-between the regional indices calculated for the entire Pacific basin and local measurements near each location of interest. Re-analysis data can be calculated close to the study area and will not have missing values as with observational data. If I could relate winds to re-analysis data and use that relationship as a downscaling transfer function, it could make forecasting wind speed changes easier because GCMs can predict temperature and pressure relatively well. Re-analysis measurements of SST and SLP from the Salish Sea and Juan de Fuca Strait or Pacific Ocean adjacent to the PNW coast may provide useful data for this study area.

Calculated re-analysis values offer the added benefit of assessing secular trends (long-term non-periodic variation) associated with Pacific Ocean climate patterns. These data are valuable to assess the effects of anthropogenic climate change on wind speed distributions. All of the indices used in this study have trends connected with secular warming removed as part of their calculation. Temporal trends are currently captured with the Year variable in the LME models, but this is mostly a catch-all variable. It would be more appropriate to have trend information captured directly by the relevant variables.

I am most interested in the behaviour of extreme wind speeds (i.e., the upper tail of the wind speed distribution). Though the bulk of observations for each of the quantiles explored is fit fairly well, extreme high values are generally poorly represented by the LMEs (Figure 14). Poor extreme value fitting is partly due to far fewer high observations for the LME model to use when attempting to find a relationship between wind speed responses and explanatory variables. Lack of data often creates large difficulties determining general relationships for extreme values [Abeysirigunawardena et al., 2009]. Using quantiles of the wind speed distribution and finding separate relationships for each level (50^{th}, 75^{th}, and 95^{th}) has helped when trying to understand the behaviour of average and extreme wind speeds, but extreme values by their nature are rare occurrences and longer time series of observations will help future modelling efforts [Crout et al., 2008].

4.4 Sensitivity Analyses

Statistical models should always be checked for the robustness of their parameter values and fit. Accordingly, I performed two sensitivity tests to evaluate alternative formulations of the relationship between PNW wind speed quantiles and explanatory variables.

Each of the final LME models was checked to see if taking the natural logarithm of wind speed quantiles was more appropriate to relate to the explanatory variables. Logarithms may be more appropriate given the highly skewed, non-normal distribution for wind speeds (Figure 4). Based on diagnostic plots (Appendix C), the log-transformed data do not offer a significantly better fit.

Alternative groupings derived from the hierarchical clustering may be appropriate given the more varied clustering at the broadest level seen in the 50th and 75th quantile dendrograms compared to the 95th quantile. The most prominent grouping that I could include in the sensitivity analysis, and that has an identified physical meaning, is the small group of Sartine and Solander Islands (Figure 11). This cluster branches high on the dendrogram and could be considered a separate and distinct group. Sartine and Solander Islands experience wind speeds that are well above those observed at other monitoring stations. Setting the hierarchical clustering factor to coast/mainland/islands does not significantly improve the LMEs based on diagnostic plots. However, AIC values for models including an extra group are slightly lower, and therefore preferred, compared to the original models. Future work should include the Islands group and could make efforts to identify physical meanings for other groups from the hierarchical clustering.

4.5 Analysis Limitations and Recommendations for Future Research

Several key limitations in the analysis presented challenges for constructing a LME model relating wind speeds and regional and local explanatory variables. The limitations, detailed below, represent opportunities for future research and I present possible solutions.

First, the abundance of data points posed computing problems. The large number of observations used in the study (~23,000) ensured no concerns with data normality, degrees of freedom, and compensated for erroneous measurements. But, the many observations also had to be fitted by the LME model for each model run. That is, any time a change was made to the model specification, a new round of fitting had to be completed. As each run could take up to an hour to complete and several hundred runs were necessary to fit each LME model for each quantile (50^{th}, 75^{th}, and 95^{th}), computing quickly became very time consuming. In retrospect, I feel that a better balance between sufficient data records and a parsimonious number of sampling locations could have been reached. During the study though, I did not know what impact reducing monitoring locations would have. Nor did I know how long LME models would take to fit. Now that data files exist in a common format, future research could invest more effort into eliminating time series records that are short or include many missing values to reduce the number of variables the LME model must fit coefficients for and therefore reduce computing time.

Second, explanatory variables that likely influence surface wind speeds, were not included in the LME model because I could not obtain satisfactory data (SST, SLP, upper air wind speed and pressure) or including the variables in the model was too cumbersome during model design (topography surrounding monitoring stations). These data could have helped define regions with similar wind behaviour or described more of the unexplained variability in observations.

Finally, many of the monitoring stations used in this study have limited or no secondary data (e.g., height of anemometer above ground, type of anemometer, or surrounding surface features). Without this type of information, wind speed observations cannot be corrected to a standard height (the World Meteorological Organization has set the standard height at 10 m above ground). No attempt was made in this study to correct wind speed observations due to the large number of monitoring locations and observations used. I relied on the large aggregation of data to compensate for any erroneous records. Future research could improve on standardizing observations, however, Pryor et al. [2009] note that the correction of differing measurement heights is likely relatively small for most monitoring stations.

In future work, re-analysis data could provide "observed" measurements from locations close to the study area that are otherwise unavailable. Values, such as SST, SLP, and upper air measurements, which would not normally be observable at the desired locations, can be calculated by re-analysis and substituted for actual observations. These data may define spatial regions with similar behaviour and could further refine monitoring station groupings. However, as Pryor et al. [2009] point out, values can vary significantly between re-analysis products. If future wind speed studies use this type of data, several sources should be compared and evaluated.

Local topography and surface roughness surrounding monitoring stations could likely be included without much difficulty if sources can be found. However, these data may only be available for significant monitoring locations, such as airports or lighthouses. Incorporating only stations with detailed information and histories was applied in other studies [Abeysirigunawardena et al., 2009; Tuller, 2004] and resulted in far fewer sampling locations than are included in this study. In light of my results of significant behaviour differences between coast and mainland sites, few sampling locations may create bias in study results.

Geographic Information System (GIS) maps may offer a method to include some level of local topography, while still maintaining a large sample of monitoring stations. GIS elements that might be used as explanatory variables include monitoring station aspect (direction facing), valley/exposed location, or upwind surface roughness. If a reliable source of GIS information could be found, possibly in conjunction with the re-analysis data discussed above, the LME model relationships could become better candidates for downscaling transfer functions.

Representing skewed distributions with LME modelling and quantiles offers many other possible directions for wind speed investigation. In this study, the LME model fit for each quantile appears to be mostly determined by lower wind speeds and not by the extreme values that I am most interested in. One option to reduce the dependence on lower values is to use a minimum threshold for acceptable values to include when determining response-explanatory relationships. A meaningful threshold (such as a relevant value from the Beaufort Scale; Table 2) could be applied before or after calculating quantiles. Applying the cut-off value before determining quantiles would reduce the number of observations used in calculations, but would still allow most months to have a value. These values may not be very representative if few observations end up being included. Applying the threshold after calculating quantiles would ensure more observations are included in each month, but will remove many months altogether. I feel a threshold, if used, should be applied to individual data before calculating quantiles, rather than aggregate measures, but the cut-off criteria described earlier (Section 2) may need to be re-visited to ensure sampling bias is not introduced.

A final opportunity for future research would utilize quantitative decision analysis. This method presents a valuable tool for implementing study results even if large uncertainties still exist in forecasts or relationships. A decision analysis focusing on one of the management problems raised during the adaptation interviews (Section 3.4) would help establish a minimum level of forecasting accuracy needed from the LME model.

5: CONCLUSIONS

In this study of PNW wind speeds, I explored the relationship between wind behaviour and several proposed climate drivers, local variables, and data sources. To this end, I created a linear mixed-effects model and used it to make wind speed forecasts. This effort represents the first time a study has explored wind behaviour in the PNW using a spatially and temporally comprehensive data set.

My research focused on three objectives: determining if relationships exist between wind speed distributions, ocean/atmospheric climate indices, and monitoring station-specific attributes (e.g., elevation, geographic location, data source); assessing the robustness of relationships for forecasting wind speeds within the study area; and conveying forecast results and potential adaptation actions in a manner easily understandable by a wide (potentially non-technical) audience. To meet the first objective, I explored wind speeds and potential explanatory variables using quantiles, hierarchical clustering, and a LME model. These tools provided a valuable method for wind speed analysis because of their flexibility to incorporate non-normally distributed data. I addressed the second objective by comparing LME forecasts to a data set covering the period 2000-2008. Finally, I attempted to convey the results from data exploration and model forecasts largely using figures and maps. Wide audiences often understand graphical representations of data more easily than tables or descriptions, and figures can impart large amounts of information succinctly [National Research Council, 2006]. I conducted informal interviews related to wind damage adaptation actions to help contextualize this study, and how it might be used in future.

Two main findings from my research are reviewed below, the difference in coast and mainland wind patterns and the extent to which this previously unidentified behaviour will affect wind damage adaptation efforts.

5.1 Difference in Coast and Mainland Behaviour

Wind speeds are significantly stronger at coast monitoring locations compared with sites further inland. While this result may seem intuitive to many readers, my research has quantitatively confirmed that stronger winds occur near the ocean and estimated this difference for the PNW. However, a related, but more pertinent, finding is the difference in how coast and mainland wind behaves.

Coast winds appear to follow a roughly decadal (~9-year cycle) pattern in the magnitude of speeds. The pattern is most evident in the 95^{th} quantile of the wind distribution, with up to a ~3 m/s difference between cycle peaks and troughs, but appears in the median wind speeds as well. Management of coastal areas is already difficult due to stronger and more variable wind speeds compared with inland sites. As an example of the impact fluctuating coast winds might have, consider the future of wind power generation in the PNW. Energy developers are increasingly considering wind farms as a viable economic option given the demand for electricity forms that do not emit carbon dioxide. However, if feasibility studies for wind farms are conducted during peak times in the decadal cycle, future generated power and revenues may not meet expectations because of falling wind speeds. Many wind turbines have a life span of only two to three decades, in which they must pay for themselves and generate a profit. Impacts to other sectors include increased difficulty planning and budgeting for emergency services and timing of ecosystem restoration activities.

Alternatively, wind speeds in mainland areas appear to follow a downward trend of approximately -0.04 m/s/year (95th quantile) to -0.03 m/s/year (50th quantile). Mainland sites do not seem to experience the cyclic pattern of coast sites, or else only very weakly. This may impact urban/rural areas near coastlines, like Vancouver and the Fraser Valley, if decreasing winds exacerbate build up of ground-level ozone and degrade air quality. Future land use and public health decisions will need to consider geographic differences in wind behaviour when choosing locations for air quality studies, to ensure representative winds are used [Vingarzan and Thomson, 2004].

My research and the finding of distinct behaviour for coast and mainland areas fill a gap in the understanding of surface winds. A cyclic pattern for coast areas and declining wind speeds for the mainland help explain disparities between previous studies (e.g., Pryor et al. [2009] suggest a declining trend for observed wind speeds in areas of the continental U.S., while Gower [2002] indicates both increasing and decreasing wind speeds measured at ocean buoys). Future studies of wind speeds near coastal areas should include the relative locations of monitoring stations as an explanatory variable to help with interpretation of possibly conflicting results.

5.2 Future Adaptation Capacity

The abilities of organizations managing resources to adapt to future wind patterns may be constrained by their lack of institutional programs acknowledging wind behaviour. Many organizations, in sectors such as environmental conservation, electricity generation, and disaster management, have policies and measures in place to deal with wind damage. However, few, if any, recognize that the frequency of severe storm events may change in the future. Interview respondents noted that institutional memories (i.e., the collective memory of employees and recorded information) often extend only 10-15 years into the past. This implies that organizations affected by wind damage may create policies or plans based on incorrect information (e.g., assume wind speeds are stationary through time rather than cyclical or trending).

My LME model needed only a few years of monitoring data to correctly forecast expected values of wind speeds for many locations. A tool, like this LME model, that could forecast probabilities of wind speeds (with some minimum accuracy) would be valuable for all of the interview respondents. Having a sense of the upcoming winter storm season, for instance, would allow managers to better budget limited resources for ecological restoration, public safety related to hazardous trees, or emergency communication procedures. A forecasting tool would help organizations fit recent weather events (included in institutional memory) into future wind behaviour changes.

APPENDICES

Appendix A: Pacific Ocean Climate Index Time Series

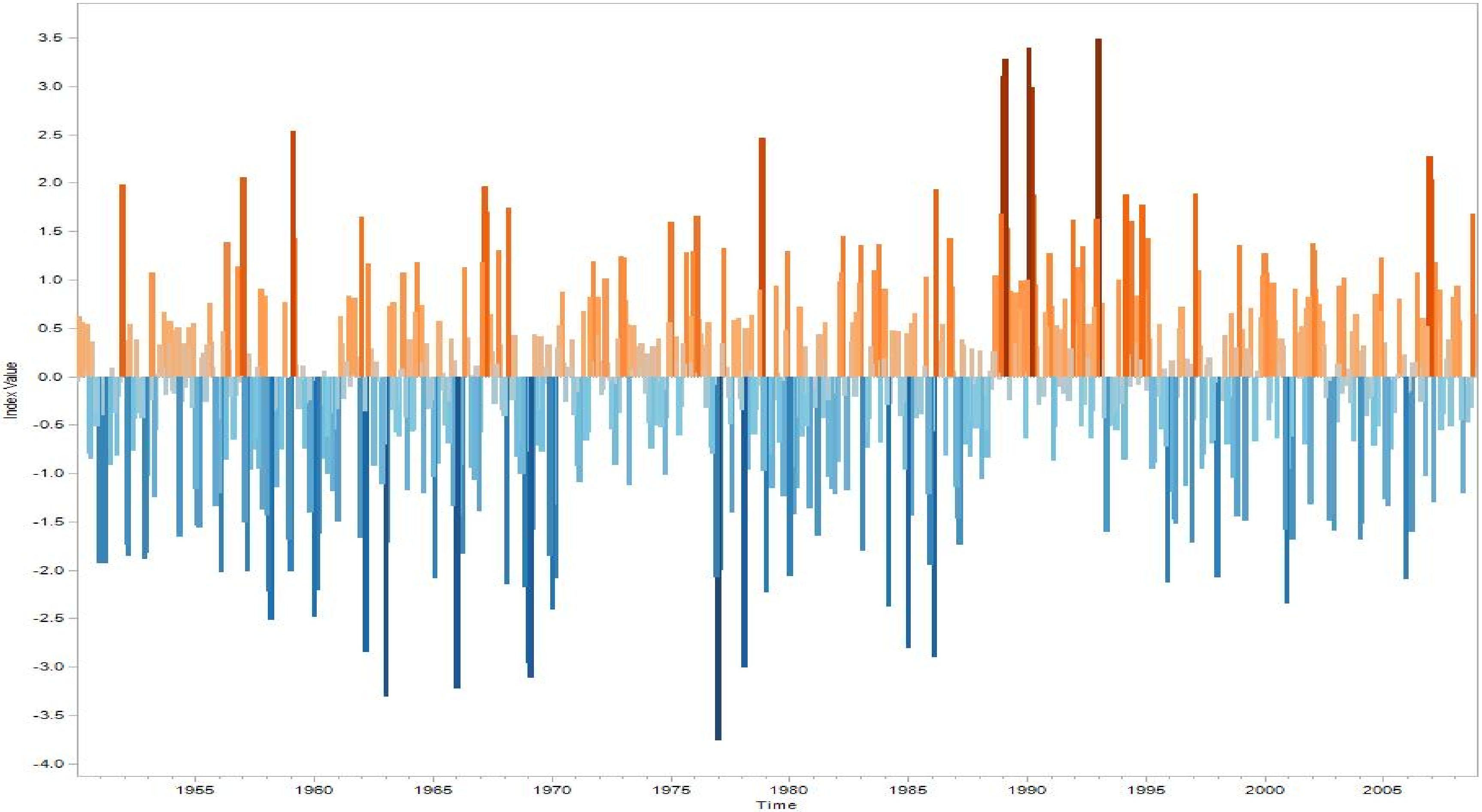


Figure A-1: Arctic Oscillation Index Values

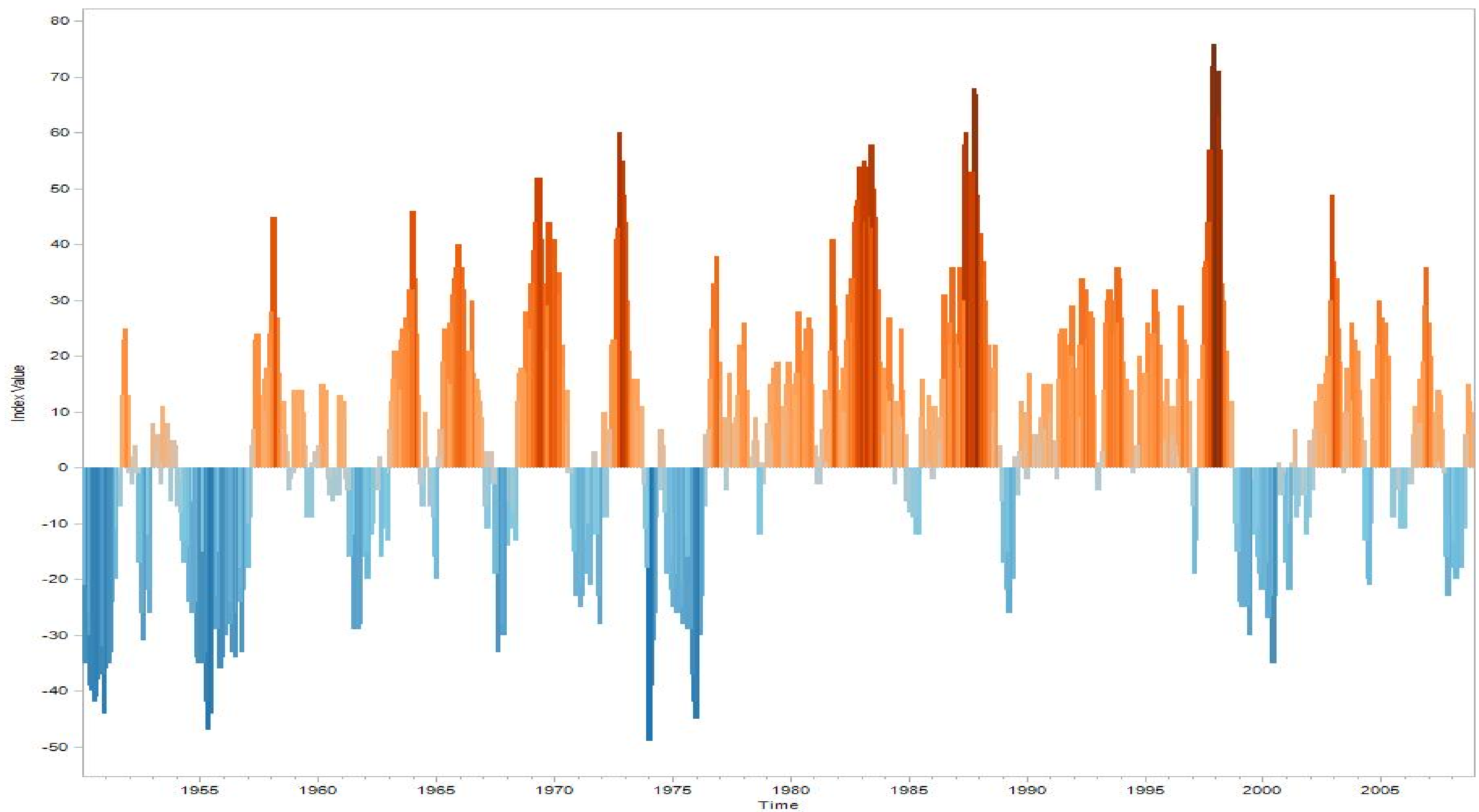


Figure A-2: Global-SST El-Niño Southern Oscillation Index Values

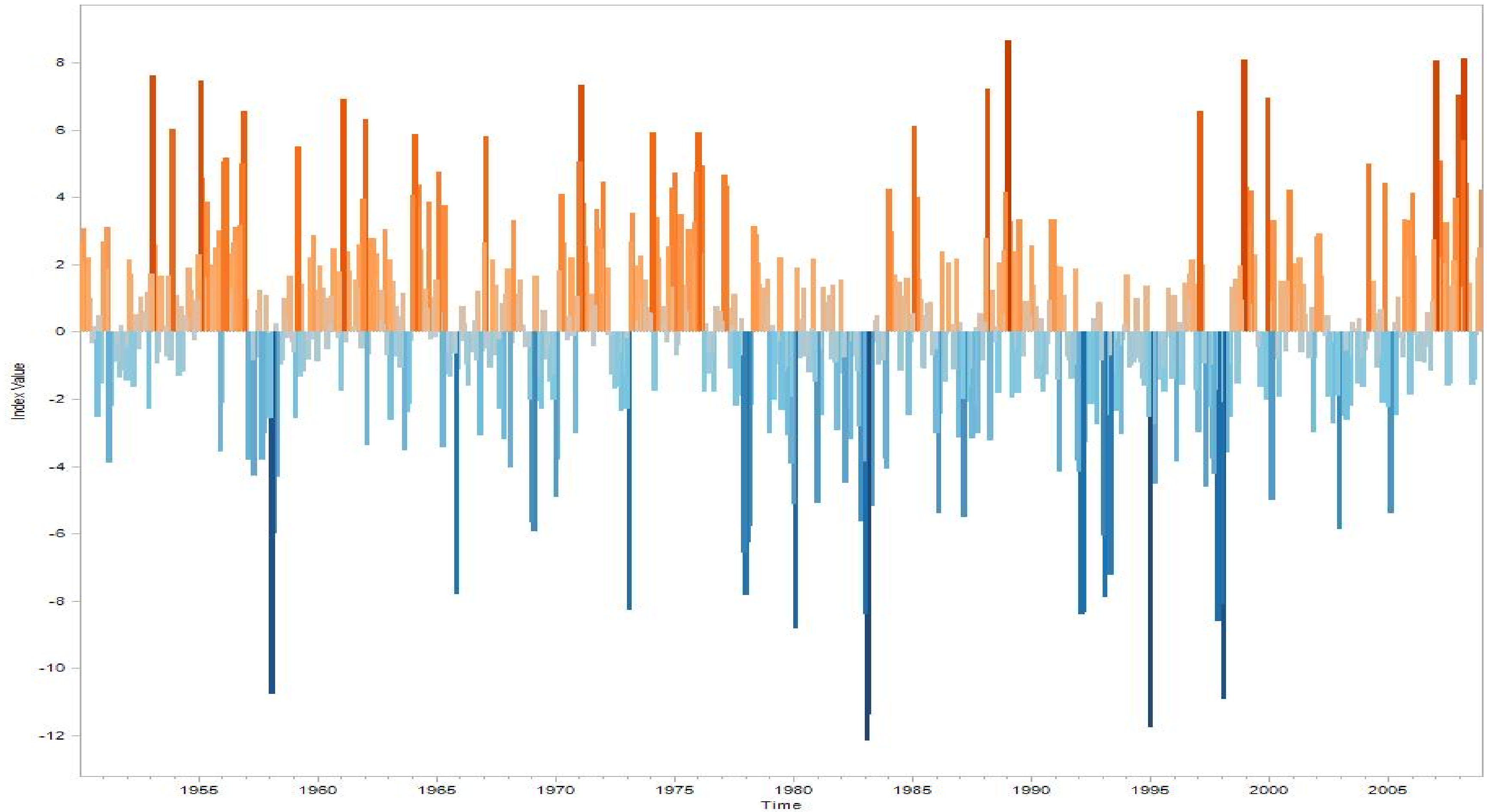


Figure A-3: Northern Oscillation Index Values

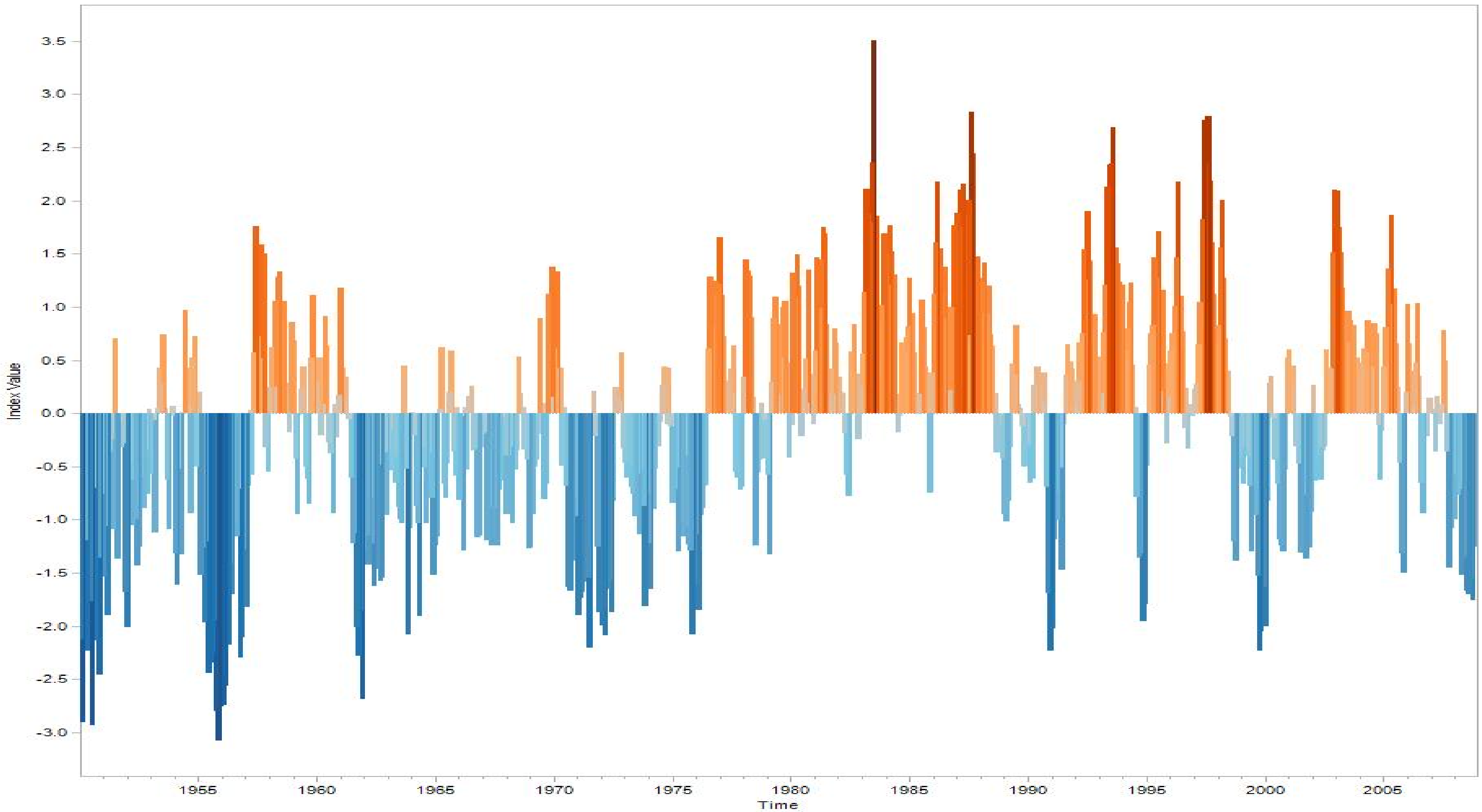


Figure A-4: Pacific Decadal Oscillation Index Values

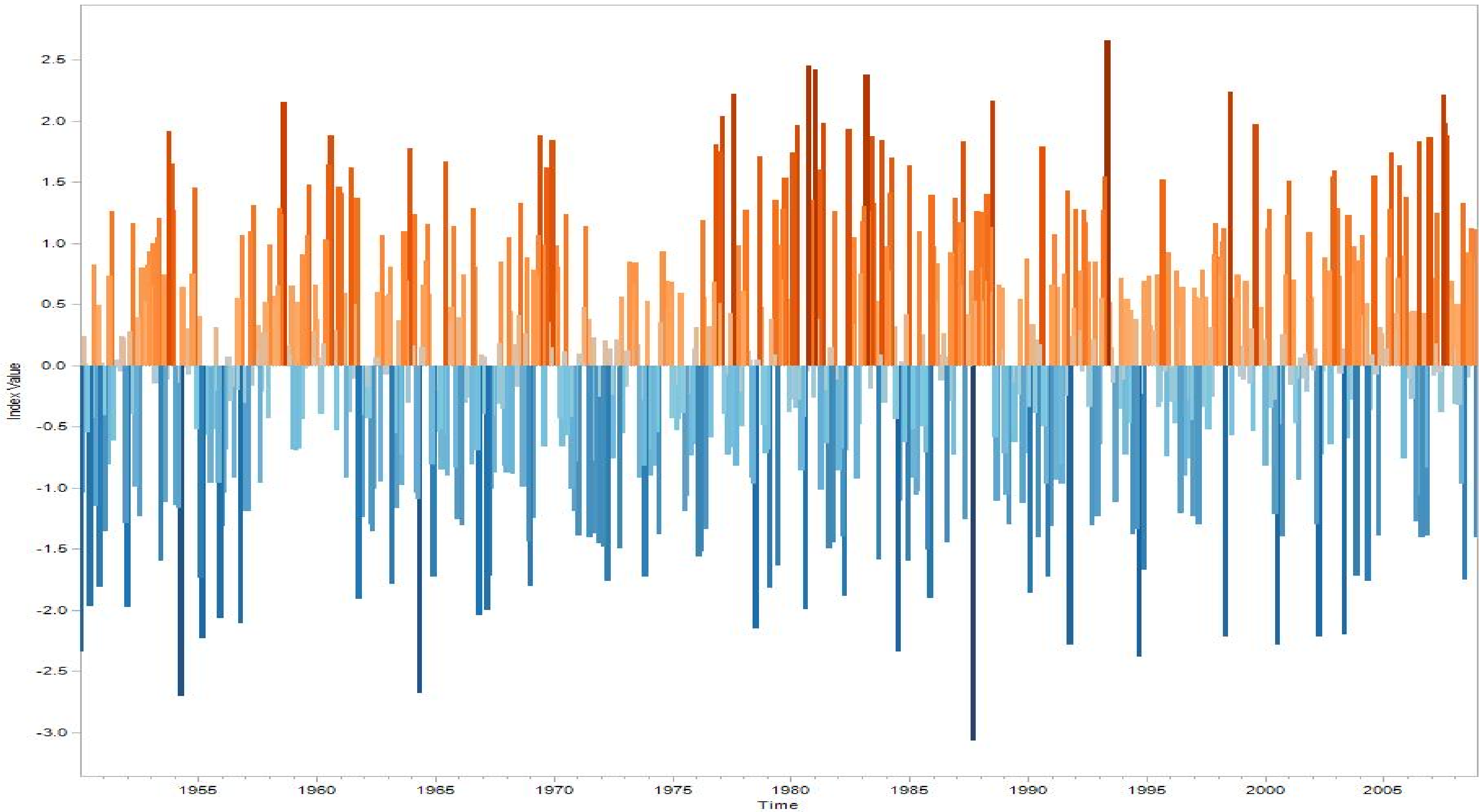


Figure A-5: Pacific/North American Oscillation Index Values

Appendix B: Data Details

Data was provided electronically for research purposes by Environment Canada (from the National Archive of Canadian Climatological Data), National Oceanic and Atmospheric Administration (from the Integrated Surface Hourly Database). Contact information is provided below, along with metadata for monitoring stations (Table B-1) and time series record lengths (Figure B-1).

Environment Canada – Gerard Morin, Meteorological Service of Canada

Climate.Atlantic@ec.gc.ca

National Oceanic and Atmospheric Administration – Gerhard Boenisch, Max Planck Institute for Biogeochemistry, Jena, Germany

boenisch@bgc-jena.mpg.de

Table B-1: Monitoring Station Metadata

Station ID	Name	WMO	WBAN	Type	Source	Latitude	Longitude	Elevation (m)
1010720	BEAR CREEK	-	-	UNKNOWN	EC	48.500	-124.000	350.5
1012055	LAKE COWICHAN	-	-	DAILY CLIMATE	EC	48.829	-124.052	171.0
1012475	DISCOVERY ISLAND	71031	-	AU8	EC	48.424	-123.225	15.3
1012562	DUNCAN BCHPA VIT	-	-	UNKNOWN	EC	48.833	-123.717	36.0
1012710	ESQUIMALT HARBOUR	71798	-	AU8	EC	48.432	-123.439	3.0
1013754	JORDAN RIVER DIVERSION	-	-	UNKNOWN	EC	48.500	-124.000	393.2
1013755	JORDAN RIVER GENERATING	-	-	DAILY CLIMATE	EC	48.417	-124.050	4.6
1013998	KELP REEFS	71036	-	AU8	EC	48.548	-123.236	0.0
1014530	LANGFORD LAKE	-	-	UNKNOWN	EC	48.433	-123.533	75.0
1014820	MALAHAT	71774	-	AU8	EC	48.575	-123.530	365.8
1015628	NORTH COWICHAN	-	-	DAILY CLIMATE	EC	48.825	-123.720	45.7
1015630	NORTH COWICHAN	71927	-	AU8	EC	48.824	-123.718	60.0
1016335	PORT RENFREW	-	-	DAILY CLIMATE	EC	48.591	-124.326	10.0
1016640	RACE ROCKS CS	71778	-	AU8	EC	48.298	-123.532	3.0
1016941	SAANICH CAMOSUN COLLEGE	-	-	UNKNOWN	EC	48.500	-123.417	38.1
1016942	SAANICH DENSMORE	-	-	UNKNOWN	EC	48.500	-123.400	59.0
1017098	SATURNA CAPMON	-	-	DAILY CLIMATE	EC	48.772	-123.114	178.0
1017099	SATURNA CAPMON CS	71914	-	AU8	EC	48.772	-123.114	178.0
1017101	SATURNA ISLAND CS	71473	-	AU8	EC	48.784	-123.045	24.4
1017254	SHERINGHAM POINT	71780	-	AU8	EC	48.377	-123.921	22.3
1018238	TRIAL ISLAND	71034	-	AU8	EC	48.395	-123.305	23.0
1018598	VICTORIA UNIVERSITY CS	71783	-	AU8	EC	48.457	-123.305	60.1
1018610	VICTORIA GONZALES HTS	-	-	-	EC	48.413	-123.325	69.5

Station ID	Name	WMO	WBAN	Type	Source	Latitude	Longitude	Elevation (m)
1018615	VICTORIA HARBOUR A	71961	-	FSS	EC	48.423	-123.388	0.0
1018620	VICTORIA INTL A	71799	-	CON	EC	48.647	-123.426	19.2
1018642	VICTORIA MARINE	-	-	MTR	EC	48.367	-123.750	31.7
1018FF6	VICTORIA U VIC	-	-	UNKNOWN	EC	48.467	-123.333	68.4
1018FJ5	VICTORIA HARTLAND CS	71038	-	AU8	EC	48.534	-123.459	154.1
101QF57	VICTORIA SHELBOURNE	-	-	UNKNOWN	EC	48.467	-123.333	49.0
1020270	ALERT BAY	-	-	NONE	EC	50.583	-126.933	59.4
1020590	BALLENAS ISLAND	71769	-	AU8	EC	49.350	-124.160	12.9
1021052	NANAIMO HARBOUR	-	-	AU8	EC	49.167	-123.933	5.0
1021261	CAMPBELL RIVER A	71205	-	ATI	EC	49.951	-125.271	105.5
1021262	CAMPBELL RIVER BCFS	-	-	UNKNOWN	EC	50.067	-125.317	128.0
1021263	CAMPBELL RIVER BCHPA GEN	-	-	UNKNOWN	EC	50.050	-125.317	30.5
1021265	CAMPBELL RIVER STP	-	-	UNKNOWN	EC	50.017	-125.233	3.0
1021330	CAPE MUDGE	-	-	MTL	EC	49.998	-125.195	4.6
1021332	CAPE MUDGE CS	71993	-	AU8	EC	50.000	-125.200	4.0
1021480	CHATHAM POINT	-	-	MTL	EC	50.333	-125.433	22.9
1021616	CHROME ISLAND	71033	-	AU8	EC	49.467	-124.683	11.3
1021830	COMOX A	71893	-	WOD	EC	49.717	-124.900	25.6
1021990	COURTENAY PUNTLEDGE BCHP	-	-	DAILY CLIMATE	EC	49.683	-125.033	24.4
1022689	ENTRANCE ISLAND CS	71772	-	AU8	EC	49.217	-123.800	5.0
1022795	FANNY ISLAND	71568	-	AU8	EC	50.453	-125.992	8.0
1025230	MT WASHINGTON	71947	-	AU8	EC	49.747	-125.287	1473.5
1025240	MUD BAY	-	-	DAILY CLIMATE	EC	49.471	-124.794	4.0
1025370	NANAIMO A	71890	-	ATI	EC	49.052	-123.870	28.0
1025371	NANAIMO WATER RESERVOIR	-	-	UNKNOWN	EC	49.150	-123.967	114.3

Station ID	Name	WMO	WBAN	Type	Source	Latitude	Longitude	Elevation (m)
10253G0	NANAIMO CITY YARD	-	-	DAILY CLIMATE	EC	49.199	-123.988	114.0
1025977	PARKSVILLE SOUTH	-	-	UNKNOWN	EC	49.333	-124.300	0.9
1025C70	NANAIMO DEPARTURE BAY	-	-	UNKNOWN	EC	49.217	-123.950	7.6
1026170	PINE ISLAND	-	-	MTL	EC	50.976	-127.728	15.0
1026270	PORT HARDY A	71109	-	FSS	EC	50.680	-127.366	21.6
1026562	QUALICUM AIRPORT	71766	-	AU8	EC	49.337	-124.394	58.2
1027114	SAYWARD 2	-	-	DAILY CLIMATE	EC	50.325	-125.930	16.0
1027115	SAYWARD BIG TREE CREEK	-	-	UNKNOWN	EC	50.233	-125.767	57.0
1027403	SISTERS ISLAND	71781	-	AU8	EC	49.487	-124.435	20.0
1027775	STRATHCONA DAM	-	-	UNKNOWN	EC	50.000	-125.583	201.2
1030185	ALBERNI CITY RESERVOIR	-	-	UNKNOWN	EC	49.267	-124.783	64.6
1030426	AMPHITRITE POINT	71112	-	MTR	EC	48.921	-125.540	26.5
1031110	BULL HARBOUR	-	-	UNKNOWN	EC	50.917	-127.950	13.7
1031353	CAPE SCOTT	71111	-	MTL	EC	50.782	-128.427	71.6
1031413	CARNATION CREEK CDF	-	-	UNKNOWN	EC	48.900	-125.000	61.0
1032731	ESTEVAN POINT CS	71894	-	AU8	EC	49.383	-126.545	7.0
1033232	GOLD RIVER TOWNSITE	-	-	DAILY CLIMATE	EC	49.783	-126.048	140.0
1033480	HOLBERG	-	-	NONE	EC	50.650	-128.000	579.0
1033481	HOLBERG CCR	71562	-	AU5	EC	50.633	-128.117	568.0
1035614	NOOTKA LIGHTSTATION	-	-	MTL	EC	49.600	-126.617	15.8
1035940	PACHENA POINT	-	-	MTL	EC	48.723	-125.097	37.0
1036206	PORT ALBERNI A	-	-	-	EC	49.250	-124.833	2.4
1036572	QUATSINO LIGHTSTATION	-	-	MTL	EC	50.441	-128.033	21.0
1036907	RUMBLE BEACH	-	-	UNKNOWN	EC	50.433	-127.483	106.7
1036B06	PORT ALBERNI (AUT)	71475	-	AU8	EC	49.317	-124.926	76.2
1037090	SARTINE ISLAND (AUT)	71478	-	AU8	EC	50.821	-128.908	111.5

Station ID	Name	WMO	WBAN	Type	Source	Latitude	Longitude	Elevation (m)
1037553	SOLANDER ISLAND (AUT)	71479	-	AU8	EC	50.112	-127.940	98.7
1037650	SPRING ISLAND	-	-	UNKNOWN	EC	50.000	-127.417	11.3
1038205	TOFINO A	71106	-	CON	EC	49.082	-125.773	24.4
1038331	UCLUELET BRYNNOR MINES	-	-	UNKNOWN	EC	49.050	-125.433	91.4
103EFJ0	NITINAT LAKE (AUT)	-	-	-	EC	48.667	-124.833	36.4
1040390	ALTA LAKE	-	-	UNKNOWN	EC	50.150	-122.950	667.5
1041710	CLOWHOM FALLS	-	-	UNKNOWN	EC	49.717	-123.533	22.9
1042255	DAISY LAKE DAM	-	-	UNKNOWN	EC	49.983	-123.133	381.0
1043150	GIBSONS	-	-	DAILY CLIMATE	EC	49.397	-123.514	62.0
1043304	GRIEF POINT	-	-	AU8	EC	49.805	-124.525	10.0
1045100	MERRY ISLAND LIGHTSTATION	71204	-	MTL	EC	49.468	-123.913	6.1
1045101	MERRY ISLAND	71210	-	AU8	EC	49.467	-123.917	20.0
10459NN	HOWE SOUND - PAM ROCKS	71211	-	AU8	EC	49.488	-123.299	4.9
1046330	PORT MELLON	-	-	UNKNOWN	EC	49.517	-123.483	7.6
1046332	PORT MELLON	71605	-	AU8	EC	49.517	-123.483	122.6
1046391	POWELL RIVER A	71208	-	CON	EC	49.834	-124.500	129.5
1046392	POWELL RIVER	71720	-	AU8	EC	49.833	-124.483	125.0
1046410	POWELL RIVER WESTVIEW	-	-	UNKNOWN	EC	49.833	-124.517	54.9
1047172	SECHELT	71638	-	AU8	EC	49.450	-123.700	86.0
1047669	SQUAMISH ST DAVIDS	-	-	UNKNOWN	EC	49.750	-123.000	21.3
1047670	SQUAMISH STP	-	-	DAILY CLIMATE	EC	49.733	-123.150	6.1
10476F0	SQUAMISH	71207	-	AU8	EC	49.783	-123.161	52.1
1048310	TUNNEL CAMP	-	-	UNKNOWN	EC	49.617	-123.133	670.6
1048898	WHISTLER	71175	-	CON	EC	50.129	-122.955	657.8
1060080	ADDENBROKE ISLAND	-	-	MTL	EC	51.604	-127.864	-
1062295	DAWSONS LANDING	-	-	UNKNOWN	EC	51.583	-127.583	-

Station ID	Name	WMO	WBAN	Type	Source	Latitude	Longitude	Elevation (m)
1062646	EGG ISLAND	-	-	MTL	EC	51.247	-127.835	-
1063461	HERBERT ISLAND (AUT)	-	-	AU8	EC	50.945	-127.636	16.5
1100001	CALLAGHAN VALLEY (SKI JUMP TOP)	71001	-	AU8	EC	50.140	-123.102	936.0
1100004	CYPRESS BOWL FREESTYLE	71004	-	AU8	EC	49.393	-123.202	958.0
1100030	ABBOTSFORD A	71108	-	ATI	EC	49.025	-122.361	59.4
1100120	AGASSIZ CDA	-	-	DAILY CLIMATE	EC	49.243	-121.760	15.0
1100360	ALOUETTE LAKE	-	-	UNKNOWN	EC	49.283	-122.483	117.3
1100875	BLACKCOMB MOUNTAIN BASE	71687	-	AU8	EC	50.133	-122.950	659.0
1100881	BLACKCOMB BASE SLIDING CENTER	71756	-	AU8	EC	50.101	-122.936	937.0
1100882	BLACKCOMB BASE SLIDING CENTRE BOTTOM	71367	-	AU8	EC	50.106	-122.942	816.6
1101140	BUNTZEN LAKE	-	-	UNKNOWN	EC	49.383	-122.867	10.0
1101300	CALLAGHAN VALLEY	71688	-	AU8	EC	50.144	-123.109	884.0
1101310	CALLAGHAN VALLEY(BIATHALON)	71003	-	AU8	EC	50.149	-123.116	856.0
1101313	CALLAGHAN VALLEY BIATHLON HIGH LEVEL	71293	-	AU8	EC	50.009	-123.119	882.7
1101316	CALLAGHAN VALLEY CROSS COUNTRY HIGH LEVEL	71304	-	AU8	EC	50.009	-123.106	915.5
1101318	CALLAGHAN VALLEY LOW LEVEL	71366	-	AU8	EC	50.006	-123.117	843.6
1101320	CALLAGHAN VALLEY(SKI JUMP BOTTOM)	71002	-	AU8	EC	50.133	-123.116	860.0

Station ID	Name	WMO	WBAN	Type	Source	Latitude	Longitude	Elevation (m)
1101562	CHILLIWACK MICROWAVE	-	-	UNKNOWN	EC	49.117	-121.900	228.6
1101890	COQUITLAM LAKE	-	-	UNKNOWN	EC	49.367	-122.800	160.9
1102255	CYPRESS BOWL NORTH	71689	-	AU8	EC	49.402	-123.208	953.0
1102256	CYPRESS BOWL SOUTH	71693	-	AU8	EC	49.379	-123.192	960.0
1102416	DELTA LADNER EAST	-	-	UNKNOWN	EC	49.083	-123.067	1.5
1103328	HANEY MICROWAVE	-	-	UNKNOWN	EC	49.200	-122.517	320.0
1103332	HANEY UBC RF ADMIN	-	-	DAILY CLIMATE	EC	49.265	-122.573	147.0
1103635	HUNTINGDON METER STATION	-	-	UNKNOWN	EC	49.000	-122.217	7.6
1103636	HUNTINGDON VYE ROAD	-	-	UNKNOWN	EC	49.033	-122.200	25.0
1104470	LADNER	-	-	UNKNOWN	EC	49.083	-123.017	1.2
1104473	LADNER BCHPA	-	-	UNKNOWN	EC	49.083	-123.050	1.5
1104555	LANGLEY LOCHIEL	-	-	UNKNOWN	EC	49.050	-122.583	100.9
1104560	LANGLEY PRAIRIE	-	-	UNKNOWN	EC	49.150	-122.650	86.9
1104565	LANGLEY WELLS	-	-	UNKNOWN	EC	49.067	-122.667	45.7
1105192	MISSION WEST ABBEY	-	-	DAILY CLIMATE	EC	49.153	-122.271	221.0
1105660	N VANCOUVER LYNN CREEK	-	-	UNKNOWN	EC	49.367	-123.033	190.5
1105663	N VANCOUVER MOSQUITO CR	-	-	UNKNOWN	EC	49.350	-123.083	344.4
1106178	PITT MEADOWS CS	71775	-	AU8	EC	49.208	-122.690	5.0
1106180	PITT POLDER	-	-	DAILY CLIMATE	EC	49.283	-122.617	5.0
1106200	POINT ATKINSON	71037	-	AU8	EC	49.330	-123.264	35.0
1106256	PORT COQUITLAM CITY YARD	-	-	UNKNOWN	EC	49.267	-122.783	6.7
1106257	PRT COQUITLAM PRAIRIE RD	-	-	UNKNOWN	EC	49.267	-122.733	2.7
1106CL2	PORT MOODY GLENAYRE	-	-	DAILY CLIMATE	EC	49.279	-122.881	129.5
1106L3K	PORT MOODY MERIDIAN	-	-	UNKNOWN	EC	49.300	-122.800	325.5
1107010	SANDHEADS CS	71209	-	AU8	EC	49.106	-123.303	0.0

Station ID	Name	WMO	WBAN	Type	Source	Latitude	Longitude	Elevation (m)
1107680	STAVE FALLS	-	-	DAILY CLIMATE	EC	49.233	-122.367	110.0
1107873	SURREY KWANTLEN PARK	-	-	DAILY CLIMATE	EC	49.193	-122.860	78.0
1107876	SURREY MUNICIPAL HALL	-	-	DAILY CLIMATE	EC	49.107	-122.828	76.0
1108446	VANCOUVER HARBOUR CS	71201	-	AU8	EC	49.295	-123.122	2.5
1108447	VANCOUVER INTL A	71892	-	ATI	EC	49.195	-123.182	4.3
1108465	VANCOUVER PMO	-	-	UNKNOWN	EC	49.283	-123.117	59.4
1108487	VANCOUVER UBC	-	-	DAILY CLIMATE	EC	49.250	-123.250	76.0
1108824	WEST VANCOUVER AUT	71784	-	AU8	EC	49.347	-123.193	168.0
1108910	WHITE ROCK CAMPBELL SCIENTIFIC	71785	-	AU8	EC	49.018	-122.784	13.0
1108914	WHITE ROCK STP	-	-	DAILY CLIMATE	EC	49.019	-122.784	13.0
1108987	WHISTLER MOUNTAIN HIGH LEVEL	71684	-	AU8	EC	50.077	-122.946	1640.0
1108988	WHISTLER MOUNTAIN LOW LEVEL	71686	-	AU8	EC	50.088	-122.976	933.1
1108989	WHISTLER MOUNTAIN HIGH LEVEL REMOTE WIND	71685	-	AU8	EC	50.074	-122.947	1643.0
1108990	WHISTLER MOUNTAIN MID-STATION	71921	-	AU8	EC	50.085	-122.964	1320.0
110FAG9	PITT MEADOWS STP	-	-	-	EC	49.217	-122.683	4.9
110JA54	BURNABY MTN BCHPA	-	-	UNKNOWN	EC	49.283	-122.917	464.8
110N6FF	N VANC SONORA DR	-	-	DAILY CLIMATE	EC	49.363	-123.098	182.9
1113420	HELLS GATE	-	-	UNKNOWN	EC	49.783	-121.450	121.9
1113540	HOPE A	-	-	-	EC	49.368	-121.498	39.0
1113541	HOPE (AUT)	71114	-	AU5	EC	49.370	-121.494	39.0
1114627	LILLOOET SETON BCHPA	-	-	DAILY CLIMATE	EC	50.673	-121.924	198.1

Station ID	Name	WMO	WBAN	Type	Source	Latitude	Longitude	Elevation (m)
1114739	LYTTON	71891	-	AU5	EC	50.224	-121.582	225.0
1117215	SHALALTH	-	-	-	EC	50.728	-122.241	243.8
1118135	TERZAGHI DAM	-	-	UNKNOWN	EC	50.783	-122.233	652.3
690230	WHIDBEY ISLAND NAS	-	24255	-	ISH	48.350	-122.667	1.0
690240	PACIFIC BEACH	-	-	-	ISH	47.217	-124.200	18.0
710010	CALLAGHAN VALLEY SK	-	-	-	ISH	50.130	-123.100	936.0
710030	CALLAGHAN VALLEY (B	-	-	-	ISH	50.150	-123.110	856.0
710040	CYPRESS BOWL FREEST	-	-	-	ISH	49.400	-123.200	958.0
710280	TATLAYOKO LAKE	-	-	-	ISH	51.660	-124.400	875.0
710310	DISCOVERY ISLAND	-	-	-	ISH	48.410	-123.230	15.0
710324	WHISTLER	-	-	-	ISH	50.130	-122.950	658.0
710360	KELP REEFS	-	-	-	ISH	48.550	-123.230	0.0
710370	POINT ATKINSON	-	-	-	ISH	49.330	-123.260	35.0
710380	VICTORIA HARTLAND C	-	-	-	ISH	48.530	-123.430	154.0
710400	WHITE ROCK	-	-	-	ISH	49.020	-122.780	15.0
711050	PINE ISLAND (MAPS)	-	-	-	ISH	50.980	-127.730	9.0
711054	SPRING ISLAND	-	-	-	ISH	50.000	-127.417	9.0
711060	TOFINO	-	-	-	ISH	49.080	-125.770	24.1
711080	ABBOTSFORD AIRPORT	-	-	-	ISH	49.030	-122.370	58.0
711090	PORT HARDY AIRPORT	-	-	-	ISH	50.680	-127.370	22.0
711100	ALERT BAY	-	-	-	ISH	50.580	-126.930	50.0
711110	CAPE SCOTT LIGHT	-	-	-	ISH	50.783	-128.433	70.0
711120	AMPHITRITE POINT	-	-	-	ISH	48.920	-125.550	27.0
711131	WHISTLER ALTA LAKE&	-	-	-	ISH	50.133	-122.950	658.0
711750	WHISTLER	-	-	-	ISH	50.110	-122.950	658.0
712000	VICTORIA (AUTO8)	-	-	-	ISH	48.420	-123.320	70.0

Station ID	Name	WMO	WBAN	Type	Source	Latitude	Longitude	Elevation (m)
712003	VICTORIA (AUTO8)	-	-	-	ISH	48.417	-123.317	67.0
712010	VANCOUVER (AUTO8)	-	-	-	ISH	49.300	-123.120	2.0
712020	VICTORIA MARINE	-	-	-	ISH	48.367	-123.750	32.0
712027	VIC. HARTLAND AUTO8	-	-	-	ISH	48.530	-123.470	49.0
712050	CAMPBELL RIVER ARPT	-	-	-	ISH	49.950	-125.270	106.0
712070	SQUAMISH (AUTO8)	-	-	-	ISH	49.780	-123.170	60.0
712080	POWELL RIVER ARPT	-	-	-	ISH	49.830	-124.500	130.0
712090	SAND HEAD (LS)	-	-	-	ISH	49.100	-123.300	1.5
712110	PAM ROCKS	-	-	-	ISH	49.480	-123.300	10.0
713325	GRIEF POINT	-	-	-	ISH	49.800	-124.510	10.0
714730	SATURNA ISL (MAPS)	-	-	-	ISH	48.780	-123.050	24.0
714735	VICTORIA HARBOUR	-	-	-	ISH	48.420	-123.330	5.0
714750	PORT ALBERNI (MARS)	-	-	-	ISH	49.250	-124.830	2.0
714755	BALLENAS IL AUTO8 &	-	-	-	ISH	49.250	-124.830	1.0
714780	SARTINE ISL (MAPS)	-	-	-	ISH	50.820	-128.900	112.0
714790	SOLANDER ISL (MAPS)	-	-	-	ISH	50.120	-127.930	99.0
714810	HELMCKEN ISL (MAPS)	-	-	-	ISH	50.400	-125.870	19.0
714830	NITINAT LAKE (MAPS)	-	-	-	ISH	48.670	-124.830	41.0
714850	HERBERT ISL (MAPS)	-	-	-	ISH	50.930	-127.630	17.0
715680	FANNY ISLAND	-	-	-	ISH	50.450	-125.980	8.0
716840	WHISTLER MT HIGH LV	-	-	-	ISH	50.060	-122.930	1628.0
716850	WHISTLER MTN HIGH L	-	-	-	ISH	50.060	-122.950	1643.0
716860	WHISTLER MT LOW LVL	-	-	-	ISH	50.080	-122.960	903.0
716870	BLACKCOMBE MTN BASE	-	-	-	ISH	50.110	-122.950	659.0
716880	CALLAGHAN VALLEY	-	-	-	ISH	50.110	-123.100	869.0
716890	CYPRESS BOWL NORTH	-	-	-	ISH	49.400	-123.200	953.0

Station ID	Name	WMO	WBAN	Type	Source	Latitude	Longitude	Elevation (m)
716930	CYPRESS BOWL SOUTH	-	-	-	ISH	49.360	-123.180	960.0
717600	BIG CREEK	-	-	-	ISH	51.250	-123.080	1670.0
717690	BALLENAS IL AUTO8	-	-	-	ISH	49.350	-124.170	5.0
717720	ENTRANCE IL AUTO8	-	-	-	ISH	49.220	-123.800	5.0
717740	MALAHAT (AUTO8)	-	-	-	ISH	48.580	-123.580	366.0
717750	P. MEADOWS CS AUTO8	-	-	-	ISH	49.200	-122.680	5.0
717770	PEMBERTON (AUTO8)	-	-	-	ISH	50.300	-122.730	204.0
717780	RACE ROCKS AUTO8	-	-	-	ISH	48.300	-123.530	5.0
717800	SHERINGHAM AUTO8	-	-	-	ISH	48.380	-123.920	21.0
717810	SISTERS IL AUTO8	-	-	-	ISH	49.480	-124.430	5.0
717830	VICTORIA UNIV	-	-	-	ISH	48.450	-123.300	60.0
717840	W VANCOUVER AUTO8	-	-	-	ISH	49.350	-123.180	178.0
717850	WHITE ROCK AUTO8	-	-	-	ISH	49.020	-122.780	15.0
717980	ESQUIMALT MARITIME	-	-	-	ISH	48.430	-123.430	3.0
717990	VICTORIA INTL ARPT	-	-	-	ISH	48.650	-123.430	19.0
717995	VICTORIA MARINE RAD	-	-	-	ISH	48.367	-123.750	31.0
718900	NANAIMO AIRPORT	-	-	-	ISH	49.050	-123.870	28.0
718905	BALLENAS IL AUTO8 &	-	-	-	ISH	49.350	-124.170	0.0
718916	CAPE MUDGE (LGT-H)	-	-	-	ISH	50.000	-125.200	4.0
718920	VANCOUVER INTL ARPT	-	-	-	ISH	49.180	-123.170	2.0
718930	COMOX (CAN-MIL)	-	-	-	ISH	49.720	-124.900	24.0
718936	CAMPBELL RIVER ARPT	-	-	-	ISH	49.950	-125.270	106.0
718937	CHATHAM POINT (LH)	-	-	-	ISH	50.330	-125.430	23.0
718940	ESTEVAN PT. (MARS)	-	-	-	ISH	49.380	-126.550	7.0
718944	ESTEVAN POINT (MAN)	-	-	-	ISH	49.383	-126.533	5.0
718950	HOLBERG	-	-	-	ISH	50.650	-128.050	579.0

Station ID	Name	WMO	WBAN	Type	Source	Latitude	Longitude	Elevation (m)
718955	HOLBERG	-	25237	-	ISH	50.650	-128.050	579.0
720202	TILAMOOK(AWS)	-	-	-	ISH	45.410	-123.810	11.0
720254	CHEHALIS-CENTRALIA	-	-	-	ISH	46.680	-122.980	53.0
720272	SKAGIT RGNL ARPT	-	-	-	ISH	48.460	-122.410	44.0
720388	PUYALLUP THUN FIELD	-	-	-	ISH	48.000	-122.280	164.0
722208	EASTSOUND	-	-	-	ISH	48.710	-122.910	8.0
726836	SCAPPOOSE INDUSTRIA	-	-	-	ISH	45.767	-122.850	1.6
726881	MCMINNVILLE MUNI	-	-	-	ISH	45.200	-123.130	159.0
726959	AURORA STATE	-	-	-	ISH	45.250	-122.770	60.0
726963	TILLAMOOK	-	-	-	ISH	45.420	-123.820	11.0
726980	PORTLAND INTERNATIONAL A	-	24229	-	ISH	45.600	-122.620	5.8
726985	PORTLAND/TROUTDALE	-	-	-	ISH	45.550	-122.400	11.0
726986	PORTLAND/HILLSBORO	-	-	-	ISH	45.530	-122.950	62.0
726989	TILLAMOOK BAY (CGS)	-	-	-	ISH	45.567	-123.917	15.0
727885	PORT ANGELES INTL	-	-	-	ISH	48.120	-123.500	88.0
727910	ASTORIA REGIONAL AIRPORT	-	94224	-	ISH	46.150	-123.880	2.7
727915	CAPE DISAPPOINTMENT	-	-	-	ISH	46.283	-124.050	55.0
727916	GRAYS HARBOR (CGS)	-	-	-	ISH	46.917	-124.100	6.0
727917	PACIFIC BEACH NF	-	-	-	ISH	47.217	-124.200	18.0
727918	PEARSON FLD	-	-	-	ISH	45.620	-122.650	8.0
727920	OLYMPIA AIRPORT	-	24227	-	ISH	46.970	-122.900	62.8
727923	HOQUIAM AP	-	94225	-	ISH	46.980	-123.930	3.7
727924	KELSO WB AP	-	24223	-	ISH	46.130	-122.900	4.9
727925	SHELTON/SANDERSON	-	94227	-	ISH	47.230	-123.150	85.0
727926	TOLEDO-WINLOCK MEM	-	24241	-	ISH	46.480	-122.800	113.0
727928	BREMERTON NTNL AWOS	-	-	-	ISH	47.500	-122.750	147.0

Station ID	Name	WMO	WBAN	Type	Source	Latitude	Longitude	Elevation (m)
727929	WILLAPA HARBOR	-	-	-	ISH	46.700	-123.817	5.0
727930	SEATTLE SEATTLE-TACOMA I	-	24233	-	ISH	47.470	-122.320	121.9
727934	RENTON MUNICIPAL	-	-	-	ISH	47.500	-122.220	9.0
727935	SEATTLE BOEING FIELD	-	24234	-	ISH	47.530	-122.300	6.1
727937	EVERETT/PAINE FIELD	-	-	-	ISH	47.900	-122.280	185.0
727938	TACOMA NARROWS	-	-	-	ISH	47.270	-122.580	89.0
727939	ALKI POINT (CGLS)	-	-	-	ISH	47.517	-122.417	1.0
727945	ARLINGTON MUNI	-	-	-	ISH	48.170	-122.170	42.0
727964	OAK HARBOR AIRPARK	-	-	-	ISH	48.250	-122.670	58.0
727965	ARLINGTON (AWOS)	-	-	-	ISH	48.167	-122.150	42.0
727970	QUILLAYUTE STATE AIRPORT	-	94240	-	ISH	47.930	-124.570	54.6
727973	BANGOR CGS	-	-	-	ISH	47.733	-122.717	0.0
727974	DESTRUCTION ISLAND	-	-	-	ISH	47.667	-124.483	24.0
727976	BELLINGHAM INTL AP	-	24217	-	ISH	48.800	-122.530	45.4
727977	QUILLAYUTE RIV CGLS	-	-	-	ISH	47.900	-124.633	1.0
727978	TATOOSH ISLAND	-	24240	-	ISH	48.383	-124.733	35.1
727979	POINT WILSON	-	-	-	ISH	48.150	-122.750	14.9
727984	NEAH BAY	-	-	-	ISH	48.370	-124.600	3.0
727985	FRIDAY HARBOR	-	-	-	ISH	48.520	-123.020	33.0
727996	NEW DUNGENESS (CGS)	-	-	-	ISH	48.167	-123.100	12.0
728950	BULL HARBOUR (DEAD)	-	-	-	ISH	50.917	-127.950	4.0
742004	BURROWS ISLAND	-	-	-	ISH	48.083	-122.100	18.0
742005	PATOS ISLAND ANACORT	-	-	-	ISH	48.733	-122.967	0.9
742006	BURLINGTON/MT VERN	-	-	-	ISH	48.470	-122.420	43.0
742010	PORT ANGELES WB AP	-	24228	-	ISH	48.133	-123.400	6.1
742015	SMITH ISLAND (CGLS)	-	-	-	ISH	48.317	-122.850	1.0

Station ID	Name	WMO	WBAN	Type	Source	Latitude	Longitude	Elevation (m)
742060	TACOMA MCCHORD AFB	-	24207	-	ISH	47.150	-122.480	88.1
742065	POINT NO POINT USCG LIGH	-	-	-	ISH	47.920	-122.530	3.7
742070	GRAY AAF	-	24201	-	ISH	47.080	-122.580	89.9
742071	GRAY AAF	-	-	-	ISH	47.080	-122.580	92.0
742075	POINT ROBINSON USCG LIGH	-	-	-	ISH	47.380	-122.370	3.0
742076	WEST POINT (CGLS)	-	-	-	ISH	47.667	-122.433	4.0
992060	ENVIRONM BUOY 46041	-	-	-	ISH	47.400	-124.500	3.0
992370	ENVIRONM BUOY 46029	-	-	-	ISH	46.330	-124.330	3.0
992460	ENVIRONM BUOY 46010	-	-	-	ISH	46.180	-124.180	3.0
992750	ENVIRONM BUOY 46043	-	-	-	ISH	46.900	-124.200	3.0
992970	ENVIRONM BOUY 46039	-	-	-	ISH	48.200	-123.400	3.0
994011	ASTORIA	-	-	-	ISH	46.200	-123.760	2.0
994013	CHEERY POINT	-	-	-	ISH	48.860	-122.750	5.0
994014	SEATTLE	-	-	-	ISH	47.600	-122.330	2.0
994015	FRIDAY HARBOR	-	-	-	ISH	48.550	-123.010	2.0
994021	NEAH BAY	-	-	-	ISH	48.360	-124.610	5.0
994024	PORT ANGELES	-	-	-	ISH	48.130	-123.430	5.0
994025	PORT TOWNSEND	-	-	-	ISH	48.110	-122.750	5.0
994029	TOKE POINT	-	-	-	ISH	46.700	-123.960	5.0
994048	TACOMA	-	-	-	ISH	47.260	-122.410	5.0
994070	DESTRUCTION ISLAND	-	-	-	ISH	47.670	-124.480	16.0
994180	SMITH ISLAND	-	-	-	ISH	48.320	-122.830	15.0
994300	TATOOSH ISLAND	-	-	-	ISH	48.380	-124.730	31.0
994350	WEST POINT (LS)	-	-	-	ISH	47.670	-122.430	3.0
994980	ENVIRONM BUOY 46041	-	-	-	ISH	47.330	-124.750	0.0
996310	ENVIRONM BUOY 46046	-	-	-	ISH	46.300	-124.200	0.0

Station ID	Name	WMO	WBAN	Type	Source	Latitude	Longitude	Elevation (m)
996500	ENVIRONM BUOY 46206	-	-	-	ISH	48.800	-125.900	0.0
996540	ENVIRONM BUOY 46204	-	-	-	ISH	51.300	-128.699	0.0
996870	ENVIRONM BUOY 46146	-	-	-	ISH	49.333	-123.717	0.0
996930	ENVIRONM BUOY 46131	-	-	-	ISH	49.900	-124.900	0.0
996960	ENVIRONM BUOY 46132	-	-	-	ISH	49.733	-127.917	0.0
997207	MOORED BUOY 46088	-	-	-	ISH	48.330	-123.160	0.0
997243	MOORED BUOY #46087	-	-	-	ISH	48.500	-124.700	0.0
997256	DESDEMONA SANDS	-	-	-	ISH	46.210	-123.950	7.0
997263	MARSH ISLAND	-	-	-	ISH	46.210	-123.610	7.0
997316	MOORED BUOY 46211	-	-	-	ISH	46.850	-124.230	0.0
997374	MOORED BUOY 46089	-	-	-	ISH	45.880	-125.760	4.0
997696	LA PUSH	-	-	-	ISH	47.910	-124.630	3.0
997706	GARIBALDI TILLAMOOK	-	-	-	ISH	45.550	-123.900	3.0

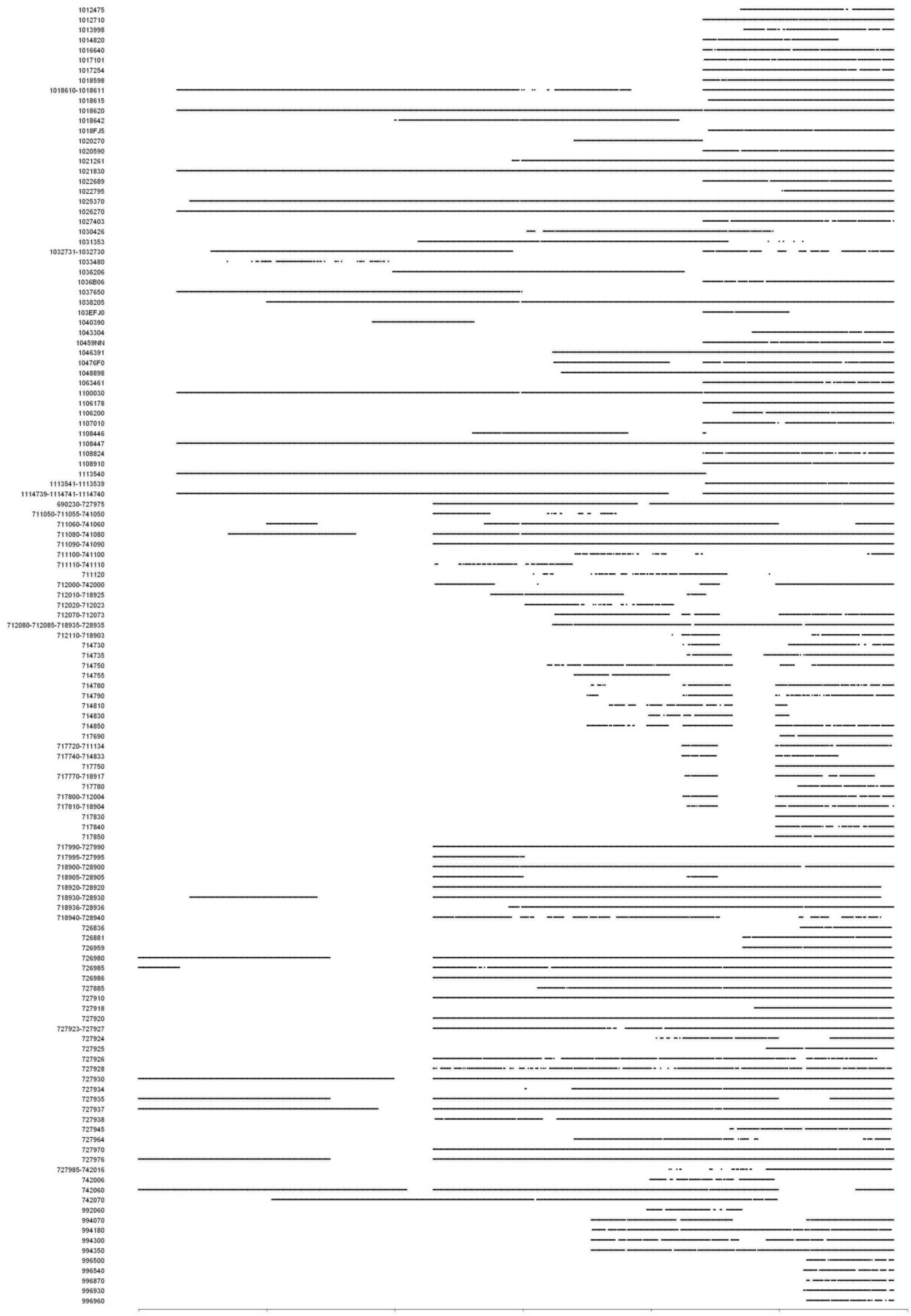


Figure B-1: Temporal Coverage of Wind Speed Monitoring Stations

Appendix C: LME Model Diagnostic Plots

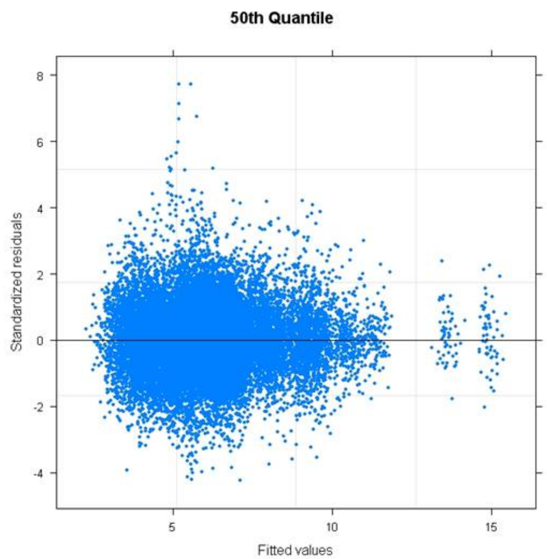


Figure C-1: Standardized Residuals

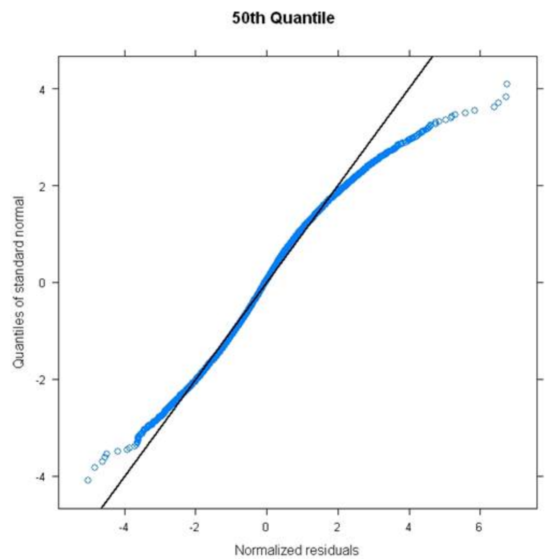


Figure C-2: Quantile-Quantile

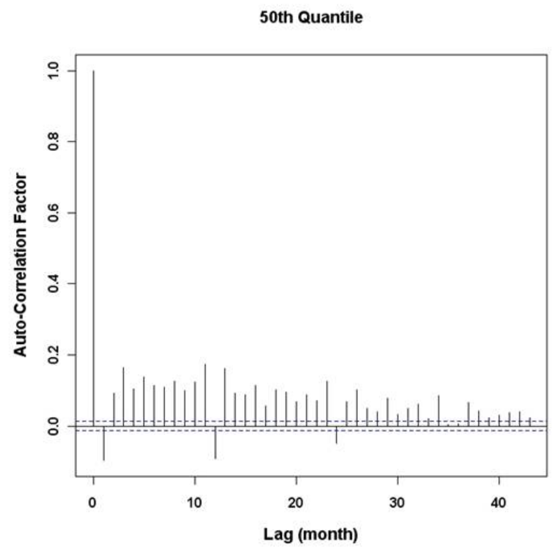
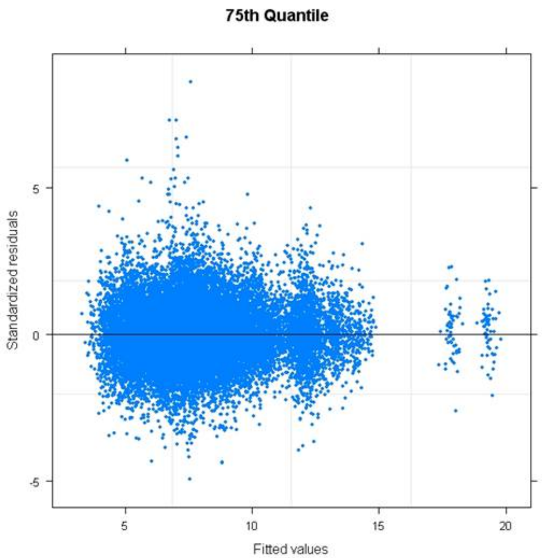
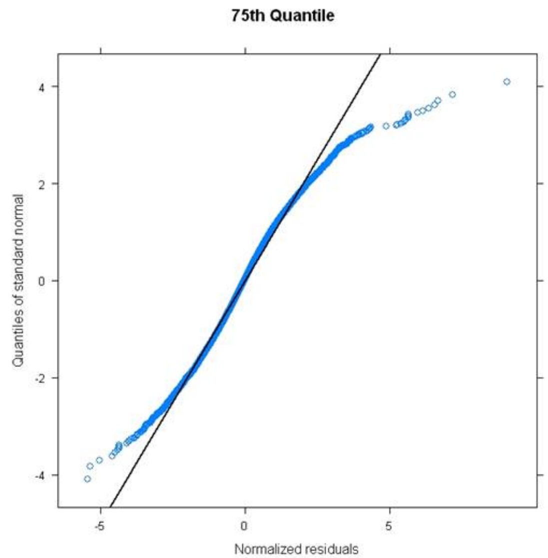


Figure C-3: Auto-Correlation Function





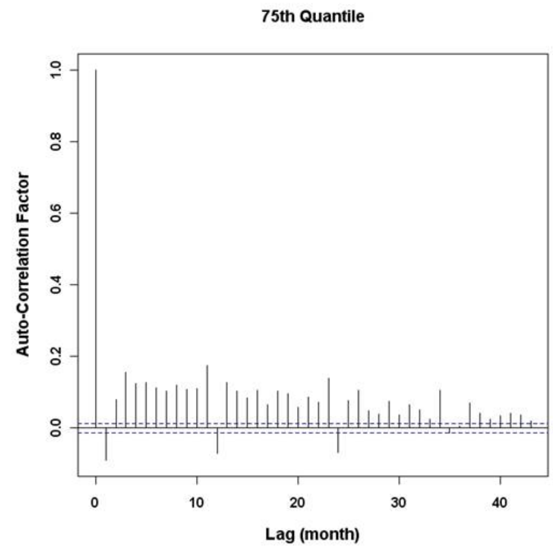


Figure C-4: Standardized Residuals

Figure C-5: Quantile-Quantile

Figure C-6: Auto-Correlation Function

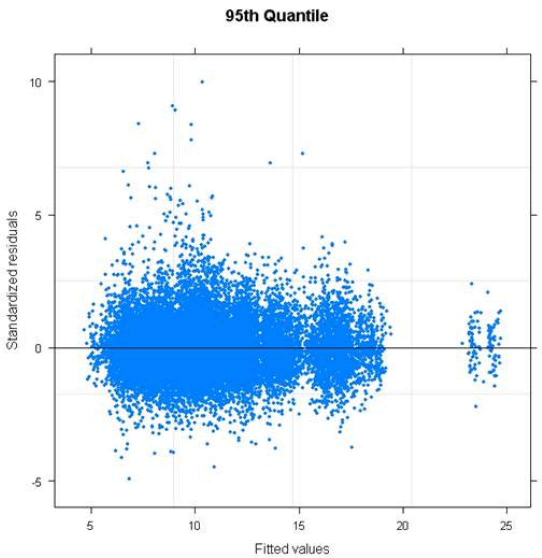


Figure C-7: Standardized Residuals

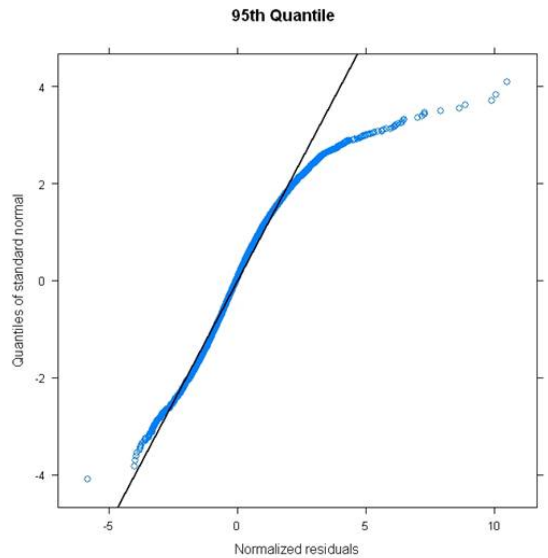


Figure C-8: Quantile-Quantile

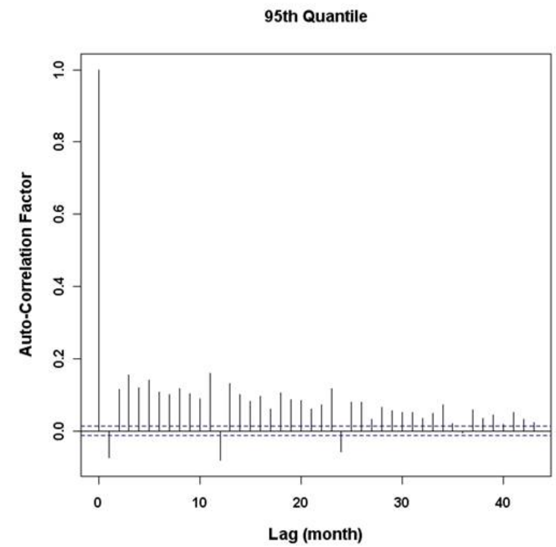


Figure C-9: Auto-Correlation Function

Appendix D: Wind Damage Adaptation Interview Questions

1. How does your organization view severe windstorms presently? For example, as a threat, beneficial, or not acknowledged.
2. Do you suffer damages from severe windstorms? To what extent?
3. What options are currently available to you to respond to damages caused by extreme wind speeds or severe wind storms?
    a. Technical responses?
    b. Policy responses?
    c. Institutional responses?
4. What options are not currently available, but could be implemented in the future?
5. What conditions would be necessary for these options to be implemented?
6. Given the following situation:
7. Annual storms (experienced over the past 50 years) with maximum wind speeds in the range of 80-100 km/h change to maximum wind speeds in the range of 60-125 km/h in the future (i.e. get more variable).
    a. What would be the likely damages or benefits, from the current baseline?
    b. What actions would you take to respond?
    c. How effective do you think these actions would be?
8. Explore Q6 for various levels of change (i.e., future scenarios).
9. Would a planning tool that helps to forecast probabilities of wind speed regimes, for a time horizon of 1-2 years, be helpful to your organization?
10. What improvements or changes would make this type of tool more helpful for your organization?

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