Multi-scale atmospheric and climate phenomena in the context of the wind resource assessment: a case study in complex, coastal terrain

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Abstract

This thesis examines aspects of the wind resource potential (the potential for energy conversion by wind turbines) in a complex, coastal terrain setting. The main objective of this study is to use a combined modelling and field based measurement approach to assess how atmospheric and climate phenomena, over a range of spatial-temporal scales, can contribute to the quantity and quality of the wind resource in a complex, coastal terrain setting. A major theme of this study is the adoption of a holistic approach, to include the examination of atmospheric and climate phenomena that are characterized over a range of spatial-temporal scales, including those at the synoptic, mesoscale and microscale. Studies aimed at establishing linkages between aspects of the wind resource and atmospheric and climate phenomena remain sparse, in both the international and New Zealand focused published literature. However, establishing and quantifying these linkages carry important practical and economic implications including: forecasting the energy extractable by wind turbines over short time periods; allowing better informed decisions regarding turbine placement to be made; and understanding how the wind resource will be affected by 21st century climate change. These implications are particularly important given the recent and forecasted growth rate of wind energy developments both globally and within New Zealand.

The methods adopted in this research involved a field based measurement campaign combined with mesoscale numerical modelling. This research was conducted on the ridge top of Porteous Hill (approximately 400m a.s.l) (45.6895° S; 170.5829° E) situated near to the township of Waitati, north of Dunedin. The choice of field site, within a complex and coastal terrain setting, permitted examination of a number of atmospheric processes and phenomena, operating over a range of spatial-temporal scales, potentially important to the wind resource in such a geographical setting. Data from four ridge top temporary automatic weather stations were used in this research, including a sonic anemometer to analyse properties of the near surface ridge top turbulence. Measurements from these stations were made at several different heights above the surface which ranged from 2m to 30m, and across different time periods between 1 September 2011 and 31 August 2013. The Air Pollution Model (TAPM) was also used in this study; TAPM was employed to test model skill in calculating metrics for wind resource quantity and to untangle linkages between processes and phenomena that operate over different scales.

Substantial variability in the monthly mean power density (a commonly used metric for wind resource quantity) was found between months over the two year examination period. Changes in the mean power density between months were linked to anomalous Southern Hemispheric monthly mean sea level pressure fields derived from reanalysis data. In particular, the wind
resource quantity in a given month examined was enhanced when high pressure centres were located anomalously north of New Zealand, and shown to be degraded when high pressure centres were located directly over New Zealand or to the southeast of New Zealand; related to the associated changes in the strength of the synoptic westerly wind over the South Island. A probabilistic analysis linking Kidson weather types to generation potential over shorter (daily) time periods yielded similar findings, with the results of this analysis subsequently used to infer how larger scale climate oscillations might also contribute to variability in the wind resource quantity.

At the sub-synoptic scale, sea breezes were often found to be of sufficient magnitude to be important for energy generation at this site, with TAPM deemed suitable for simulating a number of aspects of the circulation. Subsequent ‘idealized’ simulations carried out by TAPM revealed that the strength and direction of the ambient synoptic wind might be an important determinant of the sea breeze contribution to the wind resource. In particular, under offshore directed ambient synoptic flow of sufficient magnitude (10 ms\(^{-1}\)), the counteraction of the sea breeze could result in an extended period of calm winds below wind turbine cut-in thresholds. However, through further model based sensitivity experiments, it was estimated that the net contribution of the sea breeze to the wind resource quantity remained positive. At the microscale, ridge top wind shear was generally found to be lower than that assumed under commonly employed tools (ie. the ‘1/7th power law’) to extrapolate wind speed with height in wind resource assessments. Variability in ridge top wind shear exhibited a complex non-linear relationship with wind speed, time of day and wind direction. The application of Monin and Obukhov similarity theory (MOST) appeared limited in this setting also; the performance of MOST for extrapolating wind speed with height was often inferior to the more simple 1/7th power law method, especially in the stable boundary layer. A number of these findings potentially have practical utility for wind resource assessments, not only at this site but also in the more general context of assessments elsewhere.
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Global and national utilization of wind energy

In all societies of the world, primary energy supply is required to meet many of humanities’ basic needs (Edenhofer et al., 2011). Since approximately the middle of the 19th century, the majority of this energy has been supplied by non-renewable ‘fossil’ sources, such as oil, coal and gas. However, it is now well recognized that energy provision from such sources has contributed significantly to today’s level of atmospheric ‘greenhouse’ gas (GHG) concentrations, and subsequently to recent increases in global mean air temperature (Edenhofer et al., 2011). As a consequence of this, the development of renewable energy alternatives, such as wind energy, offers potential to mitigate anthropogenic global warming. The need and urgency for the future development of renewables is demonstrated by Hansen et al. (2008), who argue that a global phase out of coal-fired power plants is needed over the coming decades to avoid ‘dangerous’ climate change. Renewable energy generation also offers a range of wider benefits including ameliorating negative impacts to human health and to the environment from energy provision, and increasing energy security in the wake of peak oil. In combination, these benefits are considered to be the main attributors of the recent growth of the wind energy sector, which is currently the fastest growing renewable energy sector in the world, in terms of percentage increase in annual installed capacity (Islam et al., 2011).

Despite the rapid growth of renewables such as wind energy, on a global scale renewable energy sources today supply approximately 12.9% of primary energy supply, dwarfed by that of coal (28.4%), oil (34.6%) and gas (22.1%) (Edenhofer et al., 2011). Of the global contribution from renewables, the contribution from wind is relatively small, comprising only 0.2% of global primary supply. In New Zealand, the wind energy industry is relatively new (relative to maturity in other nations) and currently supplies approximately 5% of national electricity demand, but with the potential for future rapid growth in the coming decades. It has been forecasted that the extent of this growth in New Zealand is such that by 2030, 20% of New Zealand’s electricity sector could be supplied by wind energy (NZWEA, 2013).

Wind power meteorology

It is often proclaimed that New Zealand has one of the best wind resources across the globe, offering ample opportunities for future development in the wind energy sector (e.g. NZWEA,
2013). However, the intermittent ‘nature’ of airflow can cause energy generation from wind to be less predictable and less reliable than other forms of generation over short time scales. As such, a detailed examination of the temporal variability in the wind resource is needed, at a particular site, before being deemed suitable for wind energy generation. Such an examination needs to encompass a range of considerations which span a number of disciplines including geography, climatology, meteorology and engineering (Petersen et al., 1997). The interdisciplinary nature of such an examination has led to the genesis of a rapidly evolving field of applied science research coined ‘wind power meteorology’ (Petersen et al., 1997).

Atmospheric and climate phenomena that span a range of spatial-temporal scales can contribute to the intermittency of wind energy generation, and subsequently its viability. Therefore, examination of these multi-scale processes and phenomena in the context of the wind resource has profound implications, and is a central theme throughout this thesis. From a New Zealand perspective, large scale climate phenomena or ‘oscillations’ can be responsible for inter-annual variability in ‘windiness’. These include the El Niño-Southern Oscillation (ENSO), the Interdecadal Pacific Oscillation (IPO) and the Southern Annular Mode (SAM). While the influence of these large scale phenomena on New Zealand’s climate has been the focus of several studies (e.g. Renwick, 2011; Salinger et al., 2001; Kidston et al., 2009), the potential influence upon wind energy resources in New Zealand has received relatively little attention. An improved understanding of how these phenomena affect wind resources could aid inter-annual or seasonal forecasts of wind resource variability, and is also needed to predict future trends in the wind resource.

Seasonal variability in the dominant mid-latitudinal atmospheric circulation features contribute to seasonal variability in many aspects of the climate of New Zealand. Most notable, are a strong belt of westerly winds and a belt of sub-tropical semi-permanent high pressure systems (Fitzharris, 2010). While the influence of these features on many aspects of the New Zealand climate have been well researched (Sturman and Tapper, 2006), the implications for the wind resource has been given little explicit consideration in the literature. As such, establishing linkages between synoptic scale variability and observed wind resource variability could have practical implications for both seasonal and “day ahead” forecasting of the wind resource and its variability. In complex and coastal terrain regions, seasonal variation in the diurnal rate and extent of warming and cooling can also affect the developmental extent of more localized thermally generated circulation features. Subsequently, this may affect seasonal and diurnal variability in the wind resource and also affect the synoptic scale signal. For example, in certain geographical settings in New Zealand, these smaller scale circulation features have been shown to interact and complicate the synoptic signal on the wind climate (McKendry et al., 1986), which might carry important implications for the wind resource. Thermally generated
circulation features, including sea breezes and nocturnal drainage winds, commonly occur in New Zealand (Sturman and Tapper, 2006); yet a detailed examination of the implications of these features on the wind resource has been given little attention in the published literature from a New Zealand perspective.

The implications of wind turbine sitting in complex terrain is also a focus of this research. This is important from a New Zealand perspective as most turbines are situated in what might be considered complex terrain (Katurji, 2011). Over very small spatial-temporal scales, turbulence affects the “quality” of the wind resource and carries important implications for the performance of wind turbines in complex terrain (Katurji, 2011). Complex terrain can complicate the wind resource by the mechanical disruption of airflow over topographic changes or different roughness elements, and by thermal effects on the local circulation induced by inhomogeneous surfaces. From a theoretical perspective, these considerations might also result in considerable departure away from mathematical ‘tools’ that are often relied on by wind energy assessors, in resource assessments, to incorporate changes in wind speed with height (wind shear). These mathematical ‘tools’ include the $1/7^{th}$ power law and the less commonly employed Monin–Obukhov similarity theory (MOST), which are reviewed in detail in Chapter 2.

**Wind energy resource modelling**

The employment of numerical models in the context of wind resource assessments is relatively new, but is becoming more prevalent (Al-Yahyai et al., 2010). If suitably validated, model simulations can be advantageous over traditional methods of wind resource characterization (through the use of automatic weather station (AWS) measurements) for several practical reasons including: lower operating costs, higher spatial and temporal resolutions, and better representation of the actual wind climate (Al-Yahyai et al., 2010). Beyond this, modelling sensitivity studies can be carried out to identify specific physical processes that influence variability in wind regimes. However, wind speed needs to be simulated with a high level of accuracy, as even small percentage errors in wind speed estimates can lead to large financial losses for commercial scale wind farms (Schreck et al., 2008). This research will utilise The Air Pollution Model v.4 (TAPM) (Hurley, 2008) in an attempt to simulate wind speed and quantify the wind resource on monthly average time scales. TAPM is also employed in this study in an attempt to: simulate aspects of the thermally generated circulation, investigate the interaction of the sea breeze with the ambient synoptic wind, and quantify the effect of this circulation in terms of commonly applied wind resource quantity metrics.
Research objective and questions, and thesis structure

The main objective and research questions presented here are largely developed from evident gaps in the literature, which are reviewed in more detail in Chapter 2. The main objective of this study is to use a combined modelling and field based measurement approach to assess how atmospheric and climate phenomena, over a range of spatial-temporal scales, can contribute to the quantity and quality of the wind resource in a complex, coastal terrain setting. The physical setting in which this research was conducted was the ridge top of Porteous Hill, providing a case study in a complex, coastal terrain setting. To achieve the main objective, the following research questions are investigated:

- How does the observed wind power density at the site change with respect to time on monthly and seasonal scales? Can the reorganization of synoptic scale circulation features be linked to this variability?

- At the sub-synoptic scale, to what extent do thermally generated winds appear to contribute to the quantity of the wind resource?

- At the microscale, what variables appear to exert control on wind shear? If the complexity of the terrain contributes to variability in wind shear, might this violate the usefulness of the 1/7th power law or MOST in wind resource assessments?

This thesis is separated into the following eight chapters. Chapter 2 builds on the introduction presented here (Chapter 1) by providing a synthesis of the relevant literature including an overview of the wind energy sector, and a review of a number of atmospheric processes and phenomena over a range of scales important to the wind resource. In Chapter 3 the physical and climatological setting of this research is described, as are the field, modelling and analysis methods employed in this research. The results of this research are presented in three chapters separated on the basis of scale, including: synoptic scale results (Chapter 4), sub-synoptic results (Chapter 5), and microscale results (Chapter 6). The main results are brought together and discussed in Chapter 7, with focus on the interpretation of the main findings and the associated implications and limitations. Lastly, Chapter 8 summarises the main findings of this research and suggests potential avenues for future research.
Chapter 2 – Theoretical review

2.1 Introduction

Today the wind energy sector is the fastest growing renewable energy sector in the world, prompted largely by concerns surrounding CO₂ emissions and anthropogenic climate change, and the finite supply of non-renewable energy sources (Islam et al., 2011). The wind resource in a particular geographic location is a large determinant of whether energy generation from wind turbines is cost competitive against non-renewable sources of energy generation in that location. Therefore, comprehensive investigation of the wind resource at a site proposed for turbine sitting has profound implications. Wind power meteorology is an emerging discipline which studies how combined principals from applied climatology, meteorology and geography contribute to the wind resource (Petersen et al., 1997). A theoretical review of a number of these principals and applications, spanning a range of spatial-temporal scales, is a main focus of this chapter.

This chapter begins with an overview of the wind energy sector, including its historic and potential future utilization in New Zealand and globally, along with the benefits of future development (Section 2.2). Focus is then directed towards the concept of scale in the atmospheric sciences, providing a platform for subsequent sections of this chapter (Section 2.3), and for the thesis as a whole. Section 2.4 examines wind resource quantity in terms of contributions from synoptic and sub-synoptic considerations, with a review of how the wind resource is often quantified in assessments. Section 2.5 focuses on smaller scale considerations including the structure of the atmospheric boundary layer and of turbulent flows and vertical profiles within this layer. A review of the current understanding of how these concepts and processes can be modified in the presence of terrain complexity is also presented. The final section of this review (Section 2.6) concerns mesoscale numerical modelling in the context of wind resource assessments.

2.2 Overview of wind energy globally and in New Zealand

Wind energy has been used as a resource by humans for over 3000 years, with early utilization providing mechanical energy to pump water and grind grain (Ackermann and Soder, 2002). However, by the onset of modern industrialization the global utility of wind energy had shifted, with fossil fuels replacing wind energy as a primary source of energy. This replacement was largely due to the intermittent nature of the wind which limited its reliability as an energy
source at this time (Ackermann and Soder, 2002). The next major transition was catalysed by the ‘global oil shock’ of the 1970s which began to force a global revaluation of wind energy (Ackermann and Soder, 2002). At the same time, technological developments permitted wind power to be used to generate electrical energy (as opposed to only mechanical energy) which could subsequently be stored on an electricity grid and used to complement generation from other sources more effectively. On the back of these historic developments, today, wind energy is in a “boom cycle” in many parts of the world (Islam et al., 2011). The extent of this being that the wind energy sector is considered to be the fastest growing renewable energy sector in the world, in terms of annual percentage increase in installed capacity (Ackermann and Soder, 2002; Lund, 2007). In 2010 it was estimated that the wind power capacity of wind turbines already installed could meet approximately 1.8% of global electricity demand (Edenhofer et al., 2011). The growth of wind energy over other conventional sources of energy is important today, more so than ever, because wind energy is both renewable and environmentally ‘clean’. Many countries, particularly developing countries, have also achieved reduced dependence on external sources of energy through the development of local wind turbine projects, which can bring important benefits (Martinot et al., 2002).

Renewable sources of energy are increasingly being investigated today in light of peak oil discussions, centred on the idea that fossil oil reserves will eventually run out. Peak oil estimates presented in the literature are often not in agreement and range from the coming few years to as far away as 700 years (Goldemberg, 2007). Debates on when oil will peak are prevalent largely because peak oil is dependent both on the rate of future consumption and the rate at which new oil reserves will be discovered, both of which are difficult to estimate (Goldemberg, 2007). Dwindling supplies of fossil fuels, and their associated increasing prices, will at some point in the future undoubtedly force a shift in the transportation sector away from fossil oil. While biofuels have been presented as a short-term transitional solution, inherent problems have also been identified (Gnansounou, 2011). Subsequently, it has been proposed that a more promising solution lies in the future development of electric vehicles (Anderson et al., 2009). According to Lund and Kempton (2008), the future development of renewable energy options, such as wind, can be well aligned with future transitional shifts in the transportation sector. Importantly, a global scale transition towards plug-in electric vehicles in the transportation sector would only act to substantially reduce GHG emissions to the atmosphere (a major impetus for the transition) if the electricity used in the charging of vehicles is sourced from low carbon options, such as wind. It has also been proposed that plug-in electric vehicles might act as a short term energy storage option in places where there are regular supply-demand issues from wind energy (Short and Denholm, 2006).
A major impetus for the recent growth of the wind energy industry can be attributed to concerns regarding anthropogenic CO$_2$ emissions. The Intergovernmental Panel on Climate Change (IPCC) 5$^{th}$ Assessment report (AR5) early press release (27 September 2013) concluded “it is extremely likely that human influence has been the dominant cause of observed warming since 1950” (Stott, 2013), increasing the human attribution likelihood level from that of ‘very likely’ used in the prior assessment (AR4) (IPCC, 2007). Hansen et al. (2008) used paleoclimate data, in combination with the current understanding of ‘slow’ and ‘fast’ climate feedback processes to estimate that the then present (2008) global mean atmospheric CO$_2$ level (385ppm) was already in the ‘dangerous zone’. To avoid ‘dangerous’ climate change of +2°C by 2100, Hansen et al. (2008) suggests that immediate policy changes on a global scale are needed, aimed at reducing atmospheric CO$_2$ concentrations to a mean global average of 350ppm. Hansen et al. (2008) argues that relying on ‘green technologies’ such as carbon sequestration and capture will not alone be sufficient to reach this target even if these technologies are to become commercially viable in the coming years. Alternatively, Hansen et al. (2008) proposes that a global phase out of coal fired power-stations should occur over the next 10-25 years. Despite the call for urgent action by many commentators, global CO$_2$ concentrations in the atmosphere have continued to rise steadily and have now reached 400ppm at some recording stations.

The 2011 IPCC Special Report on Renewable Energy Sources and Climate Change Mitigation (hereon Edenhofer et al., 2011) examined the future potential of renewable energy sources in terms of climate change mitigation, identifying wind energy as one of the six most promising avenues for mitigation. While wind energy generation produces no direct CO$_2$ emissions, indirect CO$_2$ emissions (or CO$_2$ equivalent emissions (CO$_2$ e)) may come from: the production of associated parts; construction and assembling of the wind power plant parts; the transportation of parts; and the disposal, or future disposal, of parts or materials. These indirect emissions can be measured and compared against the emissions of other sources of energy generation (direct or otherwise) by comparing the carbon equivalent capacity (CO$_2$ e /KWh). Typical values are estimated at 10-20g CO$_2$ e /KWh for large scale wind farms in contrast to values of 800-1600g CO$_2$ e /KWh for large scale coal-fired power plants (Dones et al., 2003). The extent of this disparity immediately highlights the net reduction in emissions that could be achieved by the global transition in energy provision advocated for by Hansen et al. (2008).

Newly emerging research also suggests that wind energy generation is associated with a lower carbon equivalent capacity than other forms of renewable energy generation, under certain conditions (Kemenes et al., 2011). For example, the impoundment of rivers for purposes of hydroelectricity generation is capable of considerable GHG emissions in places due to: the conversion of terrestrial ecosystems to wetlands, the conversion of terrestrial and aquatic
organic matter into biogenic gas, and the rapid depressurization of water immediately below the hydroelectric turbines resulting in gas releases (Kemenes et al., 2011).

According to The New Zealand Wind Energy Association (NZWEA), in alignment with the national 2025 target of 90% electricity generation from renewable sources (currently at 75%), electricity generation from wind energy should grow at a greater rate than other forms of renewable energy generation in the coming years (NZWEA, 2013). As of 2012, wind energy supplies approximately 5% (622MW) of New Zealand’s total electricity generation; however it has been forecasted that an increase up to 3500MW by 2030 is possible (NZWEA, 2013). It has been proposed that the increase in installed capacity is viable because of New Zealand’s “spectacular” wind resource and because of the recent development of wind energy technologies, which in combination make wind energy cost-competitive against fossil electricity (NZWEA, 2013).

2.3 Scale of atmospheric phenomenon

‘Wind’ is the movement of air relative to the earth’s surface, and is represented as a vector quantity of both magnitude and direction. Wind can be considered in the horizontal directions or vertical direction, depending on the scale concerned with and the purpose for which the motion is being investigated (Sturman and Tapper, 2006). Wind occurs as air flows according to horizontal or vertical pressure gradients; however the underlying mechanism for generation, and modification of wind fields, depend on the scale in the atmosphere over which the wind is generated and operates.

Atmospheric phenomena operate over a range of spatial-temporal scales: from the macro scale where long waves, jetstreams and cyclones operate, down to the micro scale where small eddies and turbulence are induced by the slightest variations in surface roughness (Whiteman, 2000; Sturman and Tapper, 2006) (Figure 2.1). The concept of spatial-temporal scale has long been central to the atmospheric sciences (Orlanski, 1975), but in the past has led to strong demarcations in research incentives (for example micrometeorology and synoptic meteorology) with limited integration (Sturman and Tapper, 2006). Doswell (1987) criticized such a demarcation claiming that researchers limiting their focus to studying (mesoscale) meteorological aspects that occur over a particular length of time and space fail to grasp the idea that understanding these (mesoscale) meteorological aspects in full requires consideration of processes from microphysics to the global circulation. Today, this is perhaps better recognized, with a large body of research dedicated to conceptualizing and modelling how processes operating on different scales interact (Sturman and Tapper, 2006).
Orlanski (1975) provided an early and useful method for subdividing scales over which atmospheric phenomena operate. This was a ‘rational method’ that divided atmospheric phenomena broadly into micro, meso and macro components, each with corresponding alpha, beta and gamma subcomponents of different lengths (Figure 2.1). However, Doswell (1987) criticized Orlanski’s division as being arbitrary concerning the scale component interface (when one component begins and the other ends). Doswell (1987) also claimed that other attempts to apply a classification scheme that is based more on physical processes, such as dominant force balances, have also fallen short as these are not well understood at certain scales. Despite the criticisms of Doswell (1987), empirical evidence from pioneering studies employing spectral analysis techniques (e.g. Panofsky, 1955) was already in existence to support Orlanski’s three-fold division.

![Figure 2.1: Division of atmospheric phenomena according to time and distance scales (from: Sturman and Tapper, 2006 and adapted from Oke, 1987).](image)
Since Orlanski’s division of components, a local scale component is often described, occurring between micro and mesoscale components (Figure 2.1) (Oke, 1987). Furthermore, a synoptic scale component is often described as a length scale over which features such as anticyclones and fronts operate (Sturman and Tapper, 2006). Another distinguishing feature between Orlanski’s division scheme (and those that followed) is the removal of such a rigid demarcation between scale components, due to the idea that atmospheric phenomena may occur over more than one scale component (Figure 2.1). Given the importance of scale to the study of atmospheric phenomena, the following sections of this review have been separated based on scale, whilst allowing consideration for the overlap between scales also.

2.4 The quantity of the wind resource

It is important to acknowledge that the wind resource potential at a particular site is dependent on a broad range of considerations, spanning a number of disciplines, which have received considerable attention in the literature. These include the influence of social, cultural, economic, logistic and biophysical aspects on the feasibility of a wind turbine project in a particular setting. However, encompassing such a broad consideration is beyond the scope of this study, which instead focuses on atmospheric and climate phenomena over a range of scales.

2.4.1 Synoptic scale contributions

At the synoptic scale, wind is generated in association with anticyclones and cyclones (‘high’ and ‘low’ pressure systems, respectively) which influence horizontal (and vertical) pressure gradients over large spatial areas. These pressure gradients primarily result from the differential latitudinal receipt of solar radiation over the surface of the earth at a global scale (Sturman and Tapper, 2006). The balance of the pressure gradient force and the Coriolis force (which is induced by the earth’s rotation) (geostrophic balance), results in geostrophic winds whereby airflow is directed parallel to isobars (lines of constant pressure for a given height) (Sturman and Tapper, 2006). The geostrophic balance results in airflow directed clockwise around low pressure systems (and anti-clockwise around high pressure systems) in the southern hemisphere. The gradient wind concept is an extension of the geostrophic wind which takes into account the additional centripetal force associated with curvature of the isobars; airflow at constant speed parallel to curved isobars is referred to as the gradient wind. The relative position and strength of synoptic scale systems and associated pressure gradient forces, when integrated over periods much longer than individual weather events, is a large determinant of the quantity of the wind resource in a particular geographic location for that period (Petersen et al., 1997). However, as apparent in Figure 2.2, terrain complexity can impose regionality on
the near surface wind regime through a number of mechanisms, which is reviewed in more detail in Section 2.4.2. Furthermore, individual weather events associated with synoptic “types” can modify the structure and stability of the lower atmosphere, subsequently affecting aspects of the wind resource over smaller scales (Kirchhoff and Kaminsky, 1983), as discussed in Section 2.5.

For the New Zealand region, the seasonal variability in synoptic scale atmospheric circulation is generally well understood (Sturman and Tapper, 2006), along with how synoptic weather types can be further reorganized under large scale climatic oscillations such as ENSO, IPO, SAM (Kidson and Renwick, 2002; Renwick, 2011; Jiang et al., 2012). The mid-latitude geographical position of New Zealand is situated in an area where climate is both strongly influenced by the belt of westerly winds (known as the ‘roaring forties’) and the belt of subtropical semi-permanent high pressure. These circulation features, which make a substantial contribution to the climate of New Zealand, are not stationary but shift seasonally (Fitzharris, 2010). On average, the position of the westerlies are pushed further north in winter and spring, whereas the subtropical high has a stronger influence in summer and autumn. As a result of this, spring is often the windiest season as the subtropical high belt starts to migrate southward from its winter position and pressure gradients are enhanced (more tightly constrained) over much of New Zealand. The large land mass of the Australian continent can also act to amplify seasonal variation in the synoptic circulation over New Zealand (Fitzharris, 2010). For example, in spring the thermal low pressure that often develops in the interior of the Australian continent is thought to strengthen the westerly belt over southern New Zealand.

The rugged topography of New Zealand plays a major role in influencing the airflow and subsequently the weather and climate of New Zealand. Most notably the Southern Alps disrupt the predominant westerly gradient flow over the South Island (Figure 2.3). When airflow is directed over the Southern Alps, this disruption leads to a warm and gusty NW foehn wind (Kossmann and Sturman, 2004). When airflow is channelled around the Southern Alps the resulting near surface wind direction observed over Canterbury and coastal Otago is often from the north-east directions due to splitting of the flow. The onshore north-easterly, which is most frequent in the summer months, is induced under the direction of localised pressure gradients in the lee of the Southern Alps (Kossmann and Sturman, 2004). Then, as the strong prevailing westerly winds are funnelled through Cook Straight the pressure field undergoes curvature so that the wind direction is more aligned with the Canterbury and Otago coast (McKendry et al., 1986), as conceptualized in Figure 2.3. This ‘trough-induced NE’ over southern New Zealand also interacts with the thermally induced sea breeze, complicating the regional wind field along the east coast of the South Island (Sturman and Tapper, 2006).
Figure 2.2: Long-term spatial variability in 10m annual mean wind speed across New Zealand, estimated from spatial interpolation of climate station data (from Tait et al., 2005).

Figure 2.3: Conceptualization of the effects of the Southern Alps on regional flow patterns over the South Island (from Kossmann and Sturman, 2004).
Inter-annual variability in New Zealand’s weather and climate is influenced by large scale components in the climate system including the ENSO, the IPO, and the SAM. The ENSO cycle is associated with anomalous heat exchange in the upper ocean layers between the west and east Equatorial Pacific, and while the process is restricted to the tropics the effects are experienced globally (Renwick et al., 2010). A major effect of ENSO on New Zealand climate is that ENSO typically invokes year to year variability in the strength of westerly winds over New Zealand. For example, under El Niño, tropical shifts result in cooler than normal temperatures and stronger than normal westerlies; while the opposite is on average observed under La Niña (Renwick et al., 2010). The IPO essentially acts to modulate the ENSO cycle by changing the background state of the Pacific Ocean (Salinger et al., 2001); with positive IPO, El Niño events are more predominant with stronger westerlies (Renwick et al., 2010). Lastly, the SAM causes climate variability across latitudes between the South Pole and New Zealand, varying states on a week to week basis (Renwick and Thompson, 2006). The positive phase of SAM is associated with lighter winds over New Zealand and more settled weather, whereas the negative phase of SAM is associated with increased westerlies over southern New Zealand. It is expected that large scale components in the climate system will also be affected by climate change throughout the 21st century, however much debate remains concerning the details of these changes. For example, the SAM is projected to trend positively throughout the 21st century under a range of emission scenarios, while some dampening of this trend is expected due to stratospheric Antarctic ozone recovery (Arblaster and Meehl, 2006). It has been argued by some authors (e.g. Meehl and Washington, 1996; Trenberth and Hoar, 1997) that anthropogenic greenhouse emissions may already have been responsible for a recent increase in prevalence of strong El Niño events, although this has been the subject of debate in the literature (e.g. Harrison and Larkin, 1997).

Despite research carried out to characterize the influence of large scale circulation on New Zealand climate, there is a lack of research aimed at providing detailed and explicit links between the spatial-temporal variability in major components of the synoptic scale circulation and observed variation in the wind resource in New Zealand. Some linkages were established between synoptic scale circulation and regional wind extremes in the studies of Mullan et al. (2008, 2011), however these studies generally focused on wind extremes (such as the top one percentile wind speeds) which is of limited relevance to the overall wind resource quantity. Various studies have successfully related variation in the synoptic scale circulation, and synoptic weather ‘types’ (Kidson, 1994), to other environmental applications in New Zealand, such as fire risk assessment (Gosai et al., 2004), particulate matter pollution (Appelhans et al., 2012) and precipitation (Jiang et al., 2011).
Research explicitly linking synoptic scale circulation to wind resource quantity has received more focus in the international wind resource assessment literature, but many aspects of these studies are still considered limited (Mansbach, 2010). It is suggested that the limited availability of long term wind speed data, at heights representative of wind turbines, has been a major limitation to such studies (Schreck et al., 2008). In an attempt to better understand the climatological and meteorological controls on variability in the wind climate important to Californian wind farms, Mansbach (2010) related ‘self-organizing maps’ of MLSP to near surface observations of wind speed. In doing so, Mansbach (2010) found linkages between synoptic and local influences on the wind climate and wind resource over different time scales, and also found seasonal variability in these influences. In Colorado, Clifton and Lundquist (2012) successfully utilized a k-means clustering technique to identify relationships between wind speed at wind turbine hub height and climate oscillations, with the technique thought to have practical utility for wind turbine sitting. The possible effects climate change could invoke on wind resources has also recently motivated a small community of researchers to explore linkages with large scale climate considerations (e.g. Pryor et al., 2006; Pryor and Barthelmie, 2010; Rasmussen et al., 2011), with theses linkages intended to be helpful when assessing future changes to the wind resource.

2.4.2 Sub-synoptic scale contributions

Terrain complexity (associated with different surface types and slopes) is capable of both disturbing ambient airflow (reviewed in Section 2.5) and causing localized thermally induced circulation. These flows are generated by different surface types or slope angles which alter the local radiation and energy budgets giving rise to horizontal pressure gradients.

Thermal contrasts are especially notable between land and sea (or lake) surface types. This gives rise to land-sea breezes (or lake breezes), directed onshore during the day (sea breezes) and offshore at night (land breezes) (Figure 2.4). Differences in four thermal characteristics between land and sea surface types result in land-sea breezes: (1) solar radiation is more penetrable into water thus spreading energy to a greater depth; (2) the ‘moistness’ of water changes the Bowen ratio (ratio of sensible to latent heat); (3) the heat capacity of water is greater and so is slower to heat up and cool down; (4) convection in the water fluid medium increases the efficacy of heat transport (Sturman an Tapper, 2006). These four influences combine to give rise to different diurnal rates of heating and cooling between the land and sea, such that during the day the land is generally warmer than the sea whereas at night the sea is generally warmer than the land. During the day (early morning), warmer air over land causes the vertical expansion of air and the generation of a seaward directed horizontal pressure gradient at height (return flow). As air flows seaward with height under this horizontal pressure
gradient, the air descends under a new vertical pressure gradient generated over the sea. Finally, the circulation cell is completed by a near surface horizontal pressure gradient, with near surface winds directed onshore (Figure 2.4).

At night, the land cools more rapidly than the sea to result in a directional reversal of the horizontal and vertical pressure gradients, and subsequently a reversal of the near surface flow direction (offshore) (Figure 2.4). The strength of the land-sea breeze circulation system is strongly dependent on the thermal contrast between the land and sea, and is therefore dependent on the relative rates of heating and cooling between the land and sea. Rates of heating and cooling will be at their strongest under calm, cloudless anticyclonic conditions, which is when these circulations are expected to be strongest (Azorin-Molina, 2011).

The direction and strength of the ambient synoptic flow has also been shown to affect aspects of the sea breeze (Estoque, 1962; Arritt, 1993; Gahmberg et al., 2010), despite some differences in the results obtained between studies. One of the earliest studies to examine this idea (Estoque, 1962) found that an offshore 5 ms\(^{-1}\) ambient synoptic flow was capable of intensifying and constraining the land sea temperature gradient and subsequently intensifying the sea breeze. However, in the same study, it was found that an onshore ambient synoptic flow of the same magnitude could reduce the development of the sea breeze by weakening the land sea temperature gradient. Building on the earlier work of Estoque (1962), Arritt (1993) found that the ambient synoptic flow could limit the potential for the sea breeze to reach land. For example, under offshore synoptic winds greater than 6 ms\(^{-1}\) it was found that the sea breeze remained entirely offshore. There is evidence from other studies (e.g. Segal et al., 1982; Gahmberg et al., 2010) to suggest that an offshore ambient synoptic flow of considerable magnitude can result in reduced wind speeds and ‘calm zones’ at the sea breeze front onshore convergence zone. This phenomenon is generally attributed to a dynamic pressure effect induced under the collision of opposing air masses (Gahmberg et al., 2010).

A small number of wind resource assessments in the published literature have commented on the implications of the sea breeze on the wind resource. In one such study, Oztopal et al. (2000) broadly investigated the wind energy resource across Turkey, and reported that in summer months when land-sea breezes were shown to extend further inland with greater wind speeds, a much wider region of the coast was deemed suitable for wind energy generation. Henderson et al. (2003) explained that while offshore wind turbines can be positioned to take advantage of sea breezes in electricity generation, accurately modelling sea breezes in the context of wind resource assessments presents a challenge. Furthermore, Lavagnini et al. (2003) concluded that a number of commercial based models, used widely in the wind energy industry, can produce inaccurate results in places where the sea breeze dominates the wind regime.
In addition to land-sea breezes generated by thermal contrasts, different slopes within complex terrain are also capable of generating local winds. As with land-sea breezes, the underlying mechanism for the generation of slope winds is due to the different rates of heating and cooling (of individual slopes) (Sturman and Tapper, 2006). During the day, hill or mountain slopes with aspects favourable to optimize the receipt of incoming solar radiation, warm at a greater rate compared to air further away from the slope. This generates a horizontal pressure gradient moving air up slope under what is referred to as an anabatic wind (Figure 2.5). In a valley terrain setting, as this process occurs, the cross valley circulation of sensible heat warms the local inner-valley atmosphere to form a valley wind (Figure 2.5). At night time, preferential cooling produces the opposite effect, and air directly above the slope becomes cooler and therefore more dense than air further away. As a result, and under the influence of gravity, airflow is directed downslope which is referred to as a katabatic wind. Also at night, and analogous (but in reverse direction) to the day time valley wind, a mountain wind is generated (Figure 2.5). In review of the wind power potential in Turkey, Durak and Sen (2002) reported that wind turbine siting in hilly terrain should give better regard to anabatic-katabatic flows instead of focusing solely on hill top flow conditions. Extensive discussion of the need for better observations and experiment in the U.S in wind resource assessments was provided by Schreck et al. (2008). Within this discussion it was argued that mountain valley wind systems
should be better investigated, along with the localized channelling of airflow within valleys which is generally not well exploited in turbine siting.

Figure 2.5: Conceptualization of the anabatic and valley wind (day), and the katabatic and mountain wind (night) (from Oke, 1987).

Nocturnal low level jets (LLJs) are another important atmospheric process (operating at the mesoscale) shown to be capable of contributing to the wind resource in some locations. LLJs are a wind maxima that typically occur 100-1000m above the ground and are most pronounced under stable night time conditions (Storm et al., 2009). LLJs typically develop in the presence of a stable stratified boundary layer where turbulence is generated by shear, and reduced by buoyancy. The competing effects of shear and buoyancy on turbulence acts to limit vertical mixing, thereby decoupling layers. This permits super geostrophic conditions and wind maxima as the decoupling effect reduces surface friction, accelerating the flow (Storm et al., 2009). However, in different geographic settings other physical mechanisms have also been proposed for the development of LLJs (Reiter, 1963). It is thought that the implications for LLJs on wind turbine performance can be either positive or negative depending on the circumstance. For example, in the Great Plains region (U.S), the LLJ was shown to substantially increase nocturnal wind speeds favourable for wind turbine performance (Storm et al., 2009). However, the LLJ was also shown to be capable of modifying wind shear (changes in horizontal wind speed with height) and turbulence to impose fatigue loads on wind turbines (Storm et al., 2009).
While these processes have been idealized and described separately above, in reality, and especially over complex terrain, these localised wind systems interact over a range of scales to result in spatially complex wind fields (Sturman, 1987). Lu and Turco (1994) found that the penetration of sea breezes inland could be effectively blocked by the presence of hills. Similarly, Charabi et al. (2011) also found that the inland penetration of the sea breeze was limited by a coastal mountain barrier, but also that the increased rate of morning heating on the mountain slopes caused enhanced temperature gradients that facilitated an earlier onset of the sea breeze. Jaramillo and Borja (2004) observed that in certain geographical contexts, the interaction between land-sea breezes and mountainous terrain can lead to a bimodal distribution of wind speed with particularly low and particularly high wind speeds observed at a greater frequency. In light of these studies, there is some evidence to suggest that the interaction of these systems can carry important implications for the wind resource in certain geographic settings.

### 2.4.3 Quantifying the wind resource

Section 2.4.1 and Section 2.4.2 examined synoptic and sub-synoptic scale considerations in the context of the wind resource quantity. This section describes how measurements of wind speed are commonly used to estimate the wind resource quantity in the published literature. The kinetic energy contained within a moving mass of air, transformed from potential energy by pressure forces, acts on the blades of a wind turbine to cause rotation; this mechanical energy is then used to generate electrical energy (Şahin, 2004). The extraction of kinetic energy in the wind by wind turbines is described by Equations 2.1 – 2.5. Newton’s laws of motion, in the classical mechanics paradigm, hold for motion in the atmosphere because such motion is slow enough relative to the speed of light (Stull, 1988). It has long been known in classical mechanics that the kinetic energy of a mass in motion is derivable from Newton’s second law of motion, applicable to wind resource assessments as:

\[ E = \frac{1}{2}mv^2 \]  

Equation 2.1

where: \( E \) is kinetic energy (Joules); \( m \) is air mass (kg); \( v \) is the velocity of the wind (m s\(^{-1}\)). Converting this to power \( (P) \), or energy per unit time \( (t) \) gives:

\[ P = \frac{dE}{dt} = \frac{1}{2} v^2 \frac{dm}{dt} \]  

Equation 2.2

The mass flow rate \( (dm/dt) \) (kg m\(^3\) s\(^{-1}\)) in Equation 2.2 is represented by:
\( \frac{dm}{dt} = \rho Av \)  

where: \( A \) (m\(^2\)) is the blade swept area; \( \rho \) (kg m\(^{-3}\)) is the density of air. Substituting Equation 2.3 into Equation 2.2 gives the power available:

\[
P = \frac{1}{2} \rho Av^3
\]

Equation 2.4

Often, the power density available (Equation 2.5) is of more relevance as this removes the blade swept area \( A \) from the calculation which is dependent on the particular turbine model:

\[
\frac{P}{A} = \frac{1}{2} \rho v^3
\]

Equation 2.5

However, not all the energy available in the wind, as calculated in Equation 2.5, can be used to generate electrical energy. Betz’ Law describes the theoretical upper limit to the amount of kinetic energy in the wind that can be converted into mechanical energy to rotate the turbine blade (Şahin, 2004). This idea is contained within the power coefficient \( (Cp) \) and is often quoted in wind assessments in the literature as being equal to 0.593 (e.g. Mayhoub and Azzam, 1997; Keyhani et al., 2010; Mostafaeipour et al., 2011). However, Şahin (2004) claims that Betz’ Law fails to consider unavoidable ‘swirl losses’ which likely reduce the maximum theoretical power coefficient form 0.593 to 0.42 or less. In reality, operational wind turbines can have a power coefficient as low as 0.25 (Shaahid and Elhadidy, 1994). Therefore, after adjusting for Betz’ Law and other losses, Equation 2.5 becomes:

\[
\frac{P}{A} = \frac{1}{2} \rho v^3 Cp
\]

\( Where \ Cp < 0.593 \)

Equation 2.6

Despite issues of inefficiency, the cubic proportionality between wind speed and power available emphasizes the importance of highly accurate wind speed measurements and modelling simulations, when assessing the feasibility of the wind resource at a particular site. For example, Schreck et al. (2008) estimated that a 1% error in wind speed estimates, for a 100MW wind turbine plant, could amount to losses of up to US $12,000,000 over the predicted life time of the plant.

Equation 2.6 could be multiplied by a certain time period to estimate the energy generated over that time period. However, such an approach assumes that the wind speed would remain
constant (or would be well represented by a mean wind speed) over that time period, which is generally not true given the stochastic nature of wind speeds (Mostafaeipour et al. 2011). Therefore, in order to take account for the magnitude and duration of different wind events, a frequency distribution of wind speeds is generally relied upon, and Equation 2.6 becomes:

$$\frac{P}{A} = \frac{1}{2} \rho C_p \int_0^{\infty} v^3 f(v) dv$$

Equation 2.7

where: $f(v)$ is the distribution function.

In the literature wind speed distributions have in the past been represented by various probability functions including gamma, Rayleigh, lognormal and three parameter beta functions (Mostafaeipour et al., 2011). However, the two-parameter Weibull distribution is now the most commonly used and accepted method, and is built into a number of commercial software applications used widely in the wind energy industry (Akdag and Dinler, 2009). Much of the literature has also been devoted to assessing, and subsequently confirming, the relative appropriateness of applying the Weibull distribution in wind energy resource assessments (e.g. Celik, 2003; Kose et al., 2004; Zhou et al., 2006; Akdag and Dinler, 2009). The main weakness of the Weibull distribution is that the distribution can be less representative of wind speeds when local scale phenomena influence the wind speed distribution substantially in complex terrain (Jaramillo and Borja, 2004).

Application of the Weibull distribution function generally involves calculating both the Weibull scale parameter ($c$) (m/s) and the Weibull shape parameter ($k$) (dimensionless), based measurements of wind speed at the site under investigation (Mostafaeipour et al. 2011). A higher value of $c$ implies that the distribution is spread over a wider range of velocities about the mean velocity, and that the mean wind velocity is also higher (compared to a low value of $c$). A higher value of $k$ implies that the distribution is skewed towards higher velocities.

### 2.5 Smaller scale considerations

The previous section discussed contributions to the wind resource quantity over relatively large spatial-temporal scales. However, the “quality” of the resource at a particular location is not so easily determined (Katurji, 2011). The “quality” of the resource is instead determined by time variant properties of flow within hours, minutes, seconds, and sub-second periods. The stability and turbulence in the lowest levels of the atmosphere play an important role in influencing wind shear and the performance of wind turbines (Wharton and Lundquist, 2010). These characteristics are strongly time dependent due to the nature of turbulence and the
diurnal development of the atmospheric boundary layer structure; and also strongly spatially
dependent in complex terrain due to terrain variability.

2.5.1 The atmospheric boundary layer

Stull (1988) defines the atmospheric boundary layer (ABL), sometimes referred to as the
planetary boundary layer (PBL), as being the part of the troposphere that is directly affected by
the presence of the earth’s surface responding to forcings over a timescale of generally less than
one hour. Both horizontal and vertical motion occur within the ABL, however the relative
dominance depends on the scale considered (Stull, 1988). For example, vertical motion tends
to dominate in the microscale; whereas horizontal motion dominates over scales above this
(Sturman and Tapper, 2006). Both horizontal and vertical motions within the ABL have direct
and indirect consequences on the wind energy potential for wind turbines, as discussed in the
following sections.

2.5.1.1 Atmospheric boundary layer structure

The depth of the boundary layer can vary diurnally from hundreds of metres to a few kilometres
(Stull, 1988); however the structure of the ABL has been presented more generally. The
structure of the ABL can be presented in terms of three main regions - the outer region (or
Ekman layer), the surface layer (or inner layer), and the roughness layer (or interfacial layer),
with some spatial overlap between these (Figure 2.6).

![Figure 2.6: Schematic of ABL structure with height (z), occurring between the aerodynamic roughness
length (Zo) and the boundary-layer depth (h), for aerodynamically rough flow in neutrally-stratified
conditions (adapted from Garratt, 1994).]
The outer region is the region higher up in the ABL where flow is much less influenced by surface characteristics, but instead dominated by the Coriolis force under the rotation of the Earth. In contrast, the surface layer is largely dominated by surface characteristics while rotation has little effect on flow. Within the surface layer, turbulent fluxes are assumed to vary in magnitude by less than 10% with height (Stull, 1988). The roughness layer, located just above surface roughness elements, is strongly influenced by molecular diffusion (Garratt, 1994). Atmospheric motion within the surface layer of the ABL is of most relevance to wind resource assessments because of typical wind turbine hub heights (Schreck et al., 2008), therefore surface layer processes are the focus of the following sections.

2.5.2 Turbulent flows

Turbulence has been investigated in a number of disciplines outside of the atmospheric sciences, and how turbulence is regarded depends also on the objectives of that discipline or application (Katurji, 2011). Garratt (1994) presents (non-mathematically) four characteristics of turbulent flow within the ABL, describing that turbulent flows: (1) occur in 3-dimensional space and that velocity has a rotational component (vorticity); (2) are dissipative over time requiring a continual supply of energy to maintain the turbulence; (3) are very hard to predict displaying chaotic behavior; (4) transfer mass and energy more efficiently than processes of molecular diffusion alone.

Flow within the ABL is generally fully turbulent because of the low viscosity of air and the associated large length scales. Within the ABL there is also strong interaction between eddies; the ‘cascading process’ (Tennekes and Lumley, 1972) describes how vortex stretching enables individual eddies to extract energy from the main flow and smaller and smaller eddies result from the instability of larger eddies (Garratt, 1994). This cascading process continues down to the molecular scale where kinetic energy is converted to heat energy under viscous dissipation, adding this energy to the flow and its surroundings. There are three main sources of turbulence in the ABL: (1) mechanical forces from shear over orography or surface roughness; (2) buoyancy forces from thermal heating of the ground; (3) advection from an upstream source. As mentioned earlier molecular diffusion is most dominant within the roughness layer, here it plays a direct role in influencing intense vertical shear over a few millimetres above roughness elements (Garratt, 1994). However, molecular diffusion plays also an important indirect role outside of the roughness layer because viscosity at the surface reduces velocity here, as a result even low speed flow over the surface can produce strong vertical shears. In turn this facilitates the continual development of shear induced turbulent eddies (Holton and Hakim, 2012). Shear induced eddies interact with convective eddies (induced under thermal heating of the ground) to create a highly effective mechanism for the transportation of heat and momentum in the surface
layer, far greater than the direct influence of molecular processes alone. Properties of the turbulent flow can also be modified by the presence of hills; these have implications for wind turbine sitting and are reviewed in Section 2.5.4.

2.5.3 Vertical profiles in the surface layer

Atmospheric stability can be thought of as a measure of how easily the atmosphere can be disturbed producing vertical motion (Sturman and Tapper, 2006). Under parcel theory, the fluid of the atmosphere contains parcels of different densities (different potential temperatures) which gives rise to atmospheric instability. The atmosphere is stable when vertical motion is resisted and unstable when vertical motion is enhanced. Turbulent motion (mechanically or thermally induced) influences the stability of the atmosphere by mixing the temperature profile and changing the lapse rate. Stability is further separated into dynamic or static, depending upon the primary forces influencing stability. Static stability is largely driven by thermal gradients whereas dynamic stability is largely driven by frictional drag over the surface or by wind shear aloft (Wharton and Lundquist, 2012).

The stability in the surface layer of the ABL exhibits a strong diurnal signal (Sturman and Tapper, 2006). Unstable conditions are common in the day time after several hours of surface heating, during which convective conditions arise and result in the development of turbulent eddies and turbulent mixing. Under unstable conditions, where conditions are well mixed, there is more likely to be a more uniform velocity flow over the blade swept area with lower values of wind shear (represented by $a$ in Equation 2.8) (Petersen et al., 1997; Wharton and Lundquist, 2012). In contrast, stable conditions are more likely to occur at night time in the absence of surface heating, during which turbulence is influenced only by mechanical forces, subsequently very little vertical mixing occurs. Under stable conditions with suppressed vertical mixing, higher magnitudes of wind shear are expected over the blade swept area (Figure 2.7).

Neutral conditions are most common during dawn or dusk under a boundary layer transitional phase, or when wind speeds are very high. Neutral conditions can ensue under high wind speeds, irrespective of surface heating (time of day), due to enhanced mechanical mixing in the surface caused by the frictional drag of the high wind speeds (Petersen et al., 1997). As shown in Figure 2.8, the shape of the wind speed profile with height is influenced by the shape of the eddies. For example, in the unstable case the vertical stretching of eddies is associated with reduced wind shear; in contrast for the stable case the horizontal stretching of eddies is associated with enhanced wind shear.

Atmospheric stability is an important consideration for airflow in the surface layer because vertical profiles of wind speed (wind shear) take different shapes depending on the stability.
Subsequently, wind shear is of direct interest to wind resource assessments as this describes the change in wind speed with height, and can be used to provide estimates of power in the wind available at different heights. Beyond this, wind shear variability can also change the power output of turbines for the same wind speed observed at hub height (Wharton and Lundquist, 2012). For example, Rareshide (2009) found that moderate to high wind shear (compared to low wind shear) led to higher power output. Similarly, Wharton and Lundquist (2012) found that stable conditions (associated with very high wind shear) were responsible for up to an average 15% increase in power generation (compared to strongly convective conditions associated with very low wind shear) for a given wind speed above 5 m s\(^{-1}\). Despite these findings, the consideration of wind shear variability in wind resource assessments remains limited (Clifton et al., 2013), and the influence of wind shear on power output appears site-specific to some extent (Vanderwende and Lundquist, 2012).

Figure 2.7: Field based measurements of wind speed profiles under different atmospheric stability regimes (from Petersen et al., 1997).

Figure 2.8: Conceptualization of the influence of eddy shape on wind shear profiles for different stability regimes (from Oke, 1987).
In wind resource assessments, wind profiles within the surface layer of the ABL, are often represented by the well-known power law approximation (Equation 2.8) (often referred to as the ‘1/7th power law’) with a static wind shear exponent of 0.143 (≈1/7) commonly applied to extrapolate wind speed measurements to turbine hub heights (Wharton and Lundquist, 2010):

\[
\frac{u_2}{u_1} = \left( \frac{z_2}{z_1} \right)^a
\]

Equation 2.8

Where \(u_1\) and \(u_2\) are wind speeds at heights \(z_1\) and \(z_2\), respectively; \(a\) is the wind shear exponent.

The wind shear exponent value (\(a\)) in Equation 2.8, (often simply referred to as the ‘wind shear’ in wind resource assessments), represents the time-averaged ‘shape’ of the vertical profile of horizontal wind speeds (\(du/dz\)), which is assumed to be logarithmic. Despite the wide spread application of Equation 2.8 in the wind resource assessment literature, some commentators have raised concern about how well this represents vertical profiles of wind speed in reality, as a generalized expression (Focken and Lange, 2006; Wharton and Lundquist, 2010; Storm and Basu, 2010). Rather than being theoretically derived from principals of fluid mechanics, the power law (Equation 2.8) is derived empirically from a limited number of field experiments carried out in a select number of geographical contexts. Secondly, the power law is generally only valid under neutral stability in flat horizontally homogenous terrain. In particular, the power law neglects the influence of (variable) atmospheric stability on vertical profiles of wind speed (as conceptualized in Figure 2.7). Finally, wind shear may be variable across the blade swept area which is unaccounted for by the power law (Wharton and Lundquist, 2010). Despite these issues, a number of wind resource assessments still rely on the power law, under the assumption that a static coefficient \(a\) can realistically represent averaged vertical profiles of wind speed. In contrast, Storm and Basu (2010) call for the abandonment of standardized values for wind shear exponents in wind resource assessments.

While the influence of atmospheric stability on near surface vertical profiles of wind speed is well established in boundary-layer meteorology theory, part of the reason why atmospheric stability is often not incorporated into wind resource assessments is due to the added difficulty of measuring it (Focken and Lange, 2006). Due to practical reasons, measurements of temperature at different heights throughout the ABL are rarely available, such that parameterizations of stability are often relied on (Wharton and Lundquist, 2010). Today, the Obukhov length (\(L\)) is now generally recognized by boundary-layer meteorologists as the most useful way to parameterize stability in the surface layer for a range of applications, in which \(L\) is assumed constant in this layer (Kaimal and Finnigan, 1994):
where: $g$ is the acceleration due to gravity; $\theta_v$ is the virtual potential temperature; $\overline{w' \theta_v'}$ is the covariance of $w$ and $\theta_v$; $k$ is the von-Karman constant. The turbulent components ($u'$, $v'$, $w'$) of the wind speed are the deviations in the instantaneous orthogonal wind speed directions ($u(t)$, $v(t)$, $w(t)$). Friction velocity ($u_*$) is derived as:

$$u_* = \sqrt{\frac{4}{\overline{u'w'^2}} + \overline{v'w'^2}}$$

where: $\overline{u'w'}$ is the covariance of the $u$ and $w$ terms; $\overline{v'w'}$ is the covariance of the $v$ and $w$ terms.

The physical interpretation of the Obukhov length ($L$) is that $L$ represents the height at which thermal generated turbulence begins to dominate over shear generated turbulence (Wharton and Lundquist, 2010). Under statically unstable conditions, when the heat flux is directed away from the surface, $L$ is negative. In contrast under statically stable conditions, when the heat flux is directed towards the surface, $L$ is positive. Lastly, $L$ approaches zero for neutral stability conditions.

The seminal work of Monin and Obukhov (1954) laid the foundations for the development and widespread application of the similarity theory (MOST) framework in the surface layer. The authors proposed that dimensionless ‘state variables’ (momentum flux, heat flux, wind shear, temperature gradient), expressed as functions of the vertical coordinate, could be related through a set of governing equations (Wang and Bras, 2010). Through this, the wind speed at a height in the surface layer can be determined (Equation 2.11) and the wind speed at a reference height ($u_1$) can be extrapolated to greater height ($u_2$) in the surface layer (Equation 2.12). The Businger-Dyer stability functions (Dyer and Hicks, 1970; Businger et al., 1971), commonly found over flat terrain, are often used (Equations 2.13 - 2.16). By taking stability into account in the vertical extrapolation of wind speeds, Equation 2.12 can be considered the diabatic version of the adiabatic profile presented earlier (Equation 2.8).

$$u(z) = \frac{u_*}{k} \left[ \ln \left( \frac{z}{z_o} \right) - \varphi \left( \frac{z}{L} \right) \right]$$

$$u_2 = \frac{u_1}{\ln \left( \frac{z_2}{z_o} \right) - \varphi \left( \frac{z_2}{L} \right)}$$

where: $z_o$ is the roughness length, and $\varphi$ is a stability function dependent on the Obukhov length ($L$):
Through incorporating the effect of stability on vertical profiles of wind speed, it is expected that the use of Equation 2.12 should give more realistic predictions of upper level wind speeds than Equation 2.8, when extrapolating wind speeds from a reference height to higher elevations. Focken and Lange (2006) found the thermally corrected (diabatic) wind profile performed better than the adiabatic profile over a range of conditions, even when the validity of MOST was theoretically questionable. The inferior performance of the adiabatic profile in Focken and Lange (2006) was due to an underestimation of wind speeds in the stable \((z/L > 0)\) domain and an overestimation in the unstable domain \((z/L < 0)\) (Figure 2.9).

The MOST framework has been subject to a number of experiments aimed to test its appropriateness over flat terrain (e.g. Wyngaard and Cote, 1971; Dyer and Hicks, 1970; Businger et al., 1971; Kader and Yaglom, 1990). These early and famous experiments extensively sort out flat terrain to carry out their experiments to eliminate any influence from horizontal fluxes (Wood, 2000). It should be emphasized that the applicability of MOST is potentially limited to flat terrain, at least from a theoretical perspective (Kaimal and Finnigan, 1994). This is partly because the traditional form of MOST relies on the assumption of limited flux divergence in the surface layer which can be violated in complex terrain if surface fluxes become dependent on height (Pegahfar and Bidokhti, 2013). Even in ideal conditions, the performance of MOST can be impaired under very stable and very convective conditions (Pahlow et al., 2001). While theoretical based correction factors have been proposed under different stability regimes, these continue to lack field based examination (Pahlow et al., 2001; Gryning et al., 2007). It has also been demonstrated that MOST might not be valid in conditions where top-down forced boundary layer conditions are prevalent, such as in the
presence of low level jets (Mahrt and Vickers, 2002). A number of studies (e.g. Holtslag, 1984; Gryning et al., 2007; Pena et al. 2008) have investigated the reliability of MOST at greater elevations up to the ceiling of the surface layer and into the outer layer of the ABL. According to Gryning et al. (2007) the upper elevation limit for the applicability of MOST can be problematic for wind resource assessments, with some large modern wind turbines extending beyond the surface layer for much of the time.

Figure 2.9: Ratio bias in the extrapolation as a function of stability for the 1/7th power law (left) and MOST (right) (from Focken and Lange, 2006).

2.5.4 Flow modification by complex terrain

In New Zealand most commercial wind farms are situated in terrain that might be considered ‘complex’ (Katurji, 2011). But what constitutes ‘complex terrain’, specifically? Petersen et al. (1997) asserted that there is no widely agreed upon measure of complex terrain, despite the term being often used in the wind energy literature. Petersen et al. (1997) applied the term complex terrain in the context of orographic characteristics of the landscape where the landscape consists of a mixture of hills and mountains. This lacks quantifiable measures, but Petersen et al. (1997) also asserted that complex terrain is often used to define an ‘intermediate’ type landscape, that falls between ‘hilly terrain’ where flow is mostly attached and ‘mountainous terrain’ where flow separation occurs. Whiteman (2000) provided an even more broad definition of complex terrain to include any heterogeneous landscape. Here the term complex terrain is taken to mean any change in the homogeneity of the terrain or surface type, to give regard to a range of processes influencing airflow near the surface. As described in Schreck et al. (2008), the preference for complex terrain and hilly landscapes in turbine sitting is largely due to two reasons. Firstly, higher up in the ABL wind speeds are generally of greater magnitude due to the flow being a greater distance from sources of frictional drag. Secondly, a speed up effect is observed at height over parts of the hill as the flow is mechanically forced over it.
Orography induces complicated micro scale perturbations on the mean flow, but despite the
great deal of theoretical and experimental research directed to this topic, the specifics regarding
flow dynamics over hills have proven difficult to characterize (Wood, 2000). Jackson and
Hunt (1975) presented the first comprehensive analytical model (hereon the JH linear theory) of
flow over a gentle sloping hill, providing what Wood (2000) later described as the foundation
for a developing theoretical framework to this topic. The JH linear theory provided testable
predictions of the mean wind speed changes over the crest of the hill, and proposed (albeit with
less testability) how the turbulence structure might be affected based on 2-dimensional
geometric properties of the hill. The JH linear theory also presents turbulence over hills in the
context of MOST. The authors suggested that the turbulent structure over hills exists
differently in two vertical layers (corresponding to heights \( z < l \) and \( z > l \) (Figure 2.10) that can
be defined by the geometric properties of the hill and the surface roughness by:

\[
\frac{l}{L_H} \ln \left(\frac{l}{z_o}\right) = 2k^2
\]

Equation 2.17

where: \( c = 1 \) or \( 2 \); \( L_H \) (Figure 2.10) is the length scale of the hill (defined as the horizontal
distance upwind where the elevation = 0.5\( H \), where \( H \) is the height of the hill); \( l \) is the height of
the transition between the inner and outer layer.

Given the implicit form of Equation 2.17, \( l \) cannot be solved for explicitly and generally an
iterative procedure is used to do so. Alternatively, Belcher and Hunt (1998) proposed that for
practical purposes, and in the case of ‘real hill’ geometries, \( l \) (for \( c =1 \) in Equation 2.17) can be
estimated explicitly by:

\[
l = \frac{1}{8} \left(\frac{L_H}{z_o}\right)^{0.9} z_o
\]

Equation 2.18

Within the inner region \(( z < l )\) (Figure 2.10), the turbulent structure is expected to be in
equilibrium with the current boundary layer conditions, with production and dissipation of TKE
in local equilibrium (Mann, 2000). In the outer region \(( z > l )\), the turbulent structure is instead
dominated by rapid distortion theory (RDT), as described by Townsend (1972). Under RDT, in
the outer layer, eddies with length scales larger than the length scale of the hill are advected
over the hill faster than their own turn over times. As a result, turbulence in this layer is more
modified by stretching and compression of vertex elements under the mean shear of the flow,
and the turbulence characteristics are dominated by the upstream terrain footprint (Founda et
al., 1997).
The fractional speedup ($\Delta s$) is an important concept for wind energy applications, and describes the percentage increase in wind speed as the flow is mechanically forced over the hill. The fractional speedup is defined by convention as:

$$\Delta s = \frac{\bar{u} - u_o}{u_o} = \frac{\Delta \bar{u}}{u_o}$$  \hspace{1cm} \text{Equation 2.19}$$

Where: $u_o$ is the wind speed at a reference site sufficiently far upwind to be removed from the hill’s influence on flow.

The JH linear theory provides a simple expression for the maximum speedup ($\Delta s_{\text{max}}$) of wind velocity over a hill, defined as:

$$\Delta s_{\text{max}} = \frac{\Delta \bar{u}_{\text{max}}}{u_o \left( \frac{1}{3} \right)}$$  \hspace{1cm} \text{Equation 2.20}$$

According to Kaimal and Finnigan (1994) $\Delta s_{\text{max}}$ occurs at a height of about $\frac{L}{3}$ for most hill shapes, decaying with height above this value. It is also proposed by Kaimal and Finnigan (1994) that $\Delta s_{\text{max}}$ can be predicted with approximately $\pm 15\%$ accuracy for axisymmetric hills based on the geometry of the hill through:

$$\Delta s_{\text{max}} = \frac{1.6H}{L_H}, \text{ for } \Delta s_{\text{max}} < 1.25$$  \hspace{1cm} \text{Equation 2.21}$$

Following the theoretical work of Jackson and Hunt (1975) a number of experimental studies were conducted on real hills to explicitly test certain aspects of these theoretical predictions, the
most famous of these include Black Mountain (Bradley, 1980), Blashaval (Mason and King, 1985), Askervein (Taylor and Teunissen, 1987). These experiments were all performed on 3-dimensional low sloping isolated hills, and found relatively good agreement with certain aspects of the JH linear theory and RDT (Wood, 2000). Most notably, the behaviour of the mean flow and height at which ‘speed-up’ occurs, as predicted by the JH linear theory, appeared to hold true (Wood, 2000). Ridge top experiments examining turbulence properties within the inner layer are limited (Kaimal and Finnigan, 1994). From those that do exist, a decrease in the horizontal standard deviations relative to the respective upwind values, accompanied by relatively unchanged vertical standard deviations has generally been observed (Kaimal and Finnigan, 1994; Wood, 2000).

In Section 2.53 the application of MOST over flat terrain was reviewed. In the case of complex terrain, it would be exceedingly valuable for wind resource assessors to be able to extend surface fluxes and other scalars to mean gradients of wind speed, under the MOST framework (Kaimal and Finnigan, 1994). If this were to hold, vertical profiles of wind speed could be reliably predicted based on relatively inexpensive flux measurements made near the surface. According to RDT, certain aspects of MOST might be applicable in the lower parts of the inner layer, but less applicable in the outer layer.

Field based experiments designed to explicitly test similarity theory in complex terrain are sparse, and there is not a clear consensus in the literature regarding the extent of its validity in such a setting. Moraes et al. (2005) investigated turbulent parameters in a valley, focusing on adherence to MOST with regard to wind direction and wind speed. Specifically, it was found that in some instances MOST proved adequate provided that certain conditions were met in terms of the particular wind direction and wind speed relative to the surrounding terrain. The authors observed better adherence to MOST when air masses had travelled further over less complex terrain, as might be expected. In a similar investigation, but instead over mountainous terrain, Martins et al. (2009) found that vertical velocity fluctuations followed MOST for all stability regimes and wind directions; however the horizontal velocity fluctuations followed MOST only for a limited range of wind speeds, wind directions, and stability regimes. Shao and Hacker (1990) tested aspects of MOST in a coastal setting and reported that horizontal advection induced by surface inhomogeneity might limit the application of MOST in certain instances, in such a terrain setting. Nadeau et al. (2012) tested MOST between two layers (2m and 2.5m) in a steep alpine setting to find that vertical standard deviations appeared to adhere to MOST, while non-dimensional gradients of wind velocity did not. The authors concluded that this was partially due to very shallow drainage flows inducing negative wind shear. According to Nadeau et al. (2012) further work is needed in terms of testing similarity theory in complex
terrain so that alternative forms of the wind shear gradients in the MOST framework can be established.

2.6 Numerical modelling

Wind resource assessments presented in the literature often attempt to quantify the wind resource based on wind speed and direction measurements made from existing weather stations positioned by meteorological departments (e.g. Mayhoub and Azzam, 1997; Akpinar and Akpinar, 2005; Keyhani et al., 2010; Mirhosseini et al., 2011). However, in terms of relevance and accuracy, such an approach can be limited. This is because existing stations are often situated in places unfavourable for turbine sitting, such as at airports or in locations with high population densities (Al-Yahyai et al., 2010). Additionally, measurements from meteorological departments are generally made at 10m (or lower) in height, to be in accordance with World Meteorological Organization (WMO) guidelines, requiring extrapolation of measurements to wind turbine hub heights which can be problematic (Al-Yahyai et al., 2010). One possible solution to these problems is to implement a numerical model to simulate meteorological variables and complement existing measurements. Such an approach has received recent and growing attention in the wind resource literature (Landberg et al., 2003).

Mesoscale models are generally employed for the identification and early examination of the wind resource at a potential wind farm site. Mesoscale models typically focus on processes that affect energy generation over a few hours temporally and between 1-100km spatially (Landberg et al., 2003). Over this scale, mesoscale models consider interactions between variables such as moisture, pressure and temperature within the ABL while also taking into account the stability of the atmosphere. Mesoscale models can be grouped based on the hydrostatic assumption (Al-Yahyai et al., 2010). Hydrostatic models assume that the weight of the atmosphere is balanced by the vertical pressure gradient force, hence eliminating the requirement to explicitly calculate vertical accelerations. In contrast, non-hydrostatic models calculate vertical accelerations directly, and are therefore both more complex and more computationally expensive, but assumed to be more realistic for certain applications. Models can be further separated on the basis of whether they are prognostic or diagnostic. Prognostic models solve modified time dependent hydrodynamic and thermodynamic equations; whereas diagnostic models do not forecast forward in time or solve momentum equations explicitly, instead mean wind components are resolved by solving the steady state continuity equation (mass conservation) (Ratto et al., 1994). Both prognostic and diagnostic models can be either incompressible or inelastic on the basis of whether density is assumed constant or not, in the conservation equations. Until very recently the complexity and computational expense of prognostic models
meant that diagnostic models were most often relied upon in a number of applications (Hurley et al., 2005).

A number of researchers have employed various mesoscale models to investigate the wind resource within a particular geographical location. With this intention, traditionally the most commonly used mesoscale models have been the Karlsruhe Atmospheric Mesoscale Model (KAMM), the fifth generation Penn. State/NCAR mesoscale model (MM5), or the Weather Research and Forecasting model (WRF). More recently, The Air Pollution Model (TAPM) (Hurley, 2008) has been employed in a small number of studies explicitly examining the wind resource in New Zealand and Australia (e.g. Craine et al., 2004; Cullen et al., 2012). The application of TAPM is the focus of this section hereafter.

2.6.1 TAPM

TAPM is a prognostic, non-hydrostatic (optionally), incompressible mesoscale model that employs vertical terrain following coordinates; TAPM also uses a nesting technique to allow for the inclusion of more localized scale flows (Hurley et al., 2008). TAPM’s philosophy differs from that of other mesoscale models, with TAPM designed primarily to provide practical assistance for environmental consultants. To this end the model is relatively ‘user-friendly’ and computationally inexpensive (Soriano et al., 2003; Cullen et al., 2012).

While TAPM is most frequently employed in air pollution modelling, both air pollution modelling and wind resource assessment modelling require very accurate simulations of ABL wind speed and key surface layer parameters. Given this link, investigating the usefulness of TAPM in wind resource assessments is warranted. TAPM relies on downscaling the larger-scale climatology to provide more localized simulations of near surface meteorological variables. The downscaling process in TAPM involves a number of parameterizations (Table 2.1). Like all current generation mesoscale numerical models, TAPM relies on elements of MOST to parameterize surface layer fluxes, despite the application of MOST being contentious in complex terrain, as discussed earlier.

The performance of TAPM in simulating meteorology in a complex and coastal terrain setting was examined by Zawar-Reza et al. (2005). TAPM was found capable of simulating the two most frequent wind flow patterns in that geographical context: the south-westerly identified as being associated with the general passage of cold fronts, and the north-easterly identified as being associated with sea breezes and lee trough formation. Zawar-Reza et al. (2005) described statistical measures of TAPM’s ability to resolve near-surface wind speed as ‘very good’, but slightly less than observed in some other studies (e.g. Hurley et al., 2002). The authors concluded that TAPM’s slightly reduced performance was likely due to the complexity of the
terrain, whereby under very calm conditions (anticyclonic nights) TAPM consistently over predicted the intensity of drainage winds. A similar conclusion was reached by Soriano et al. (2003), with steep terrain deemed responsible for TAPM over predicting wind speeds under katabatic events.

The ability of TAPM to resolve wind speed and direction over a range of different terrain conditions was examined by Mocioaca et al. (2009). The authors found that wind speed was poorly simulated in coastal locations due to an overestimation of the intensity of the sea breeze, and due to an inadequate prediction of the timing of transitional phases associated with the sea breeze. Mocioaca et al. (2009) also noted that statistical measures of agreement were generally greater at ridge top locations than over plains or valleys; however the authors did not investigate whether this was due to TAPM actually resolving the ridge top wind regime appropriately, or whether this was simply because the over prediction of land-sea breezes was less likely for these locations. There are some discrepancies in the published literature regarding the skill of TAPM in simulating aspects of thermally generated winds. For example, in contrast to the findings of Mocioaca et al. (2009), Soriano et al. (2003) found TAPM to be capable of predicting the timing and direction of the sea breeze ‘excellently’ while only ‘slightly’ over predicting intensity. Luhar and Hurley (2004) also found the spatial and vertical structure and timing of the sea breeze to be well simulated by TAPM. In light of these studies it appears the skill of TAPM, in terms of providing simulations of wind regimes relevant to wind resource assessments in complex terrain, is site-dependent to some extent.

Beyond these studies, notable gaps exist in the literature in terms of the provision of evidence to suggest that TAPM is appropriate for wind resource assessments in complex terrain. First, wind speed and direction simulated by TAPM is most often compared against observations at 10m height or less. While this is appropriate for air pollution studies, this is not representative of most wind turbine hub heights. Second, there is a lack of studies specifically aimed at assessing TAPM’s simulated wind speeds over ridge top terrain. Third, the ability of TAPM to reproduce probability distribution functions of observed wind speed, that are important to wind resource assessments, is completely absent from the examinations of TAPM performance in the literature.
Table 2.1: Parameterizations in the TAPM model (adapted from Hurley et al., 2005).

<table>
<thead>
<tr>
<th>Parameterization</th>
<th>Description</th>
<th>Author/ reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Turbulence</td>
<td>Prognostic equations for $E - \epsilon$, Diagnostic equations for other quantities</td>
<td>Duynkerke (1988)</td>
</tr>
<tr>
<td>Soil</td>
<td>Force-restore approach for temperature and moisture with three soil types</td>
<td>Kowalczyk et al. (1991)</td>
</tr>
<tr>
<td>Vegetation</td>
<td>Surface energy balance with Twenty-seven vegetation types</td>
<td>Kowalczyk et al. (1991)</td>
</tr>
<tr>
<td>Surface layer fluxes</td>
<td>MOST</td>
<td>Dyer and Hicks (1970)</td>
</tr>
<tr>
<td>Microphysics</td>
<td>Warm rain including condensation, evaporation, auto-conversion, collection</td>
<td>Katzfey and Ryan (1997)</td>
</tr>
<tr>
<td>Radiation (clear-sky)</td>
<td>Shortwave, Longwave (surface and elevated)</td>
<td>Mahrer and Pielke (1977)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Dilley and O’Brien (1998)</td>
</tr>
<tr>
<td>Radiation (cloudy-sky)</td>
<td>Shortwave and Longwave</td>
<td>Stephens (1978)</td>
</tr>
<tr>
<td>Grid nesting</td>
<td>One-way at lateral boundaries for prognosed momentum, temperature and moisture</td>
<td>Davies (1976)</td>
</tr>
<tr>
<td>Data assimilation (optional)</td>
<td>Momentum equations nudged based on observed inputs of wind speed</td>
<td>Stauffer and Seaman (1994)</td>
</tr>
</tbody>
</table>

2.7 Summary

Commercial scale wind energy utilization is relatively new within New Zealand, but is forecasted to grow rapidly in the coming decades in alignment with government targets for renewable energy generation. However, wind resource assessments for New Zealand presented in the published literature are sparse, especially in terms of explicitly linking the wind resource to synoptic and sub-synoptic atmospheric phenomena, and larger scale climate oscillations. The complexity of New Zealand’s terrain also likely complicates such linkages and, to some extent, imposes an aspect of regionality to these relationships. Mesoscale numerical models such as TAPM might be useful for untangling some of these linkages, and for simulating the wind resource quantity in the absence of a comprehensive field based measurement campaign, which warrants further research.
While larger scale considerations can be key determinants of wind resource quantity, microscale considerations are more associated with wind resource quality. Turbulence and wind shear within the lowest levels of the atmosphere have been shown to affect both the energy that can be extracted from the wind by wind turbines, and also the fatigue imposed on wind turbines. Wind turbines are often selectively placed in complex terrain which can modify features of the flow and turbulence in ways which are not yet completely understood. A simple adiabatic $1/7^{th}$ power law is often relied on by wind resource assessors to extrapolate wind speeds with height through a procedure that is not well aligned with boundary-layer meteorology theory. Furthermore, the performance of the $1/7^{th}$ power law might be a function of the terrain complexity, but the extent of this is not apparent in the published literature. A superior alternative to this extrapolation tool might lie within the MOST framework. However, there are theoretical limitations associated with the application of MOST in complex terrain, which might limit practical utility in wind resource assessments; the extent of these limits requires further investigation.
Chapter 3 - Methods

This chapter begins with an overview of the physical and climatological setting in which this research was carried out (Section 3.1). Section 3.2 describes the data collection procedure implemented including: the towers and instruments used, the time periods of data acquisition, and the completeness of data obtained. Section 3.3 describes the data filters and calibration factors used for each data set, and provides justification as to why these were used. Section 3.4 describes the model setup and calibration procedure used to optimize the skill of model simulations. Lastly, Section 3.5 describes the methods used in data analysis; the analysis is separated according to spatial and temporal scale following the research questions presented in Chapter 1.

3.1 Study site

3.1.1 Physical setting

Waitati is the largest township of the Blueskin Bay region; it is situated approximately 25km north of Dunedin (Figure 3.1) with a population of approximately 500 people. The landscape and terrain of the Blueskin Bay region can be considered complex, defined by its coastal setting and undulating topography of ridges and valleys (Cullen et al., 2012). Porteous Hill (approximately 400m a.s.l) lies within the Blueskin Bay region, adjacent to State highway 1, and 7km north-west of Purakanui Inlet (Figure 3.1). Porteous Hill (45.6895° S; 170.5829° E) was chosen as the physical setting to carry out this research for three main reasons. First, the site is complex in that the hill is not isolated from other forms of topography and the upwind terrain slope and roughness varies with wind direction (Figure 3.2 and Figure 3.3). This allowed investigation into how the terrain complexity (associated with certain wind direction sectors) influences properties of the local circulation. Second, the wind resource at the site is currently under examination with two existing ridge top towers making measurements of wind speeds at heights up to 30m above the surface. The measurements from these existing towers were useful in providing measurements at heights above the surface which are otherwise difficult and expensive to obtain. Third, preliminary spatial analysis of the wind resource across the wider Blueskin Bay region has been carried out in previous studies (Bowden, 2011; Cullen et al., 2012); one of the main conclusions reached in these studies was that Porteous Hill holds potential for generation in the region.
On Porteous Hill, steep slopes exceeding 30° surround the ridge top to the north and west directions, while the terrain is much less steep near the ridge top to the south and east directions (Figure 3.2 and Figure 3.3). Given that the slope of the hill is not axisymmetric, the length scale of the hill ($L_H$) (conceptualized in Figure 2.10) varies with wind direction (Table 3.1). While $L_H$ is calculated as being particularly large for the N-NE and N-NW sectors, owing to the presence of a second hill with slightly higher elevation positioned just north of Porteous Hill (Figure 3.3) the $L_H$ concept is not strictly valid here. In terms of wind directions where the $L_H$ concept is more valid, the smallest $L_H$ values (highest average slope) are observed for the W-NW and NE-E sectors while the largest $L_H$ value (lowest average slope) is observed for the S-SW sector. Based on the orientation of Porteous Hill to the coastline, the sea breeze sector is from the NE-SE.

Figure 3.1: Top panel- the location of Porteous Hill within the Blueskin bay region, and the location of a nearby AWS (T5) used in this study. Bottom panel- Photo of Porteous Hill (in background) from the perspective of Purakanui Inlet (shown in above map) facing NW.
Figure 3.2: Top panel- slope angles of Porteous Hill from a 15m resolution DEM (Columbus et al., 2011). Black contours are 20m contours > 200m a.s.l, grey contours are 20m contours < 200m a.s.l. Bottom panel- enlargement of the ridge top (highest two contours) of Porteous Hill and the relative positions (from GPS measurements) of measurement towers. Orientation of sonic anemometer heads for T4-R1 and T4-R2 is indicated by directional arrows.
Figure 3.3: 15m resolution DEM (Columbus et al., 2011) of Porteous Hill (in foreground) and surrounding landscape facing north; coordinates z:x:y exaggerated 2:1:1. The colour white indicates ocean.

Table 3.1: Length scale of hill ($L_H$) and surface type corresponding to different wind direction bins on Porteous Hill

<table>
<thead>
<tr>
<th>Wind direction bin</th>
<th>$L_H$ (km) and upwind surface type</th>
</tr>
</thead>
<tbody>
<tr>
<td>N-NE*</td>
<td>2.30</td>
</tr>
<tr>
<td>NE-E</td>
<td>0.85 (coastal)</td>
</tr>
<tr>
<td>E-SE</td>
<td>1.00 (coastal)</td>
</tr>
<tr>
<td>SE-S</td>
<td>1.10 (coastal)</td>
</tr>
<tr>
<td>S-SW</td>
<td>1.32 (forest block)</td>
</tr>
<tr>
<td>SW-W</td>
<td>1.25</td>
</tr>
<tr>
<td>W-NW</td>
<td>0.81</td>
</tr>
<tr>
<td>NW-N*</td>
<td>1.93</td>
</tr>
</tbody>
</table>

While not evident in the digital elevation model (DEM), the vegetation of the area surrounding Porteous Hill is generally comprised of agricultural grassland, exotic pine, remnants of beach forest and manuka (Cullen et al., 2012). The surrounding area is rural, comprised of agricultural and forestry land (Cullen et al., 2012). A forestry block is situated on the S-SW side of Porteous Hill, consisting of exotic pine 20 - 30m tall, at an elevation of 380m a.s.l (Figure 3.4). The nearest edge of the forest block is approximately 250m (following the terrain) from the 30m tower on the ridge top of Porteous Hill (T1) (shown in Figure 3.2).
3.1.2 Climatological setting

As described in Chapter 2, the mid-latitudinal position of New Zealand lies within a seasonally variable belt of westerly winds and semi-permanent high pressure cells, which strongly influences the climate of New Zealand. Topography also plays a major role in influencing the airflow and subsequently the weather and climate of Southern New Zealand and the Dunedin region. Most notably, the Southern Alps disrupt gradient flow from the predominant westerly winds associated with the progression of west to east moving anticyclones and frontal systems. This disruption often causes gusty north-west foehn winds or trough-induced north-east winds
over Dunedin. This trough-induced north-east wind often combines with the sea breeze to dominate the day time wind regime over Dunedin in summer months.

The vastness of the surrounding oceans also has a major influence on Dunedin climate by moderating temperature such that seasonal (and diurnal) changes in temperature near the coast are less variable than those further inland. Furthermore, air masses arriving near the coast are generally moisture laden after travelling vast distances over water (Fitzharris, 2010). Sea breezes along coastal locations of Otago can occur in all months of the year, including at the study site over a NE-SE sector (Bowden, 2011; Cullen et al., 2012). The prevailing wind direction is from the north-east and south-west (Garr and Fitzharris, 1991), which was also observed in the previous examinations of Bowden (2011) and Cullen et al. (2012) across the Blueskin Bay region. The model simulations of Bowden (2011), carried out to examine spatial variability in the wind regime across the Blueskin Bay region, suggest that terrain complexity across much of the domain affects the wind regime by channelling the prevailing synoptic winds and by generating nocturnal drainage winds.

The coastal climate of the Otago region is characterized by average daily temperatures of 10.6°C, with a winter daily average of 6.5°C and a summer daily average of 14.1°C (Garr and Fitzharris, 1991). Average rainfall is 889mm per year, which is slightly below the national average. The mean daily wind run for the Otago region is above the national average, as is the number of gales (Garr and Fitzharris, 1991).

### 3.2 Data collection procedure

Data from four on-site (on the ridge top of Porteous Hill) temporary automatic weather stations (AWS) (T1 to T4) were used in the field measurement campaign of this study. Two existing towers were used (T1 and T2) (Figure 3.5), commissioned by Energy 3/Gerrard Hassan Ltd. (GH Ltd.) and Windflow Technology Ltd., respectively. Additional towers T3 and T4 (Figure 3.6) were set up as part of this research effort to complement existing measurements by making near-surface measurements of wind speed and direction, air pressure, radiation (four components) and turbulence. The relative positions of towers T1 to T4 on the ridge top of Porteous Hill are shown in Figure 3.2 through overlaying GPS measurements of tower locations over a 15m resolution DEM (Columbus et al., 2011). A comprehensive description of each of these towers is given in Table 3.2, including the specific instruments employed and associated measurement accuracy, measurement heights and sampling rates.

Data acquisition periods and data completeness for different towers are given in Appendix A.2. The temporal component of the field measurement campaign (shown in Appendix A.2) was
designed so that the towers set up in this study (T3 and T4) made measurements over a relatively short time period (14 March 2013 – 23 May 2013), compared to that of T1 (March 2013 – August 2013) and T2 (September 2011– August 2013). This was justified on the basis that seasonal variability in near-surface measurements of radiation and turbulence (at T3 and T4) was not of direct interest, whereas seasonal variability in wind speed and direction (at T1 and T2) was of direct interest. An additional station (T5) (45.9013° S; 170.5147° E) (shown in Figure 3.1) located nearby, belonging to the National Institute of Water and Atmospheric Research (NIWA) CliFlo station network, was used to provide measurements of air pressure and temperature over a longer time period than provided by T3.

All data were stored on CSI CR1000 data loggers, which were powered by a battery and a solar panel. Measurements of wind speed from NRG #40 cup anemometers on T1 and T2 and the RM Young 5013 anemometer on T3 were averaged over 10 minute intervals (Table 3.2), as common in wind resource assessments (Wharton and Lundquist, 2010). Other measurements on T3, including temperature and relative humidity (Viasala HMP45C) and radiation (incoming and outgoing short and longwave radiation) (Kipp and Zonen CNR1) were sampled at 30 second intervals and averaged over 10 minute intervals. Measurements of air pressure (Viasala PTB110) (T3) were sampled at 30 second intervals and averaged over 1 hour intervals. Eddy-covariance measurements on T4 were sampled and stored at 20Hz, and then later averaged over 10 minute intervals to allow comparisons between other variables over the same time interval. The sampling time for eddy-covariance measurements was 20Hz. The eddy-covariance sampling frequency was chosen in alignment with other studies, although few, that have made eddy-covariance measurements in the context of wind resource assessments (e.g. Wharton and Lundquist, 2010). The high frequency storage of eddy-covariance data enabled several “data quality” filters to be employed in data pre-processing, which are described in Section 3.3. The NRG #40 cup anemometers at 15m and 30m heights on T1 were calibrated against one another before deployment in the field (GH Ltd., pers. comm.). This procedure was particularly important to minimize any bias in wind shear calculations, given that wind shear is calculated based on relative differences in wind speed between the two heights.

As shown in Appendix A.2 (Table A.2) the completeness of the data collected could generally be considered good, but varied between T1 to T4. The completeness of data across all months in which data were collected was 100% for T1 and T3. Five days of eddy-covariance data were lost (T4) due to unresolved issues with the external SD card used to store data in the data logger. Data completeness was also only 16.3% for T2 in the month of September 2012 due to battery problems. Data were also missing between 22 June and 26 July 2013 for T2 due to data logging issues (Windflow Technology Ltd., pers. comm.).
Figure 3.5: T1 (left) and T2 (right) towers commissioned by Energy 3/ GH Ltd. and Windflow Technology Ltd., respectively. Height above ground level of instruments is also indicated.

Figure 3.6: T3 (left) and T4 (right) temporary AWS employed for this study.
Table 3.2: Data collection procedure for measurements made on Porteous Hill by towers (T1-T4).

<table>
<thead>
<tr>
<th>Tower/ AWS (commissioned by)</th>
<th>Instrument</th>
<th>variables measured directly (units)</th>
<th>Measurement height</th>
<th>Data sampled (averaged)</th>
<th>Instrument accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>T1 (Energy 3 and GH Ltd.)</td>
<td>NRG #40C</td>
<td>U (m s⁻¹)</td>
<td>30m</td>
<td>1 Hz (10min)</td>
<td>±0.3 m s⁻¹</td>
</tr>
<tr>
<td></td>
<td></td>
<td>σ_u (m s⁻¹)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>NRG #200P</td>
<td>Wind direction (°)</td>
<td>30m</td>
<td>1 Hz (10min)</td>
<td>±1 % of reading</td>
</tr>
<tr>
<td></td>
<td>NRG #40C</td>
<td>U (m s⁻¹)</td>
<td>15m</td>
<td>1 Hz (10min)</td>
<td>±0.3 m s⁻¹</td>
</tr>
<tr>
<td></td>
<td></td>
<td>σ_u (m s⁻¹)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>NRG #200P</td>
<td>Wind direction (°)</td>
<td>15m</td>
<td>1 Hz (10min)</td>
<td>±1 % of reading</td>
</tr>
<tr>
<td>T2 (Windflow Technology Ltd.)</td>
<td>NRG #40C</td>
<td>U (m s⁻¹)</td>
<td>10m</td>
<td>1 Hz (10min)</td>
<td>±0.3 m s⁻¹</td>
</tr>
<tr>
<td></td>
<td></td>
<td>σ_u (m s⁻¹)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>NRG #200P</td>
<td>Wind direction (°)</td>
<td>10m</td>
<td>1 Hz (10min)</td>
<td>±1 % of reading</td>
</tr>
<tr>
<td></td>
<td>NRG #40C</td>
<td>U (m s⁻¹)</td>
<td>6m</td>
<td>1 Hz (10min)</td>
<td>±0.3 m s⁻¹</td>
</tr>
<tr>
<td></td>
<td></td>
<td>σ_u (m s⁻¹)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>T3 (this study)</td>
<td>RM Young 5013</td>
<td>U (m s⁻¹)</td>
<td>3.3m</td>
<td>1 Hz (10min)</td>
<td>±0.3 m s⁻¹</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Wind direction (°)</td>
<td></td>
<td></td>
<td>±5°</td>
</tr>
<tr>
<td></td>
<td>Violas HMP45C</td>
<td>Temperature (°C)</td>
<td>2.5m</td>
<td>30sec (10min)</td>
<td>± 0.2°C*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Relative humidity (%)</td>
<td></td>
<td></td>
<td>±3% RH*</td>
</tr>
<tr>
<td></td>
<td>Violas PTB110</td>
<td>Pressure (hPa)</td>
<td>2m</td>
<td>30sec (1 hour)</td>
<td>±0.3 hPa*</td>
</tr>
<tr>
<td></td>
<td>Kipp and Zonen</td>
<td>Kı, Kı, Lı, Lı, Lı, Lı</td>
<td>2.5m</td>
<td>30sec (10min)</td>
<td>±5% of daily total</td>
</tr>
<tr>
<td></td>
<td>CNR1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>T4 (this study)</td>
<td>CSI CSAT-3 Sonic anemometer</td>
<td>u(t), v(t), w(t)</td>
<td>2m</td>
<td>20 Hz (10min)</td>
<td>±0.08 m s⁻¹</td>
</tr>
<tr>
<td></td>
<td></td>
<td>ü, ü, ü</td>
<td></td>
<td></td>
<td>(horizontal)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>σ_u, σ_v, σ_w</td>
<td></td>
<td></td>
<td>±0.04 m s⁻¹</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(m s⁻¹)</td>
<td></td>
<td></td>
<td>(vertical)</td>
</tr>
</tbody>
</table>

Where: \( u(t), v(t), w(t) \) = instantaneous wind speed in 3 spatial dimensions; \( \bar{u}, \bar{v}, \bar{w} \) = 10 minute average wind speed in 3 spatial dimensions; \( \sigma_u, \sigma_v, \sigma_w \) = standard deviations of wind speed in 3 spatial dimensions; \( U \) = ten minute average cup wind speed; \( K_{in} \) = incoming shortwave radiation, \( K_{out} \) = outgoing shortwave, \( L_{in} \) = incoming longwave radiation, \( L_{out} \) = outgoing longwave radiation. *reported accuracy is at 20°C.
3.3 Data pre-processing procedure

This section describes and justifies the various data filters and correction factors used in data pre-processing. The section is split into different subsections for each AWS that was described earlier in Table 3.2.

AWS T1

A small number (<0.1% of total) of 10 minute time stamps recorded unrealistically high (>100 ms$^{-1}$) wind speed events at both 15m and 30m heights. It was deemed that these occurrences were due to data-logging issues and were erroneous; these occurrences were subsequently filtered from the dataset.

AWS T2

Wind direction measurements made at T2 were corrected by +114° as directed (Windflow Technology Ltd., pers. comm.). This was necessary as the offset (instrument orientation away from South) was not preprogrammed into the data logger at T2. ‘Drop-out’ wind events were also evident in the 10m wind speed time series data at T2 (GH Ltd., pers. comm.). These events occurred when wind speeds appeared to stochastically drop to 0ms$^{-1}$, while wind speeds >0 ms$^{-1}$ were concurrently recorded at the 6m height. This is evident in Appendix A.1 (Figure A.1) with a substantially higher frequency of 0 ms$^{-1}$ wind speeds recorded at the 10m height than at the 6m height. It was not possible to confidently separate which of these occurrences were due to instrument failure from those which were meaningful; as a result it was not possible to filter for this effect and subsequently wind speed measurements at the 10m height were not used in any analysis.

AWS T4

Under certain conditions the accuracy of measurements made from sonic anemometers (CSAT-3 T4) can be impaired. These are briefly discussed here along with a number of filters designed to minimize any bias on measurements made. Often, the most substantial cause for inaccuracy in measurements made from sonic anemometers comes from the influence of precipitation (CSI, 2012). This causes the sonic anemometer transducer heads to become temporarily obscured causing a low signal to noise ratio, subsequently this can lead to missing data or can cause non-stationary conditions which limit the accuracy of flux measurements. To remove
this influence, as far as practical, the following filters were employed such that if any 10 minute time stamp met either of the below conditions it was filtered from the time-series:

**Filter 1:** loss of measurements – 10 minute time stamps in which less than 95% of the 20Hz measurements (<11400 of 12000) were present were removed.

**Filter 2:** non-stationarity – 10 minute time stamps were checked for stationarity following the method of Bendat and Piersol (1966). Within this method subintervals were created over the averaging interval, and the variances in the wind speed ($\sigma_u^2$) and means in the turbulent heat flux ($Q_H$) were compared to the median ($x$) of that same value over each of the subinterval periods. Cases were then defined for each subinterval on the basis of $\sigma_u^2 < x$ or $x \leq \sigma_u^2$.

The number of changes ($N$) between these two cases in a time series indicated whether the results are independent random observations. By comparing $N$ to the known probabilities of random data, a t-test was carried out to determine whether or not the averaging interval exhibits stationarity. Under this definition, ten minute time stamps exhibiting non-stationarity under this definition were removed.

Two separate runs were carried out for the sonic anemometer measurement campaign (T4-R1 and T4-R2). This was done under the assumption that sonic anemometer measurements can be highly sensitive to interference from other nearby towers, or by the sonic anemometer mounting mast itself, leading to inaccurate measurements under certain wind directions (Kaimal and Finnigan, 1994). The sonic anemometer in R1 (14 March 2013 – 28 March 2013) was set up facing 90° to ensure that the sea breeze signal was accounted for. In contrast, the sonic anemometer in R2 (28 March 2013 – 23 May 2013) was set up facing 315° to ensure the influence of the prevailing SW-W flow signal was accounted for. The orientation of R1 and R2 is shown in Figure 3.2, labelled as T4-R1 and T4-R2 respectively. In light of this the following (further) filter was applied:

**Filter 3:** wind direction – Different wind direction filters were applied to R1 and R2 because of the different orientation of potential upwind interference between runs. Data were filtered when wind directions in R1 (R2) were from 250°-290° (110°-150°), in an attempt to remove the interference from upwind obstacles.

While not directly related to the measurement performance of sonic anemometers, it is well known that certain conditions can lead to failure of MOST even in flat terrain. These conditions include when $L$ and $u^*$ fall outside certain limits (Martins et al., 2009). Therefore, because the intention here is to test the appropriateness of MOST in complex terrain, any conditions that potentially limit the appropriateness of MOST in flat terrain should also be removed. Subsequently, the following filters were also applied:
**Filter 4:** Obukhov length ($L$) – when $|z/L| > 2$, data were filtered, as done in the studies of Cullen (2003); Martins *et al.* (2009).

**Filter 5:** Friction velocity ($u^*$) – when $u^* < 0.02$, data were filtered, as done in the studies of Basu *et al.* (2010); Pena and Hahmann (2012).

The influence of Filters 1-5 is illustrated in Figure 3.7. The scatter of data corresponding to a substantial and stochastic overestimation of wind speeds at T4 is noticeably absent after the filters were applied. Out of the 1999 possible 10 minute runs for the T4-R1 time series, the employment of Filters 1-5 removed 754 10 minute runs (37%). Out of the 7285 possible 10 minute runs for the T4-R2 time series, the employment of Filters 1-5 removed 2577 10 minute runs (35%).

Figure 3.7: Relationship between T3 and T4 wind speeds before (left) and after (right) Filters 1-5 were applied. The red line shows a 1:1 relationship, while blue line shows 1:1 line adjusted for the height difference in instruments assuming an adiabatic wind profile with constant shear of 1/7.

It is often acknowledged that tilted sonic anemometer transducer heads can substantially alter flux measurements (Kaimal and Finnigan, 1994). To limit this, as far as practical, T4 was placed over relatively flat terrain on the ridge top with the transducers levelled parallel to the terrain, as recommended by the instrument manufacturer (CSI, 2012). Additionally, a correction of the coordinate system was applied, as often done in similar studies (Founda *et al.*, 1997). This correction involves a shift from standard Cartesian coordinates to stream-wise coordinates, when analysing data, helping to correct further problems associated with instrument misalignment. The correction algorithm is described in detail in Kiamal and Finnigan (1994) and involves rotation of the individual wind vectors into the mean wind direction with $\bar{u} = \bar{w} = 0$. 
Air pressure is needed to calculate air density which is subsequently required in power density calculations (Equation 3.3). While measurements of pressure were made for the period 14 March 2013 – 23 May 2013 at T3, air pressure measurements were also taken from T5 to enable calculation of air density over a longer time period. By comparing calculations of air density from measurements made at T3 to those made at T5 (Equation 3.7 and Equation 3.8), over a time period when measurements were available from both stations (March-May 2013), it was determined that measurements at Musselburgh (T5) gave a reasonable approximation of the air density at Porteous Hill. For example, the difference in monthly average air density between Musselburgh (T5) and Porteous Hill (T3) was less than 0.6% for the period March – May 2013. Air density calculated from measurements at T5 showed strong seasonality, approaching a maximum in winter and a minimum in summer, reflecting seasonality in temperature and pressure that subsequently affect air density. Air density calculated from measurements at T5 between September 2011 and August 2013, had a maximum between seasonal difference of 3.7%. Importantly, interseasonal difference in air density recorded at T5 was substantially larger than the observed difference in air density bias at T5. This immediately highlights the advantage of using T5 as a proxy of air density on Porteous Hill instead of assuming a constant air density, which is often assumed in other studies when direct measurements are not available to be input into power density calculations (Keyhani et al., 2010).

3.4 Model setup and calibration procedure

The mesoscale numerical model used in this study was TAPM v.4 (described in Chapter 2). An attractive feature of TAPM is that the model can be run without any input from field based measurements; instead input data is accessed from a range of databases (Table 3.3). TAPM can be very sensitive to the lateral inner grid boundaries assigned in the model setup, especially in complex terrain (Hurley, 2008). To optimize the realism of the simulated wind regime, the sensitivity of TAPM to the number of grid domains and to the grid resolution was analysed in different runs and compared to observations, as suggested by Zoras et al. (2007). Following this, ‘the one factor at a time’ method (Daniel, 1973) was used to test the model sensitivity to different specifications. Given the computational resources needed to carry out different TAPM ‘runs’, as required in model calibration and sensitivity testing, it is commonplace to calibrate the model over a period of time shorter than the entire time period of the study (in this case 1 September 2011 – 31 August 2013). The calibration period (14 March 2013 – 23 May 2013) was chosen to overlap with available observations from all on-site towers (T1, T2, T3 and T4).
Over the calibration period, the performance of TAPM in terms of simulating wind speed, was compared to hourly average observed wind speed at T1, through the Pearson correlation coefficient \( r \) and the index of agreement (IOA) (Equation 3.1) measures (Willmott, 1981), as in Hurley et al. (2002).

\[
IOA = 1 - \left( \frac{\sum_{i=1}^{N} (P_i - O_i)^2}{\sum_{i=1}^{N} (|P_i - \bar{O}| + |O_i - \bar{O}|)^2} \right)
\]

Equation 3.1

where: \( P_i \) is the predicted wind speed at the \( i \)-th time step; \( O_i \) is the observed wind speed at the \( i \)-th time step; \( \bar{O} \) is the average observed wind speed.

TAPM simulates meteorological variables at set heights in the ABL including (at the lowest levels) 10m, 25m and 50m. Since measurements were made at 15m and 30m at T1 (as opposed to 10m and 25m), no direct comparisons could be made. Instead TAPM simulated wind speeds were extrapolated from 25m to 30m based on the log law (Equation 3.2) and using the median observed roughness length calculated from profile measurements of wind speed on T1:

\[
u_2 = u_1 \frac{\ln \left( \frac{z_2}{z_o} \right)}{\ln \left( \frac{z_1}{z_o} \right)}
\]

Equation 3.2

where: \( u_2 \) and \( u_1 \) are the wind speeds at height \( z_2 \) and \( z_1 \), respectively; \( z_o \) is the roughness length which is derived in Section 3.5.3 (Equation 3.11).

Four setup runs (R1, R2, R3, R4) were tested in the calibration procedure by varying the number of nested meteorological grid domains (3 or 4) and the number of grid points in the latitudinal and longitudinal directions (25 X 25 or 40 X 40). For all setup runs, 25 grid points were used in the vertical spatial dimension. With 3 domains, the domain shape was square with grid spacing set at: 30 000m (domain 3), 10 000m (domain 2) and 3 000m (domain 1). With 4 domains, the domain shape was square with grid spacing set at: 30 000m (domain 4), 10 000m (domain 3), 3 000m (domain 2) and 1000m (domain 1). An additional run (R5) was carried out to test the non-hydrostatic mode of TAPM. According to Hurley (2008), the non-hydrostatic mode may provide more realistic simulations than the hydrostatic mode if the terrain is steep and strong winds are prevalent. However, given that solutions to the non-hydrostatic equations are more complex, when run in this mode the computational run time can increase substantially and numerical instability issues may also arise (Hurley, 2008).
### Table 3.3: Description of input data used in TAPM, adapted from Hurley (2008).

<table>
<thead>
<tr>
<th>Input data type</th>
<th>Database source</th>
<th>Temporal resolution</th>
<th>Spatial resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Terrain height and land cover</strong></td>
<td>US Geological survey (USGS)</td>
<td>Not temporally variable</td>
<td>1km</td>
</tr>
<tr>
<td></td>
<td>Earth Resources Observation Systems (EROS)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Soil type</strong></td>
<td>Food and Agriculture Organizations of the United Nations (FAO-UNESCO) global soil classes</td>
<td>Not temporally variable</td>
<td>4km</td>
</tr>
<tr>
<td><strong>Leaf area index</strong></td>
<td>Boston University LIA MODIS dataset</td>
<td>5 year monthly mean</td>
<td>4km</td>
</tr>
<tr>
<td><strong>Sea surface temperature</strong></td>
<td>US National centre for Atmospheric Research (NCAR)</td>
<td>10 year monthly mean</td>
<td>100km</td>
</tr>
<tr>
<td><strong>Synoptic scale meteorology</strong></td>
<td>Australian Bureau of Meteorology</td>
<td>6 hour analyses</td>
<td>75km – 100km</td>
</tr>
<tr>
<td></td>
<td>National Centre for Environmental protection (NCEP)/ NCAR reanalysis</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### 3.5 Data analysis procedure

This section describes and justifies the use of data analysis procedures employed in this study. The section is separated into subsections on the basis of the spatial-temporal scales being analysed.

#### 3.5.1 Synoptic scale contributions

*Long term wind resource quantity*

In an attempt to extend wind speed and direction measurements back over a longer time period than that measured directly at T1, necessary to examine variability in the wind resource over seasonal time scales, the measure-correlate-predict method (MCP) was used. The MCP method is common in wind resource assessments and involves testing correlations between a reference
and a target site; where the target site is that under investigation for generation, and where the reference site (located nearby) has measurements of wind speeds made over extended periods of time (Dinler, 2013). Here the MCP method was used to reconstruct 30m wind speed time series over a longer temporal period (1 September 2011 – 31 August 2013) than that in which measurements were made at T1 (1 March – 31 August 2013). Wind speed at 6m height on T2 was used as the predictor for concurrent wind speed at 15m and 30m heights on T1 (the predictand). First, to determine the optimal setup of the linear regression model, the performance of the model was tested over two different ‘training’ time periods using: (1) 70 days (14 March 2013 – 23 May 2013) coinciding with the measurement period of T3/T4; (2) 112 days (1 March 2013 – 21 June 2013) coinciding with the longest continuous time period when wind speed measurements were concurrently available from both T1 and T2. This was carried out to investigate the extent to which the relationship between predictor and predictand variables is time dependent. The dummy variable day/night was also added in the step-wise method to the linear regression model to test the hypothesis that this addition might further improve model performance. The use of another nearby AWS ‘Taiaroa AWS’ (shown in Figure 3.1) belonging to CliFlo network of stations was also considered, due to the long term record (since 2003) of wind speed at this station. However, homogeneity problems with long-term wind data and instrumentation changes limited the usefulness of this station, as previously described in Bowden (2011). This limited the use of the station in terms of calculating Weibull parameters that are sensitive to missing data, and also limited the use of this station as a predictor in the MCP regression model. Subsequently, it was decided that the ‘Taiaroa AWS’ could not be used reliably in the analysis.

To quantify the wind resource, Weibull parameters were calculated and used to estimate the monthly mean power density in the wind $\frac{P}{A}$ (Wm$^{-2}$) (introduced in Section 2.4.3), as common in wind resource assessments (Celik, 2003). Weibull parameters were calculated based on hourly averaged wind speed as recommended by Celik (2003). To calculate the Weibull parameters, the energy pattern factor (EPF) method was used (Akdag and Dinler, 2009):

$$\frac{P}{A} = \frac{1}{2} \rho \int_0^\infty u^3 f(u)du = \frac{1}{2} \rho \frac{\Gamma(1+\frac{3}{k})}{\left[\Gamma(1+\frac{1}{k})\right]^\frac{3}{2}}$$

Equation 3.3

where: $\rho$ is air density (kg m$^{-3}$); $\Gamma(x)$ is the normal gamma distribution; $k$ is the Weibull parameter. $\Gamma(x)$ was approximated using Stirling’s approximation of the gamma function (Celik, 2003), with up to the 4th order terms of the expansion given in Equation 3.4:

$$\Gamma(x) = x^{x-0.5}e^{-x}\sqrt{\pi}(1 + \frac{1}{12x} + \frac{1}{288x^2} - \frac{139}{51840x^3} - \frac{571}{2488320x^4}) + O(\frac{1}{x^5})$$

Equation 3.4
The $k$ parameter is calculated by first calculating the $EPF$ based on time-series of wind speed ($u$) data:

$$k = 1 + \frac{3.69}{EPF^2}$$  \hspace{1cm} \text{Equation 3.5}

where:

$$EPF = \frac{\overline{u^3}}{(u)^3}$$  \hspace{1cm} \text{Equation 3.6}

Air density was calculated using Equation 3.7 for the period of time when on site pressure measurements were made at T3, and Equation 3.8 for the period of time when pressure measurements were made off site at T5, as in Rehman and Al-Abbadi (2005). Equation 3.8 is a modified version of Equation 3.7, and was employed to adjust for the different heights above sea level of stations T3 and T5.

$$\rho = \frac{P}{RT}$$  \hspace{1cm} \text{Equation 3.7}

where: $P$ (hPa) is air pressure at measurement height; $R$ is the gas constant in dry air = 297.05 J Kg$^{-1}$ K$^{-1}$; $T$ (K) is air temperature

$$\rho = \frac{P_0}{RT} \exp\left(-\frac{gz}{RT}\right)$$  \hspace{1cm} \text{Equation 3.8}

where: $P_0$ (hPa) is sea-level adjusted pressure; $z$ (m) is height a.s.l.; $g$ is acceleration due to gravity = 9.81 m s$^{-1}$.

A validation test was carried out whereby the MCP method and TAPM simulations were compared against direct measurements from T1, in terms of performance in calculating monthly mean wind speed, Weibull distribution parameters and monthly mean power density for the period when observational data were available at T1 (March 2013 – August 2013). This was carried out with the intention that, given an acceptable level of performance in the MCP method and in TAPM over this validation period, the MCP method and TAPM could be used to calculate monthly average power density prior to March 2013.

**Monthly average MSLP linkage**

Reanalysis data assimilates satellite data and in-situ meteorological data into global circulation models to provide global data sets for a range of meteorological parameters at various levels throughout the troposphere. The widely used NCEP/NCAR global reanalysis dataset (Kalnay et al., 1996) at 2.5$^\circ$ grid resolution was used to plot monthly average mean sea level pressure
(MSLP) for the New Zealand region, for the period between September 2011 and August 2013. This aligned with the time period of the reconstructed time series at T1 (by the MCP method) and permitted a qualitative investigation into how the reorganization of synoptic scale circulation over monthly and seasonal time scales might contribute to variation in the wind resource potential. The MSLP field was also plotted in space for the five month composites displaying the highest monthly mean power density (top 20th percentile) minus the five months displaying the lowest monthly mean power density (bottom 20th percentile). Statistical difference of MSLP composites in space was calculated based on the student’s t-test.

Kidson types linkage

In the previous subsection, the methodology was designed to examine links between changes in the monthly average MSLP and changes in the monthly wind resource potential in a qualitatively and semi-quantitatively way. However, substantial variability in the synoptic situation exists over the course of one month, and some of this variability might not be adequately accounted for when only the monthly mean state of the atmosphere is considered. In the analytical procedure described in this subsection, the mean synoptic state of the atmosphere was defined over much shorter time periods (12 hours) and linked to wind ‘events’ through a probabilistic analysis of Kidson type classifications (Kidson, 1994). This was carried out to capture intramonthly variability in the synoptic situation, and to examine the sensitivity of the linkages to the averaging time period chosen.

Kidson type classifications were presented twice daily for the period between September 2011 and August 2013. Kidson types are based on an objective technique used to classify variability in local atmospheric circulation and weather types over the New Zealand region (Figure 3.8). Kidson types are classified into 12 types twice daily (0000 UTC and 1200 UTC) from the 1000hPa height NCEP/NCAR reanalysis data (Renwick, 2011). The classification procedure involves a combined principal component analysis (PCA) and cluster analysis procedure (Kidson, 2000). The first stage of the classification involves defining principal components (PC) based on the covariance matrix of the grid point values, to obtain five significant leading PCs. Cluster analysis (k-means clustering) is then undertaken with the time-series PCs to identify departure patterns (similarity to the mean 1000hPa height field). Within this, each height field (corresponding to a certain time step) is projected onto the PC function patterns of the 1000hPa height. The difference (root-mean square difference) is then calculated based on comparisons between the PC scores under a given height field and the PC scores for the mean cluster patterns, and is used to classify the synoptic type.
Figure 3.8: Composite patterns of 1000hPa height for the various Kidson types and regime groups. Frequency of occurrence is also given for each type analysed for the period January 1958 to July 1997 (from Kidson, 2000).

Links between the Kidson types and the wind resource potential were investigated in a probabilistic way through the use of a binary logistic regression model within the generalized linear model (GLM) family of statistical tests. The use of the GLM approach has received recent attention in environmental studies (Jiang et al., 2011). Within this approach the normal linear regression model is generalized so that the response variable is related through a link function with the variance of each observation as a function of its predicted value. The use of multivariate methods (such as GLMs) are advantageous (over univariate methods) in many situations as they permit the researcher to investigate the influence of the simultaneous combined interaction of predictor variables on the predictand.

Initially, two separate binary logistic regression models were employed, the first with ‘minimum generation day’ set as the binary response variable (predictand) and the second with ‘maximum generation day’ set as the binary response variable (predictand). Although somewhat sensitive to the particular turbine characteristics, small standard modern day wind turbine power curves (energy extracted as a function of wind speed) have cut-in wind speeds
generally $> 3$ ms$^{-1}$ (wind speeds below 3 ms$^{-1}$ do not generate any power), while wind speeds in the range of 10-25 ms$^{-1}$ produce almost constant and approximately maximum power (Capps et al., 2012). Based on these considerations, a ‘maximum generation day’ was defined over a 12 hour period where the 12 hour average wind speed was between 10 and 25 ms$^{-1}$; in contrast a ‘minimum generation day’ was defined over a 12 hour period where the 12 hour average wind speed was less than 3 ms$^{-1}$. Maximum and minimum generation day events were defined from the MCP 30m data over the period 1 September 2011 – 31 August 2013. The two covariates (categorical predictor variables) used in each of the logistic regression models were Kidson type and month of year, with the intention of investigating what Kidson types and months were responsible for changing the probability of a maximum or minimum generation day occurrence. Month of year was included in the analysis based on the assumption that the relationship between a particular Kidson type and wind speed may be also dependent on month. An additional (for both minimum generation day occurrence and maximum generation day occurrence) binary logistic regression model was employed with a single covariate as Kidson regime group (Figure 3.8). The logistic regression model can be expressed mathematically in matrix notation as:

$$\ln \left[ \frac{p_i}{(1-p_i)} \right] = X_i^T \beta$$  \hspace{1cm} \text{Equation 3.9}$$

Where: $p_i$ is the probability of a binary event occurrence, $X_i^T$ is the input data matrix transposed and $\beta$ is the parameter vector.

The logistic regression model can also be expressed conceptually as:

$$\ln \left[ \frac{p_i}{(1-p_i)} \right] = \text{constant} + \text{effect of covariate 1} + \text{effect of covariate 2} + \cdots + \text{effect of covariate n}$$  \hspace{1cm} \text{Equation 3.10}$$

In the logistic regression model the parameters contained within the vector $\beta$ (Equation 3.9), must be specified relative to a reference category for each covariate. The Kidson type H and blocking Kidson regime group was chosen as the reference category in the Kidson type/regime group covariates to model the effects of differences away from conditions where there is very little or no synoptic pressure gradient. The month of December was arbitrarily chosen as the reference category in the month of year covariate. The performance of the model was assessed by plotting a receiver operating characteristic curve (ROC) which allowed the relationship between sensitivity and specificity of the model to be analysed. In this analysis ‘an area under the curve’ (AUC) $> 0.7$ was used as an indicator of model skill (Jiang et al., 2011)
3.5.2 Sub-synoptic scale contributions

Observations

Over the T3 period, ten days were selected where the development of a localized thermally generated circulation was likely to occur. To identify these days, synoptic analysis of MSLP from the NCEP/NCAR re-analysis data was used along with local ridge top measurements of incoming shortwave solar radiation \( (K_{in}) \) from T3. Days where relatively weak synoptic scale pressure gradients were present and days where the diurnal cycle of \( K_{in} \) was relatively unimpeded by clouds (shown in Figure 5.1), were deemed most favourable for the development of thermally generated circulation. Over these select days, an analysis of wind speed and wind direction with respect hour of day was carried out. This was done based on observational data from T1 (15m and 30m) and T3 (3.3m), with comparisons made between these heights to investigate the extent to which features of the circulation extend throughout the lower part of the ABL (up to 30m). After exploring thermally induced wind phenomenon under ideal conditions, the analysis was carried out for all data (not just ideal conditions) under different seasons to investigate the seasonality of the timing, magnitude and persistence of thermally induced winds.

TAPM simulations

Modelled simulations of wind speed and wind direction with respect to time were also analysed using the same ten days deemed favourable for the generation of thermal winds. This was carried out, and compared to observations, to determine the capability of TAPM in simulating the onset and magnitude of thermally generated winds. After exploring TAPM’s ability to generate thermally induced circulation features under ideal conditions, the analysis was again carried out for all data (not just ideal conditions) under different seasons to investigate seasonal changes in the timing, magnitude and persistence of the circulation; this analysis was then compared to observations.

To explore the possible effects of ambient synoptic flow on sea breeze dynamics, idealized TAPM experiments were setup by artificially adjusting the ambient synoptic wind speed and direction in the model. Separate experiments were carried out across a two day subset of the ten day study period examined earlier; these two days (March 21 – March 22, 2013) were dominated by weak synoptic pressure gradients and clear skies. The study period for idealized TAPM experiments was limited to two days, as idealized simulations carried out by adjusting ambient synoptic conditions in TAPM can result in numerical and thermodynamic instabilities when run over extended periods of time (Zawar-Reza, pers. comm.). Six experiments were
carried out by separately forcing the following ambient synoptic conditions over this two day period: (1) 3 m\(s^{-1}\) synoptic westerly; (2) 5 m\(s^{-1}\) synoptic westerly; (3) 10 m\(s^{-1}\) synoptic westerly; (4) 3 m\(s^{-1}\) synoptic north-easterly; (5) 5 m\(s^{-1}\) synoptic north-easterly; (6) 10 m\(s^{-1}\) synoptic north-easterly.

In an attempt to quantify the overall contribution of the sea breeze to the wind resource quantity at this site, a simple model experiment was carried out whereby TAPM was rerun over the period 1 September 2011 – 31 August 2013 with water ‘removed’ from all model domains. The wind resource quantity (calculated in terms of the monthly mean power density) was then reassessed relative to the default model setup where water was present. The removal of water in this experiment was carried out by recoding water surface types to ‘mid-dense tussock’ across all model domains. ‘Mid-dense tussock’ was chosen as the replacement surface type as this was the predominant surface type on Porteous Hill, hence eliminating the possibility for the development of additional (unrealistic) thermally induced local winds, potentially generated under (unrealistic) land use gradients.

### 3.5.3 Microscale considerations

#### Geometric properties of Porteous Hill

The geometry of Porteous Hill, expressed in terms of \(L_H\) (conceptualized in Figure 2.10), was determined from the 15m resolution DEM of Columbus et al. (2011). From this, \(L_H\) was determined for the centre direction vector within each of the eight wind direction bins (ie. 22.5\(^\circ\), 67.5\(^\circ\), 112.5\(^\circ\), 157.5\(^\circ\), 202.5\(^\circ\), 247.5\(^\circ\), 292.5\(^\circ\), 337.5\(^\circ\)). The roughness length \((z_o)\) was calculated for each wind direction bin by solving the simple adiabatic wind profile equation for \(z_o\) at each 10 minute time step:

\[
    z_o = \exp\left(\frac{u_2 \ln z_1 - u_1 \ln z_2}{u_2 - u_1}\right)
\]

Equation 3.11

Although \(z_o\) is dependent on stability, for simplicity, this was not taken into consideration in this calculation. In part, this is justified because this dependency is often corrected for by MOST relationships (e.g. Conway and Cullen, 2013) however vertical gradients in wind speed do not appear to follow traditional MOST here, most of the time (as shown in Chapter 6 and Chapter 7). Furthermore, provided that stability is similar under different wind directions, this would not change the wind direction-\(z_o\) signal; therefore permitting comparisons of \(z_o\) between wind direction sectors, which was the intention here. The median \(z_o\) value and the corresponding \(L_H\) value, within each wind direction bin, were then used to estimate the height
of the corresponding inner length through the employment of Equation 2.18. The median $z_o$ value was used in this estimation (as opposed to the mean) given that the distribution of $z_o$ within each wind direction bin strongly exhibited non-normal distribution (not shown). The height (m) at which maximum speedup occurs ($h(\Delta s_{\text{max}})$) was estimated to occur at $l/3$ (as discussed in Section 2.5.4); while the magnitude of $\Delta s_{\text{max}}$ was estimated by Equation 2.21.

**Controls on wind shear**

The wind shear exponent ($a$) (hereon ‘wind shear’) was calculated by solving Equation 2.8 for $a$ and by using 10 minute averaged wind speed differences at T1 between 15m and 30m. Wind shear was calculated between 15m and 30m on T1, but not between 3.3m (T3) and 15m (T1). While lower level wind shear (3.3 - 15m) was of interest, it was deemed that estimates and conclusions drawn would be less reliable across this level because of the following reasons. First, different instruments (anemometer types) were used to measure wind speed at 3.3m compared to 15m (Table 3.2), therefore this would make it difficult to distinguish the signal of interest (wind shear) from noise induced by instrument differences, as considered to be problematic in some similar studies (Taylor and Teunissen, 1987). Second, given the position of T3 relative to T1 (Figure 3.2), airflow being measured at T3 is potentially sheltered from the T1 tower under certain wind directions which would subsequently affect the reliability of wind shear calculations.

Only wind speeds greater than 3 ms$^{-1}$ (at both 15m and 30m measurement heights) were used in the calculation and subsequent analysis of wind shear; this is common in the wind resource assessment literature (Carta et al., 2013) for three main reasons. First, wind turbines, based on standard modern day power curves, only generate electricity when the wind speed is greater than 3 ms$^{-1}$ (Capps et al., 2012), therefore the wind shear analysed here is relevant to operational conditions. Second, very low wind speeds can cause unrealistic wind shear calculations because wind speed cannot be reliably measured by cup anemometers under such conditions, related to anemometer cut-in thresholds (Wharton and Lundquist, 2010). Third, it is well recognized that wind direction measurements are less reliable under very low wind speeds, therefore by removing low wind speeds more confidence can be placed in results obtained when investigating the wind direction- wind shear signal.

The distribution of wind shear values observed between 15-30m was then considered relative to the commonly reported 0.143 value relied on in the ‘$1/7$th power law’. Contributions to observed variability in wind shear were also explored considering wind speed and direction and time of day, under the hypothesis that these variables exert important controls on wind shear. Evidence is presented in Chapter 5 to suggest that these variables exhibit some degree of
multicollinearity, which should be taken into consideration when examining the relationship between each variable and wind shear. Therefore, in an attempt to explore the unique individual effect of each variable on wind shear, the relationship between each variable and wind shear was considered after isolating the individual effect of other variables. Isolation of other variables was carried out by filtering subsets of the data where certain conditions were met and considering the induced changes to the relationship with wind shear.

*MOST and wind shear*

Theoretically, MOST is expected to be valid only within the lower part of the inner layer of hill ridge tops (Kaimal and Finnigan, 1994). To assess this, plots were produced examining the statistical relationship between standard deviations in the horizontal and vertical velocity normalized by friction velocity \( \left( \frac{\sigma_u}{u^*}, \frac{\sigma_v}{u^*}, \frac{\sigma_w}{u^*} \right) \) and stability \( z/L \) from eddy-covariance measurements made near the surface (2m) on the ridge top of Porteous Hill. This method is commonly employed in other studies to examine the suitability of MOST (e.g. Martins et al., 2009; Basu et al., 2010; Nadeau et al., 2012; Pegahfar and Bidokhti, 2013). The relationship between \( \frac{\sigma_u}{u^*}, \frac{\sigma_v}{u^*}, \frac{\sigma_w}{u^*} \) and \( z/L \) found in other studies (Table 3.4) was also plotted, along with new relationships fitted to the observed data based on adjustable parameters of the formulations. Equation fitting was carried out using a non-linear least square optimization algorithm, specifically, the Lavenberg-Marquardt algorithm was used to specify and iterate parameter values. Coefficient of determination values \( (R^2) \) for the fit of the non-linear regression formulations to the observed data were also calculated under this method. Adjustable parameter values and associated coefficient of determination values were also assessed under different conditions such as different wind speeds and directions.

The performance of MOST was then tested in terms of its ability to extrapolate 15m wind speeds to 30m, based on comparisons against observed wind speeds at 30m. The extrapolation of MOST was carried out using the Businger-Dyer stability functions (Dyer and Hicks, 1970; Businger et al., 1971) commonly found over flat terrain, as presented in Chapter 2 (Equations 2.11 - 2.16). The performance of MOST as an extrapolation tool was also compared against the performance of the more simple, and less physically derived, 1/7th power law (Equation 2.8).
Table 3.4: Non-linear regression formulations used for different variables and stability regimes. Parameters $\alpha$, $\beta$ and $\gamma$ are adjustable parameters in the best fit equations of this study.

<table>
<thead>
<tr>
<th>Variable; stability</th>
<th>Formulation</th>
<th>Parameter values</th>
<th>Authors</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\frac{\sigma w}{u^*} \frac{z}{L} &gt; 0$</td>
<td>$\frac{\sigma w}{u^*} = \alpha \left(1 + \frac{\beta z}{L}\right)$</td>
<td>$\alpha = 1.25$ $\beta = 1$ $\gamma = 3$</td>
<td>Kaimal and Finnigan (1994)</td>
</tr>
<tr>
<td>$\frac{\sigma u}{u^*} \frac{z}{L} &gt; 0$</td>
<td>$\frac{\sigma u}{u^*} = \alpha \left(1 + \frac{\beta z}{L}\right)^{1/3}$</td>
<td>$\alpha = 2.85$ $\beta = 10.55$ $\gamma = 3$</td>
<td>Nadeau et al. (2012)</td>
</tr>
<tr>
<td>$\frac{\sigma v}{u^*} \frac{z}{L} &gt; 0$</td>
<td>$\frac{\sigma v}{u^*} = \alpha \left(1 + \frac{\beta z}{L}\right)^{1/3}$</td>
<td>$\alpha = 2.33$ $\beta = 5.46$ $\gamma = 3$</td>
<td>Nadeau et al. (2012)</td>
</tr>
<tr>
<td>$\frac{\sigma w}{u^*} \frac{z}{L} &lt; 0$</td>
<td>$\frac{\sigma w}{u^*} = \alpha \left(1 - \frac{\beta z}{L}\right)^{1/3}$</td>
<td>$\alpha = 1.25$ $\beta = 3$ $\gamma = 3$</td>
<td>Kaimal and Finnigan (1994)</td>
</tr>
<tr>
<td>$\frac{\sigma u}{u^*} \frac{z}{L} &lt; 0$</td>
<td>$\frac{\sigma u}{u^*} = \alpha \left(1 - \frac{\beta z}{L}\right)^{1/3}$</td>
<td>$\alpha = 2.84$ $\beta = 3.61$ $\gamma = 3$</td>
<td>Nadeau et al. (2012)</td>
</tr>
<tr>
<td>$\frac{\sigma v}{u^*} \frac{z}{L} &lt; 0$</td>
<td>$\frac{\sigma v}{u^*} = \alpha \left(1 - \frac{\beta z}{L}\right)^{1/3}$</td>
<td>$\alpha = 2.15$ $\beta = 3.99$ $\gamma = 3$</td>
<td>Nadeau et al. (2012)</td>
</tr>
</tbody>
</table>

3.6 Research synopsis

A summary of the methodology, as presented in this chapter, is displayed in Figure 3.9. The methodology sections in Figure 3.9 are divided into ‘field and modelling methods’ and ‘analysis methods’ with further subsections separated on the basis of the spatial-temporal scale considered.
Main objective

To use a combined modelling and field-based measurement approach to assess how atmospheric and climate phenomena, over a range of spatial-temporal scales, can contribute to the quantity and quality of the wind resource in a complex terrain setting.

Synoptic scale

- NCAR/NCEP reanalysis data of monthly averaged MSLP.
- Kidson types classified twice daily.

Sub-synoptic scale

- Measurements of incoming shortwave radiation to determine conditions likely to generate thermal winds.
- Observations of thermal winds based on measurements of wind speed/direction at different heights.
- Simulated wind speed and wind direction by TAPM over periods where thermally generated winds were observed.

Micro scale

- Tower based measurements of wind shear between 15m – 30m.
- Eddy-covariance based measurements of turbulence properties, momentum fluxes and surface layer stability.

Field and modelling methods

Analysis methods

- Reconstruct winds speed over 2 years using MCP method.
- Determine the validity of wind resource quantity as simulated by TAPM.
- Investigate qualitative linkages between position of monthly average MSLP and wind power density.
- Statistically examine probabilistic relationships between Kidson types and generation event occurrence.

- Detect the presence of thermally generated winds based on observations.
- Investigate the ability of TAPM to simulate thermally generated winds, in terms of magnitude and timing, against observations.
- Using TAPM, attempt to quantify the importance of thermally generated winds in terms of power density.

- Examine the appropriateness of the 1/7th power law and MOST in estimating upper level wind speeds.
- Examine controls on wind shear variability.
- Statistically investigate the appropriateness of MOST in the complex terrain setting.

Figure 3.9: Overview of the methodology used in this thesis, as presented in this chapter.
Chapter 4 – Synoptic scale results

In this chapter the results concerning the reconstruction of time series of wind speed are presented, along with how synoptic scale considerations can be linked to variability in the reconstructed time series over different temporal resolutions. Methods for reconstruction include the MCP method and the numerical model TAPM, with results presented comparing the relative performance of these methods against observations. Variability in MSLP fields are linked with changes in wind speed and direction on monthly time scales, and variability in Kidson types are statistically linked to changes in generation potential on daily time scales.

4.1 Reconstruction using MCP method

4.1.1 Optimization of MCP regression

To reconstruct 30m wind speed time series data over a longer temporal period (1 September 2011 – 31 August 2013) than that in which measurements were made at T1 (1 March 2013 – 31 August 2013), the measure correlate predict (MCP) method was used, as common in wind resource assessments. As shown in Table 4.1, the overall performance of the MCP method (indicated by the adjusted $R^2$ values of the model) was considered good at predicting both 15m and 30m T1 wind speeds under all time period and predictor variable configurations. The model, under all configurations, was slightly better at predicting 30m wind speeds than 15m wind speeds, however these differences were found to be small. Furthermore, 30m wind speeds are of more interest, due to being more representative of (small) wind turbine hub height and are the focus hereon.

When the model was trained over a longer time period (112 days as opposed to 70 days) the performance of the model increased slightly, however the values of the constant ($\alpha$) and the slope ($\beta$) of the regression equation remained almost unchanged at both 15m and 30m. This provides confidence that the relationship between predictor and predictand variables was not strongly time dependent over the time periods considered. The inclusion of a day/night dummy variable in the regression model did not improve the statistical performance of the model, with the $R^2$ values at both 15m and 30m found to be unchanged compared to the model configuration that did not differentiate between day and night over the same time period. This provides confidence that the inclusion of the day/night dummy variable is unwarranted in the regression model used in the MCP method in this study. Regression analysis was not performed to predict T1 wind directions from T2 wind directions. As shown in Figure 4.1,
wind direction distributions from T1 were similar to those of T2, except over the SW-W sector where rotation of wind direction is observed between T1 and T2.

Table 4.1: Performance of the MCP linear regression model: $T1 = \alpha + \beta T2$ under different training periods and predictor variable configurations.

<table>
<thead>
<tr>
<th>Training time period</th>
<th>Predictor(s)</th>
<th>Predictand</th>
<th>$\alpha$</th>
<th>$\beta$</th>
<th>$adj. R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>14 March 2013 – 23 May 2013</td>
<td>T2 6m</td>
<td>T1 15m</td>
<td>-0.263</td>
<td>1.058</td>
<td>0.929</td>
</tr>
<tr>
<td></td>
<td>T1 30m</td>
<td></td>
<td>-0.040</td>
<td>1.079</td>
<td>0.933</td>
</tr>
<tr>
<td>1 March 2013 – 21 June 2013</td>
<td>T2 6m</td>
<td>T1 15m</td>
<td>-0.278</td>
<td>1.064</td>
<td>0.940</td>
</tr>
<tr>
<td></td>
<td>T1 30m</td>
<td></td>
<td>0.030</td>
<td>1.073</td>
<td>0.945</td>
</tr>
<tr>
<td>1 March 2013 – 21 June 2013</td>
<td>T2 6m with</td>
<td>T1 15m</td>
<td>-0.169</td>
<td>1.048</td>
<td>0.940</td>
</tr>
<tr>
<td></td>
<td>‘day only’</td>
<td>T1 30m</td>
<td>0.010</td>
<td>1.063</td>
<td>0.946</td>
</tr>
<tr>
<td>1 March 2013 – 21 June 2013</td>
<td>T2 6m with</td>
<td>T1 15m</td>
<td>-0.341</td>
<td>1.073</td>
<td>0.940</td>
</tr>
<tr>
<td></td>
<td>‘night only’</td>
<td>T1 30m</td>
<td>0.039</td>
<td>1.080</td>
<td>0.945</td>
</tr>
</tbody>
</table>

Figure 4.1: Difference in wind direction distributions between T2 (left) and T1 (right) for the 1 March – 21 June 2013 regression period. Colour legend indicates wind speed bins in ms⁻¹.

4.1.2 Performance of MCP regression

Before considering how the MCP method performed in terms of predicting Weibull parameters, it was important to first test whether observational data from T1 followed a Weibull distribution. This is especially important in complex terrain where local circulation and topographic blocking might distort wind speed distributions away from the traditionally
reported Weibull distribution. The closeness of fit to the Weibull distribution as indicated by
the Q-Q plot in Figure 4.2, suggests that 30m observed wind speed at T1 could be adequately
modelled by a Weibull distribution for wind speeds greater than approximately 1 ms\(^{-1}\).

After the optimal setup for the linear regression model was determined, the MCP method was
used to reconstruct wind speeds at T1 for the period 1 September 2011 - 31 August 2013.
Since it was determined that wind speeds could be adequately modelled by a Weibull
distribution in this geographical setting, the MCP time series data (at an hourly resolution) was
then used to calculate the monthly mean wind speed and the monthly Weibull distribution
parameters, necessary to calculate the mean power density in the wind at 30m. The mean
monthly wind speed, the monthly Weibull distributions, and the monthly power
density, were examined for the overlap period between March 2013 and 31 August 2013 where both
observational data at T1 and the MCP-reconstructed data at T1 were available.

The performance of the MCP method in terms of predicting the monthly mean 30m wind speed
varied between months, however for all months examined the percentage bias in predicted
monthly mean wind speeds (relative to observed monthly mean wind speeds) was less than 3%
(Figure 4.3). The MCP method did not consistently under predict or over predict monthly
mean wind speeds, with both positive and negative biases observed. Furthermore, the bias in
the mean monthly predicted wind speed for August 2013 was less than 2%, despite August
2013 being outside of the training period for the regression model. This suggests that the
performance of the MCP was not restricted to the time period in which the regression equations
were trained. The percentage bias was the same direction for both wind speed and power
density for all months except for March 2013, where a positive percentage bias in MCP mean
wind speed was accompanied by a negative percentage bias in MCP mean power density. In all
months, the percentage bias in the MCP mean power density was greater than the percentage
bias in the MCP mean wind speed (Figure 4.3). The absolute value of the percentage bias in
the predicted monthly mean power density was less than 13% for all months, and the bias was
as low as -3.5% for March 2013. Overall, there was a tendency for the MCP method to under
predict the monthly mean power density, with a negative bias observed in four out of five of the
available test months (Figure 4.3).
Figure 4.2: Top panel- histogram of wind speed in $1\text{ms}^{-1}$ bins and the best fit Weibull distribution for 30m observations at T1 from 1 March 2013 – 31 August 2013. Bottom panel- Q-Q plot showing closeness of observations (open blue circles) to probability distribution from the Weibull fit (red line).

Figure 4.3: Monthly mean wind speeds (top panel) and power density (bottom panel) from 30m observations and the MCP linear regression for the overlap period. Dotted red line indicates the percentage bias in MCP linear regression predictions. MCP data are not available for July 2013.
The performance of the MCP method in terms of predicting the Weibull distribution was considered consistently good between months, with the distribution of the MCP method closely following that of the observational data (Figure 4.4). The largest difference between Weibull distributions modelled from the MCP method and observations occurred for March 2013, with the MCP slightly under predicting the frequency occurrence of wind speeds less than 3 ms\(^{-1}\) and greater than 10 ms\(^{-1}\).

![Image](image-url)

**Figure 4.4:** Monthly Weibull distributions from observational data (black curve) and the MCP linear regression (red curve) at 30m for: March 2013 and April 2103 (top panel), May 2013 and June 2013 (middle panel), July 2013 and August 2013 (bottom panel). MCP data not available for July 2013.

The monthly mean power density at 30m for the longer two year period (September 2011 to August 2013), as calculated by the MCP method, is presented in Figure 4.5. A $\pm 13\%$ error bar about the monthly mean is also presented in Figure 4.5 under the assumption that the maximum error observed in the overlap period (Figure 4.3) is likely to be similar to the maximum error over the entire two year period; this assumption is discussed further in Section 7.1.1. The
monthly mean power density was shown to vary considerably between months across the two year period, and monthly mean power density varied by more than 800% between the highest (June 2012) and lowest (February 2013) months. The monthly mean power density averaged across the two year period was 341 Wm$^{-2}$ with a standard deviation of 202 Wm$^{-2}$ and a coefficient of variation of 0.59. Under the classification scheme used in Mostafaeipour et al. (2011), all types of monthly classifications (‘excellent’, ‘good’, ‘marginal’ and ‘poor’) were present over the two year period, emphasising the extent of the inter-monthly variability (Figure 4.5). Variability was also observed between the mean power density of a certain month in one year (2011/2012) and the mean power density for the same month in the subsequent year (2012/2013). For example, only two months (May and August) out of twelve were found to have the same classification type between subsequent years. All other months changed classification types between years but only switched up or down one classification between subsequent years, with the exception of June which switched two classes from ‘excellent’ to ‘marginal’ between 2012 and 2013. The influence of the estimated ±13% uncertainty about the mean MCP power density was also found to result in a switch between classifications in some months examined (Figure 4.5). This is especially apparent for the ‘marginal’ classifications where a -13% variation could result in ‘marginal’ classifications switching to ‘poor’ in two instances; in contrast a +13% variation could result in ‘marginal’ classifications switching to ‘good’ in four instances. Although the MCP data were not available for July 2013 (Figure 4.5), the month was classed as ‘excellent’ (>500Wm$^{-2}$) based on observational data from T1 presented earlier in Figure 4.3.
Figure 4.5: Monthly mean power density at 30m for two year period based on MCP method. Error bars represent an estimated ±13% uncertainty about the mean. Classifications of power density ‘goodness’ based on Mostafaeipour et al. (2011) with coloured horizontal lines representing the upper limit for a given classification. September 2012 and July 2013 months not available for MCP data.
4.2 Reconstruction using TAPM

The performance of the mesoscale numerical model TAPM was examined over the period 1 September 2011 to 31 August 2013, in terms of its ability to simulate monthly mean wind speeds, monthly Weibull distribution parameters, and the monthly mean power density.

4.2.1 Calibration of TAPM

The calibration period of the model (14 March 2013 – 23 May 2013) was chosen to overlap with the time period in which observations were available from all ridge top towers (T1, T2, T3 and T4). As shown in Table 4.2, over this period the performance of TAPM (based on the \( r \) and \( \text{IOA} \) measures) was found to increase as the grid resolution and number of grid domains was increased. While R3 was found to have a slightly higher \( r \) value than R4 (and identical \( \text{IOA} \)), given that the mean modelled wind speed in R4 was closer to the mean observed wind speed, the performance of TAPM under the R4 setup was considered superior. The addition of the non-hydrostatic mode in R5 slightly increased the closeness of the mean modelled wind speed to the mean observed wind speed, while no change in the other statistical measures of performance was observed. Given this result, all further TAPM simulations were carried out with the R5 setup. It should also be noted that the value of the \( \text{IOA} \) value under this setup is encouraging given that \( \text{IOA} > 0.5 \) is indicative of model skill (Hurley et al., 2002).

<table>
<thead>
<tr>
<th>TAPM setup run and description</th>
<th>Mean observed wind speed (m s(^{-1}))</th>
<th>Mean modelled wind speed (m s(^{-1}))</th>
<th>( r )</th>
<th>( \text{IOA} )</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>R1 25 X 25</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 Domains, hydrostatic</td>
<td>5.1</td>
<td>5.5</td>
<td>0.37</td>
<td>0.63</td>
</tr>
<tr>
<td><strong>R2 25 X 25</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4 Domains, hydrostatic</td>
<td>5.1</td>
<td>6.0</td>
<td>0.39</td>
<td>0.64</td>
</tr>
<tr>
<td><strong>R3 40 X 40</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 Domains, hydrostatic</td>
<td>5.1</td>
<td>4.8</td>
<td>0.52</td>
<td>0.72</td>
</tr>
<tr>
<td><strong>R4 40 X 40</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4 Domains, hydrostatic</td>
<td>5.1</td>
<td>5.0</td>
<td>0.51</td>
<td>0.72</td>
</tr>
<tr>
<td><strong>R5 40 X 40</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4 Domains, non-hydrostatic</td>
<td>5.1</td>
<td>5.1</td>
<td>0.51</td>
<td>0.72</td>
</tr>
</tbody>
</table>
4.2.2 Validation of TAPM

The model was then run with the R5 configuration (Table 4.2) over the period from 1 September 2011 to 31 August 2013. Figure 4.6 shows the performance of TAPM in simulating 30m monthly mean wind speeds and monthly mean power density over the period 1 March 2013 to 31 August 2013, where direct comparisons could be made against 30m wind speeds observed at T1. As shown in Figure 4.6, the performance of TAPM, in terms of simulating monthly mean wind speeds, varied strongly between months, with the absolute value of the percentage bias less than 3% for March 2013 – May 2013 but as much as 22% for August 2013. TAPM was also capable of both under and over predicting mean monthly wind speeds. In terms of the performance of TAPM (Figure 4.6) compared to the MCP method (Figure 4.3) over the same time period, TAPM performance was inferior (higher absolute percentage bias) when predicting monthly mean wind speed for all months except April 2013, where the percentage bias for TAPM (MCP) was -1.75% (-2.70%). The percentage bias for TAPM was the same direction for both wind speed and power density for all months except for July 2013, where a positive percentage bias in TAPM mean wind speed was accompanied by a negative percentage bias in TAPM mean power density (Figure 4.6). As for the MCP method (Figure 4.3), for all months the percentage biases in the TAPM mean power density was greater than the percentage bias in the TAPM mean wind speed (Figure 4.6). The absolute value of the percentage bias in the predicted monthly mean power density was as much as 60% for August 2013, while the lowest bias month (most accurately simulated month) was July 2013 with a percentage bias of -7%. As with the MCP method (Figure 4.3) there was a tendency for the TAPM method to under predict the monthly mean power density, with a negative bias observed in five out of six of the available test months (Figure 4.6).
In terms of the ability of TAPM to simulate the monthly probability distributions of wind speed (represented by the Weibull distribution), the performance of TAPM varied greatly between months (Figure 4.7). For example, the Weibull distribution based on TAPM simulated wind speeds was very similar to that of observations and the MCP method for the period March 2013 – May 2013, but much less so for the period June 2013 – August 2013. For the month of August 2013, the poor performance in terms of TAPM’s ability to simulate the Weibull distribution parameters is also evident in the large percentage bias in the mean power density of 60% for August 2013 (Figure 4.6). A skewness in the Weibull distribution towards higher wind speeds (e.g. July 2013) does not necessary imply a greater mean power density, with TAPM displaying a negative bias in mean power density for July 2013 in Figure 4.6.

Figure 4.6: Monthly mean wind speeds (top panel) and power density (bottom panel) from 30m observations and TAPM for overlap period. Dotted red line indicates the monthly percentage bias in TAPM simulations.
Figure 4.7: Monthly Weibull distributions from observational data (black curve) and the MCP linear regression (red curve) and TAPM simulations (blue curve) at 30m for: March 2013 and April 2013 (top panel), May 2013 and June 2013 (middle panel), July 2013 and August 2013 (bottom panel). MCP data not available for July 2013.

Although the performance of TAPM, in terms of simulated monthly mean power density, was considered very poor in some months over the validation period (e.g. June 2013 and August 2013, Figure 4.6 and Figure 4.7), it was important to investigate whether these two months might be anomalies over a longer time period. To assess this, the ability of TAPM to predict the monthly mean power density over the two year period was compared against the MCP predictions used as a reference baseline, as presented earlier in Figure 4.5. Based on the finding that MCP predictions could result in a 13% bias in the mean power density for a given month over the MCP validation period, the percentage bias in TAPM was assessed based on the MCP monthly mean power density being 13% greater or lower than the ‘true’ mean power density (Figure 4.9). Therefore, it is estimated that the ‘true’ values of the percentage bias in the monthly mean power density simulated by TAPM lie between the ‘low extent’ and ‘high extent’ percentage bias lines (grey shading) in Figure 4.9. To assess the performance of TAPM,
while also taking into consideration the estimated uncertainty of the MCP method as a baseline method, a month adequately simulated by TAPM was defined as a month in which the lower absolute value of the ‘low extent’ and ‘high extent’ percentage bias in TAPM power density is less than 20%. Based on this definition, only 11 out of 22 available months (50%) were simulated adequately by TAPM. As a separate measure, the performance of TAPM was assessed by the ability to correctly classify each month as ‘excellent’, ‘good’, ‘marginal’ and ‘poor’ (relative to the classifications produced by the MCP method). Overall, TAPM over predicted the occurrence of poor and good months and under predicted the occurrence of marginal – moderate and excellent months (Figure 4.8). Comparing concurrent TAPM and MCP classifications for a particular month (Figure 4.9), TAPM was correct in classifying 11 out of 22 months, which again suggests approximately half of months simulated by TAPM were done so adequately.

![Percentage occurrences of classifications based on MCP and TAPM monthly mean power densities.](image)

Given this result, it was not considered appropriate to use TAPM in simulations prior to September 2011 when the performance of the model could not be assessed. The performance of TAPM in terms of simulating important features of the sub-synoptic circulation is presented in Chapter 5.
Figure 4.9: Monthly mean power density from 30m MCP and TAPM simulations for entire period 1September 2011 – 31August 2013. Error bars represent an estimated ±13% uncertainty in the MCP method. Grey shaded area indicates the percentage bias uncertainty for TAPM, between the high extent bias (green line) and low extent bias (red line) based on a ±13% variation from the mean MCP value. Dotted horizontal line indicates zero percent bias (perfect estimate).
4.3 Monthly average MSLP linkage

Although only two years of data were available to consider seasonal variability in wind resource quantity, certain seasons examined appear to exhibit a greater tendency for higher mean power density (Figure 4.5). For example, all ‘excellent’ and ‘good’ classifications occurred in spring or winter months, while all ‘poor’ classifications occurred in summer or autumn months. The links between seasonality and wind resource quantity are explored in this section, taking into account the variability in the average synoptic-scale mean sea level pressure (MSLP) situation between months of different seasons. Monthly average MSLP was plotted from the NCEP/NCAR reanalysis dataset for the New Zealand region (20°S – 55°S; 140°E - 165°W) over the period September 2011 – August 2013. By interpreting wind roses for the same month, the synoptic scale controls on the between month wind resource variability were investigated in a qualitative way.

The westerly wind belt clearly dominated the monthly average synoptic situation in all spring months examined except for October 2011 (Figure 4.10). In such months, the wind rose was dominated by strong and frequent westerly winds, which appear to be responsible for the ‘excellent’ wind resource classifications observed for September and November 2011 and October 2012 in Figure 4.5. In the summer months examined (Figure 4.11) high pressure centres were located further south and dominated the average synoptic scale situation over New Zealand. Subsequently, strong westerly winds were less frequent and less strong in the wind roses for summer months. Instead, in summer months, the strongest and most frequent winds occurred over the NE-SE sector, most likely linked to sub-synoptic circulation features as discussed in the following chapter, but very rarely do these winds exceed 13 ms\(^{-1}\). Absent from December 2011 and February 2011 were strong (>13 ms\(^{-1}\)) westerly winds, with these months classed as ‘poor’ in terms of wind resource quantity in Figure 4.5. Furthermore, the two summer months (January 2012 and January 2013) found to display the highest monthly mean power densities in Figure 4.5 appear to be anomalies in this season; the wind regime in these months was more dominated by a strong (>13 ms\(^{-1}\)) westerly than by the sub-synoptic circulation features over the NE-SE sector that appeared characteristic of summer months.

Autumn months examined (Figure 4.12) appeared to display characteristics present in both the summer months (Figure 4.11) and the spring months (Figure 4.10), in terms of the average synoptic situation and the direction of the most frequent and strong winds observed in wind roses. The autumn months displaying the highest monthly mean power density (Figure 4.5) were May 2012, April 2013 and May 2013, and classed as ‘marginal – moderate’. Comparing the average synoptic situation and wind roses between these autumn months and the autumn months classified as ‘poor’ (April 2012 and May 2013), the months classed as ‘marginal –
moderate’ experienced more frequent and stronger westerly or south-westerly synoptic winds, with the monthly averaged centre of high pressure located slightly further north in these months. For the winter months (Figure 4.13) the between month variation in the average position and direction of contours in the synoptic scale pressure gradients can be clearly linked to the between month variation displayed in the wind roses. In June 2012 and June 2013, synoptic pressure gradients on average followed a west to south-west direction which is reflected in the wind roses of these months whereby the strongest and most frequent winds occurred across the W-SW sector. In contrast, in August 2012 and August 2013 pressure gradients on average followed a north-west to north direction with the wind rose for these months instead dominated by frequent north-east winds, after synoptic winds are ‘realigned’ to the coastline (as discussed in Chapter 7). All of the winter months were classified as being at least marginal to moderate (all > 200 Wm\(^{-2}\)) (Figure 4.5). June 2012, which had the highest monthly mean power density of the winter months examined, was dominated by anomalously strong and frequent west to south-west winds, with the average position of synoptic high pressure situated to the north of New Zealand.

These findings were reiterated by statistically examining composite anomalies in MSLP between the highest and lowest generation potential months (Figure 4.14). As evident in Figure 4.14, the months with the highest monthly mean power density displayed high pressure centres located on average to the north of New Zealand. In contrast, the months with the lowest monthly mean power density displayed high pressure centres located on average further south over New Zealand and to the south-east of New Zealand. Furthermore, these differences were found to be statistically significant, with centres of these differences significant at the \( p <0.01 \) level. This reinforces the idea that the average latitudinal position of high pressure centres and the position of the westerly wind belt in a given month examined was a key determinant of the wind resource quantity of that month.
Figure 4.10: Top panels- September (S), October (O), November (N) 2011 (left to right); bottom panels- S, O, N 2012 (left to right). Contour map of MSL Pressure (hPa) from reanalysis data with wind rose based on 30m MCP data where blue = <3 ms$^{-1}$, yellow = 3-6 ms$^{-1}$, green = 6-13 ms$^{-1}$, red = >13ms$^{-1}$. MCP data (wind rose) not available for S 2012.
Figure 4.11: As for Figure 4.10 but with top panel- December (D), January (J), February (F) 2011/2012 (left to right); bottom panel- D, J, F 2012/2013 (left to right).
Figure 4.12: As for Figure 4.10 but with top panel- March (M), April (A), May (M) 2012 (left to right); bottom panel- M, A, M 2013 (left to right). Wind rose in bottom panels produced from 30m observational data at T1 available over this time period.
Figure 4.13: As for Figure 4.10 but with top panel- June (J), July (J), August (A) 2012 (left to right); bottom panel- J, J, A 2013 (left to right). Wind rose in bottom panels produced from 30m observational data at T1 available over this time period.
4.4 Kidson types linkage

In this section links between Kidson types and regime groups, month of the year, and wind speed are examined in the context of the wind resource potential. As a preliminary examination, Figure 4.15 shows that different Kidson types might be useful in classifying maximum and minimum generation events, given that substantial variability in wind speed was observed between different Kidson types. Following this, the potential for Kidson types to classify maximum and minimum generation events is examined under a probabilistic approach through the employment of a logistic regression model.
Figure 4.15: Box plot of MCP 30m wind speed under different Kidson types for period 1 September 2011-31 August 2013. Bottom, middle and top of box display 25th percentile, median and 75th percentile respectively; T-bars and circles display outliers from this distribution.

4.4.1 Minimum generation events

To test whether the additional inclusion (additional to Kidson type) of month of year as a predictor variable was warranted in the logistic regression model, the skill of the model was examined before and after its addition. The skill of the model was assessed based on the area under curve (AUC) of the ROC. The addition of month of year was found to slightly increase the skill of the model (AUC increased from 0.711 to 0.722), in predicting the occurrence of a minimum generation day, and was therefore included in the analysis (Figure 4.16). Furthermore, the inclusion of month of year slightly changed the odds ratio for the Kidson types due to the interaction of these covariates in the model. The AUC of 0.722 indicates the overall utility and skill of the model, with a critical value of 0.7 generally used as a threshold to assess model skill (Jiang et al., 2011).

A separate logistic regression model was employed to assess the linkage between Kidson regime groups and the odds of a minimum generation day. In this case the skill of the model was reduced with an AUC of 0.605; however the model was still shown better than a ‘by chance’ prediction associated with an AUC of 0.5, and with the difference statistically significant at $p < 0.05$. 

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As shown in Table 4.3, seven out of eleven of the model covariate comparisons for the Kidson types displayed statistically significant changes in the odds of a minimum generation day occurrence (when assessed relative to the H Kidson type base category). Of these seven statistically significant changes, six were negative indicating a decreased probability of a minimum generation day occurrence under these Kidson types. These Kidson types are generally associated with relatively strong west or south-west synoptic pressure gradients over the South Island (the T, SW, HW, W and HNW Kidson types) with the exception of the NE Kidson type. Only one statistically significant positive change in odds was found (indicating an increased probability of a minimum generation day), which was for the HSE Kidson type. Of the eleven covariate comparisons for month of year, only four of these were statistically significant in terms of the change in the odds of a minimum generation day occurrence (when assessed relative to December as base category) (Table 4.3). All of these statistically significant changes were positive and indicate an increased probability of a minimum generation day occurrence in the February, April, June and August months. The model covariate comparisons for regime groups were statistically significant comparing the trough group against the blocking group, under which the odds of minimum generation decreased for the trough group.
Table 4.3: Odds ratio of a minimum generation day under Kidson types and month in the logistic regression model, and under Kidson regime group (in a separate logistic regression model). NS indicates that there is no significant difference (at the 95% confidence level) in the odds ratio of a minimum generation day for a certain covariate comparison.

<table>
<thead>
<tr>
<th>covariate (base category)</th>
<th>Model covariate comparisons</th>
<th>Odds ratio (expβ) of minimum generation day</th>
<th>p-value</th>
<th>Change in odds of minimum generation day</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kidson type (H)</td>
<td>TSW vs H</td>
<td>0.538</td>
<td>0.079</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td>T vs H</td>
<td>0.197</td>
<td>0.000</td>
<td>-80.3%</td>
</tr>
<tr>
<td></td>
<td>SW vs H</td>
<td>0.044</td>
<td>0.000</td>
<td>-95.6%</td>
</tr>
<tr>
<td></td>
<td>NE vs. H</td>
<td>0.383</td>
<td>0.003</td>
<td>-61.7%</td>
</tr>
<tr>
<td></td>
<td>R vs H</td>
<td>0.819</td>
<td>0.539</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td>HW vs H</td>
<td>0.110</td>
<td>0.000</td>
<td>-89.0%</td>
</tr>
<tr>
<td></td>
<td>HE vs H</td>
<td>0.716</td>
<td>0.228</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td>W vs H</td>
<td>0.195</td>
<td>0.000</td>
<td>-80.1%</td>
</tr>
<tr>
<td></td>
<td>HNW vs H</td>
<td>0.257</td>
<td>0.000</td>
<td>-74.3%</td>
</tr>
<tr>
<td></td>
<td>TNW vs H</td>
<td>0.639</td>
<td>0.142</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td>HSE vs H</td>
<td>1.545</td>
<td>0.047</td>
<td>54.5%</td>
</tr>
<tr>
<td>Month (December)</td>
<td>Jan vs Dec</td>
<td>1.744</td>
<td>0.119</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td>Feb vs Dec</td>
<td>2.371</td>
<td>0.010</td>
<td>137.1%</td>
</tr>
<tr>
<td></td>
<td>Mar vs Dec</td>
<td>1.144</td>
<td>0.697</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td>Apr vs Dec</td>
<td>2.089</td>
<td>0.028</td>
<td>108.9%</td>
</tr>
<tr>
<td></td>
<td>May vs Dec</td>
<td>1.258</td>
<td>0.531</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td>Jun vs Dec</td>
<td>2.019</td>
<td>0.048</td>
<td>101.9%</td>
</tr>
<tr>
<td></td>
<td>July vs Dec</td>
<td>1.328</td>
<td>0.413</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td>Aug vs Dec</td>
<td>2.046</td>
<td>0.038</td>
<td>104.6%</td>
</tr>
<tr>
<td></td>
<td>Sep vs Dec</td>
<td>1.822</td>
<td>0.174</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td>Oct vs Dec</td>
<td>0.504</td>
<td>0.173</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td>Nov vs Dec</td>
<td>1.454</td>
<td>0.347</td>
<td>NS</td>
</tr>
<tr>
<td>Kidson regime group (blocking)</td>
<td>trough vs blocking</td>
<td>0.374</td>
<td>0.000</td>
<td>-62.6%</td>
</tr>
<tr>
<td></td>
<td>zonal vs blocking</td>
<td>0.777</td>
<td>0.063</td>
<td>NS</td>
</tr>
</tbody>
</table>

4.4.2 Maximum generation events

As shown in Figure 4.17 the inclusion of month of year as an additional variable (additional to Kidson type) in the logistic regression was warranted when assessing the odds of a maximum generation day. This is indicated by the AUC increasing from 0.805 to 0.827 upon the
inclusion of month of year in the model. Again the AUC value of 0.827 indicates the overall utility of the model for predicting the occurrence of maximum generation days.

A separate logistic regression model was employed to assess the linkage between regime groups and the odds of a maximum generation day. In this case the performance of the model was again reduced with an AUC of 0.653; however the model was still shown better than a ‘by chance’ prediction associated with an AUC of 0.5 and with the difference statistically significant at $p < 0.05$.

Figure 4.17: ROC curve for logistic regression predicting maximum generation day occurrence with single predictor variable as Kidson type (green curve, AUC = 0.805), and two predictor variables as Kidson type and month of year (blue curve, AUC = 0.827). The diagonal line (AUC = 0.5) indicates ‘by chance’ prediction.

For the logistic regression predicting the occurrence of a maximum generation day (Table 4.4), ten out of eleven comparisons for the Kidson type covariates were statistically significant. Of these statistically significant comparisons, nine displayed positive changes in the odds of maximum generation, indicating an increased probability of a maximum generation day event occurrence. Furthermore, all of these changes were found to be relatively large (the lowest being 278.4%) indicating that under these Kidson types the probability of a maximum generation day occurring was several times higher than for the H Kidson type. The Kidson types linked with the highest probabilities of maximum generation days were again associated with relatively strong west or south-west synoptic pressure gradients over the South island (the T, SW, HW, W and HNW Kidson types). These Kidson types were also shown earlier (Table 4.3) to be linked a lower probability of a minimum generation day occurrence. However, other Kidson types not associated with strong west or south-west synoptic pressure gradients were also shown here to be linked with greater probabilities of maximum generation day occurrence (relative to H Kidson type), including the TSW, TNW and NE Kidson types (Table 4.4).
TSW and TNW Kidson types were not presented as being statistically significant in the earlier analysis (minimum generation) in Table 4.3, suggesting that a higher probability of maximum generation day occurrence for a particular Kidson type was not necessarily associated with a lower probability of minimum generation day occurrence for the same Kidson type. Only one negative statistically significant change in odds is present in Table 4.4 belonging to the HSE type, indicating that for the HSE Kidson type (relative to the H Kidson type) there was a decreased probability of maximum generation day occurrence, but also an increased probability of minimum generation day occurrence (Table 4.3).

Six out of eleven months showed a statistically significant change in the odds of a maximum generation day (relative to December) and all of these changes were positive indicating a greater probability of a maximum generation day in these months (Table 4.4). With the exception of May, these months all occurred in winter or spring. Again, an increased probability of maximum generation (Table 4.4) was not necessarily associated with a decreased probability of minimum generation (Table 4.3). For example, none of the months that displayed an increased probability of maximum generation (Table 4.4), displayed a statistically significant decreased probability of minimum generation (Table 4.3). For the model covariate comparisons under regime groups, both the trough and zonal groups were shown to increase the probability of a maximum generation day (compared to the blocking group), with the increases statistically significant.

The findings of the logistic regression linking Kidson types to a maximum or minimum generation day were broadly consistent with the links between changes in the monthly averaged MSLP and changes in the monthly mean power density presented earlier (Figure 4.10 - 4.14). The top panel of Figure 4.18 illustrates that between 1 September 2011 and 31 August 2013, substantial variability occurred between seasons in terms of the frequency of certain Kidson types. The largest variability between seasons occurred for the SW, W, HSE, and H Kidson types. In particular, spring recorded a much higher percentage frequency of the SW Kidson types than any other season, and also recorded a much lower percentage frequency of the H and HSE Kidson types. Winter and spring seasons also recorded a much higher percentage frequency of the W Kidson type compared to summer and autumn seasons. These observations were reflected in the differences in the monthly average MSLP presented earlier in Figures 4.10 - 4.13. For example, generally the average position of high pressure centres was found to be further north (with a westerly belt over the South Island) in spring months followed by winter months, compared to autumn and summer months where high pressure centres were on average positioned more directly over New Zealand. Importantly, the same four Kidson types (SW, W, HSE and H Kidson types) shown to display the largest variability between seasons (Figure 4.18) were also shown earlier in the logistic regression to be very important discriminants of a
maximum or minimum generation day. In particular, the SW and W Kidson types were linked to an increased probability of a maximum generation day (Table 4.4) while the HSE and H Kidson types were linked to a decreased probability of a minimum generation day (Table 4.3). Therefore, it is evident that the variability in these Kidson types observed between months and seasons was a large contributor to the variability in the average power density and wind resource potential observed between months and seasons.

Table 4.4: Odds ratio of maximum generation day under Kidson types and month comparisons in the logistic regression model, and under Kidson regime group (in a separate logistic regression model). NS indicates that there is no significant difference (at the 95% confidence level) in the odds ratio of a maximum generation day for a certain covariate comparison

<table>
<thead>
<tr>
<th>covariate (base category)</th>
<th>Model covariate comparisons</th>
<th>Odds ratio (expβ) of maximum generation day</th>
<th>p-value</th>
<th>Change in odds of maximum generation day</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kidson type (H)</td>
<td>TSW vs H</td>
<td>4.289</td>
<td>0.022</td>
<td>328.9%</td>
</tr>
<tr>
<td></td>
<td>T vs H</td>
<td>6.173</td>
<td>0.001</td>
<td>517.3%</td>
</tr>
<tr>
<td></td>
<td>SW vs H</td>
<td>37.343</td>
<td>0.000</td>
<td>&gt;1000%</td>
</tr>
<tr>
<td></td>
<td>NE vs. H</td>
<td>4.787</td>
<td>0.007</td>
<td>378.7%</td>
</tr>
<tr>
<td></td>
<td>R vs H</td>
<td>1.585</td>
<td>0.590</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td>HW vs H</td>
<td>9.381</td>
<td>0.000</td>
<td>838.1%</td>
</tr>
<tr>
<td></td>
<td>HE vs H</td>
<td>5.564</td>
<td>0.002</td>
<td>456.4%</td>
</tr>
<tr>
<td></td>
<td>W vs H</td>
<td>7.351</td>
<td>0.000</td>
<td>635.1%</td>
</tr>
<tr>
<td></td>
<td>HNW vs H</td>
<td>22.702</td>
<td>0.000</td>
<td>&gt;1000%</td>
</tr>
<tr>
<td></td>
<td>TNW vs H</td>
<td>3.784</td>
<td>0.030</td>
<td>278.4%</td>
</tr>
<tr>
<td></td>
<td>HSE vs H</td>
<td>0.001</td>
<td>0.000</td>
<td>-99.8%</td>
</tr>
<tr>
<td>Month (December)</td>
<td>Jan vs Dec</td>
<td>2.587</td>
<td>0.091</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td>Feb vs Dec</td>
<td>1.686</td>
<td>0.423</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td>Mar vs Dec</td>
<td>1.271</td>
<td>0.714</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td>Apr vs Dec</td>
<td>2.351</td>
<td>0.158</td>
<td>NS</td>
</tr>
<tr>
<td></td>
<td>May vs Dec</td>
<td>3.490</td>
<td>0.023</td>
<td>249.0%</td>
</tr>
<tr>
<td></td>
<td>Jun vs Dec</td>
<td>4.852</td>
<td>0.004</td>
<td>385.2%</td>
</tr>
<tr>
<td></td>
<td>July vs Dec</td>
<td>5.151</td>
<td>0.004</td>
<td>415.1%</td>
</tr>
<tr>
<td></td>
<td>Aug vs Dec</td>
<td>5.390</td>
<td>0.002</td>
<td>439.0%</td>
</tr>
<tr>
<td></td>
<td>Sep vs Dec</td>
<td>5.026</td>
<td>0.004</td>
<td>402.6%</td>
</tr>
<tr>
<td></td>
<td>Oct vs Dec</td>
<td>3.608</td>
<td>0.016</td>
<td>260.8%</td>
</tr>
<tr>
<td></td>
<td>Nov vs Dec</td>
<td>2.052</td>
<td>0.191</td>
<td>NS</td>
</tr>
<tr>
<td>Kidson regime group (Blocking)</td>
<td>trough vs blocking</td>
<td>3.954</td>
<td>0.000</td>
<td>295.4%</td>
</tr>
<tr>
<td></td>
<td>Zonal vs blocking</td>
<td>1.930</td>
<td>0.004</td>
<td>93.0%</td>
</tr>
</tbody>
</table>
4.4.3 Long term climatology

Of interest is whether the between season variability in Kidson types observed over the two year period of this study (2011 – 2013) is representative of that present in the longer term climatology (here represented as 1948 – 2013). As shown in Figure 4.18, the Kidson types broadly displayed similar patterns in seasonal variability when comparing the time period of this study to the longer term climatology. While the same general patterns were present, the extent of the between seasonal variability for certain Kidson types appeared greater for the period of this study. For example, while the SW and W Kidson types were still most pronounced in spring in the 1948 – 2013 period (Figure 4.18), the 2011 – 2013 period displayed approximately an 11% and 2% increase in the SW and W Kidson types respectively (compared to the 1948 – 2013 period), in terms of changes in the seasonal frequency of these Kidson types within spring (Figure 4.19). For the 1948 – 2013 period, spring still recorded the lowest percentage frequency of the HSE Kidson type compared to other seasons (as was observed in the two year study period); however spring recorded a higher percentage frequency of the H Kidson type than summer in the long term record, which was not observed in the two year study period. This is further illustrated in Figure 4.19, where the seasonal frequency occurrence of H Kidson types in spring was approximately 6% less for the 2011 – 2013 period, compared to 1948 – 2013 period. The implications of these findings are discussed further in Chapter 7.

Figure 4.18: Top panel - seasonal frequency of Kidson types over the time period of this study (2011 – 2013); bottom panel - long term seasonal frequency of Kidson types (1948 – 2013).
Figure 4.19: Seasonal frequency of Kidson types in 2011 – 2013 minus seasonal frequency of Kidson types in 1948 – 2013.
Chapter 5 – Sub-synoptic scale results

In this chapter results are presented based on an investigation of the presence and magnitude of sub-synoptic thermally induced circulation features, along with how these features appear to affect the wind regime and subsequently the wind resource. Case study days were first selected to consider thermally induced circulation features under ideal conditions, with TAPM simulations compared to observations to examine the skill of TAPM in simulating such occurrences. The results of a number of idealized TAPM experiments are also presented; carried out to consider the interaction of the ambient synoptic wind with the sea breeze, and in attempt to quantify the net contribution of the sea breeze to the wind resource quantity.

5.1 Case study of thermally induced circulation

As described in Section 3.5.2, ten days were selected for a case study to examine features of the thermally induced circulation. These days were selected based on two criteria: (1) Incoming shortwave radiation was relatively unimpeded by clouds; (2) No strong synoptic gradients were present, as far as practical. As shown in Figure 5.1 the ten days selected under this criteria had relatively clear skies unimpeded by clouds, with only small drops in incoming shortwave radiation over short periods of time (often in the afternoon); the downward trend between days was due to changes in available shortwave radiation approaching winter months. Of the selected days, the H and HSE Kidson types were present in up seven of the ten days (Figure 5.1), associated with very weak synoptic gradients over New Zealand. The selection criteria could not be based solely on choosing these Kidson types, as for a number of other days (not shown here) these Kidson types were often also associated with cloudy conditions, potentially limiting the development of thermally induced circulation features. However, all other Kidson types presented in Figure 5.1 (the HE, TNW, R types) were also associated with relatively weak synoptic gradients.
Figure 5.1: Select ten days (not continuous) deemed most conducive to the development of thermal circulation, selected from days over the period 14 March – 23 May 2013 when T3 data were available. For each day, 24 hour incoming shortwave radiation is shown along with the particular Kidson type recoded at 1200 hours NZST.

5.1.1 Observations over case study days

The ten days selected in Figure 5.1 were then used as a basis for analysing observed diurnal changes in wind speed and wind direction, with the analysis carried out at three separate heights above the surface: 30m (T1), 15m (T1) and 3.3m (T3) (Figure 5.2). The occurrence of a sea breeze was evident at all heights in Figure 5.2, as indicated by the increase in contour level (percentage of winds pertaining to a particular hour of day and wind direction) in the afternoon and for wind directions from 45–120° (associated with winds from the surrounding sea). The contours reached a maximum occurrence at approximately 1500 hours and with winds from 70°. Afternoon wind speeds also approached a local maximum at this time, indicating when the sea breezes were strongest in magnitude. As evident in the rapid change in contour levels and changes in diurnal wind speed at this time, the onset of the sea breeze occurred at approximately 1100 hours and continued till approximately 2000 hours. These findings, in terms of frequency of occurrence and duration of the sea breeze, were broadly consistent between measurement heights in Figure 5.2. However, changes in the magnitude of the sea breeze were observed between different heights, with the sea breeze wind speed of greater magnitude at higher elevations.

During this case study, a nocturnal peak (local maximum) in wind speed was observed in the diurnal wind speed record (Figure 5.2). This nocturnal peak was observed at all elevations and occurred approximately between 2100 hours and 0600 hours, as indicated by the increase in contour levels and diurnal wind speed over this period. The magnitude of the nocturnal wind was of a similar magnitude to the late afternoon sea breeze, and was associated with wind directions 315 – 45°.
Figure 5.2: Diurnal variability in wind speed and wind direction for 30m, 15m and 3.3m heights, for ten select days deemed conducive to the development of thermal circulation. Left panels- colours display average wind speed pertaining to a particular wind direction and hour of day; contours display the hourly frequency occurrence (%) of wind direction. Right panels- Box plot of wind speed for a given hour with bottom, middle and top of box display 25th percentile, median and 75th percentile respectively; T-bars and circles display outliers from this distribution.

5.1.2 Model simulations over case study days

The ability of TAPM to simulate the observed diurnal changes in wind speed and wind direction, associated with thermally induced circulation features was examined (Figure 5.3). Within this examination TAPM was run over the same select days deemed conducive to development (Figure 5.1). TAPM was found to be broadly of capable of simulating the magnitude and duration of the sea breeze on these days, despite slightly under predicting the frequency occurrence of the sea breeze (Figure 5.3). It was hypothesized that this under prediction of frequency occurrence of the sea breeze by TAPM was partly due to TAPM also simulating a relatively high magnitude and low frequency afternoon synoptic wind event from 270 – 365°, which was absent from observations (Figure 5.3). Evidence supporting the hypothesis is presented in Figure 5.4 showing diurnal changes in wind speed and direction in
time series. Three of the ten days simulated by TAPM did not display diurnal changes in terms of the rotation of wind direction towards the afternoon sea breeze (indicated by asterisks in Figure 5.4). This was likely due to a strong ambient synoptic forcing in the model impairing the potential for sea breeze development on these days.

Figure 5.3: As for Figure 5.2 but here comparing TAPM against observations at 30m.

Figure 5.4: Diurnal time series of wind speed and wind direction for TAPM simulations of the 10 select days in Figure 5.3. Grey boxes indicate night time (2000 – 0800 hours), white boxes indicate day time (0800 – 2000 hours), asterisks indicate a day time period where there is no substantial rotation in wind direction from the preceding night.
To further explore the hypothesis that modelled ambient synoptic conditions on certain days (those indicated by asterisks in Figure 5.4) prevented the occurrence of sea breeze days simulated by TAPM (Figure 5.3), ambient synoptic conditions in the model were modified. In particular, ambient synoptic conditions were set to zero in TAPM (horizontally homogenous initialization) for the three days where there was no diurnal rotation in wind direction in Figure 5.4. The results of the model experiment are compared against observations, in terms of diurnal changes in wind direction and wind speed in Figure 5.5. Comparing Figure 5.5 to Figure 5.3 shows that the low frequency afternoon synoptic wind event from 270 – 365° simulated by TAPM in Figure 5.3 was, as expected, due to ambient synoptic winds over these days, with this phenomenon clearly removed from Figure 5.5. Furthermore, as hypothesized, after removal of this phenomenon by forcing ambient synoptic winds to zero in the model, the frequency of wind directions associated with the sea breeze approximately doubles from 6% to 12% (Figure 5.5), confirming that the ambient synoptic wind over these days was preventing the potential for sea breeze development.

TAPM simulations presented in Figure 5.5 also displayed the same nocturnal wind patterns as in TAPM simulations presented in Figure 5.3, in which a relatively strong nocturnal wind occurred at approximately 2100 hours and continued until approximately 0900 hours. This provides evidence that the modelled nocturnal wind phenomenon was a thermally induced circulation feature, as the removal of strong ambient synoptic westerly winds from the model did not remove this apparent phenomenon. However, there are clear differences comparing the nocturnal wind phenomenon simulated by TAPM and the nocturnal wind phenomenon in observations (Figure 5.3). The most notable of which is that the nocturnal wind simulated by TAPM was centred around 270°, in contrast to the observed nocturnal wind centred around 0°. Furthermore, the nocturnal wind simulated by TAPM occurred later in the evening and persisted longer into the morning, compared to observations.
5.2 Idealized model experiments

To further explore the possible influence of ambient synoptic conditions on sea breeze dynamics, idealized TAPM experiments were setup by artificially adjusting the ambient synoptic wind speed and direction, as described in Chapter 3. The interaction between the sea breeze and the ambient synoptic westerly was shown to be somewhat dependent on the strength of the synoptic westerly wind (Figure 5.6). As shown in Figure 5.6, when the synoptic westerly wind was of relatively low magnitude (3 ms$^{-1}$ or 5 ms$^{-1}$), the westerly wind speed sharply decreased in magnitude between approximately 0700 and 1100 hours. Following this, the wind direction was then rotated to the sea breeze wind direction (45-120$^\circ$), with wind speed increasing until reaching a maximum magnitude at approximately 1300 hours with a magnitude of approximately 4 ms$^{-1}$. In contrast, when the synoptic westerly was of relatively high magnitude (10 ms$^{-1}$), the interaction between the sea breeze and the synoptic westerly resulted in a greater reduction of wind speed for a greater period of time. Under these conditions, the development of the sea breeze between approximately 1100 hours and 2100 hours reduced wind speeds, and generally resulted in wind speeds less than 3 ms$^{-1}$.
Examining the interaction between the sea breeze and the ambient synoptic north-easterly, the sea breeze was found to result in an intensification of the magnitude of the ambient synoptic north-easterly, under all magnitudes of the ambient synoptic north-easterly modelled (Figure 5.7). However, the diurnal intensification of wind speeds was found to be most pronounced when the ambient north-easterly was of low magnitude (3 ms$^{-1}$). Furthermore, the rotation of wind direction from the north-east to the sea breeze sector (45-120°) was only evident when the ambient north-easterly was of low magnitude. For example, when the ambient north-easterly was of relatively high magnitude (10 ms$^{-1}$) wind direction did not display any diurnal dependence.
5.3 Seasonal variation

In the previous section, aspects of the thermally induced circulation were considered exclusively when certain conditions were met over select days. In contrast, this section investigates aspects of the thermally induced circulation based on seasonal differences under all conditions (not just conditions most ideal for development). Observational findings (left panels, Figure 5.8) are first presented followed by model simulations (right panels, Figure 5.8).

A sea breeze was clearly discernible and contributed to the observed wind climatology in all seasons, with the possible exception being winter (Left panels, Figure 5.8). This is evident based on the increase in wind contour levels associated with the timing and wind direction of
the sea breeze in these seasons, as found earlier under ideal conditions. The sea breeze was not clearly evident in winter observations with contour levels not clearly associated with the idealized timing and magnitude of the sea breeze; instead winds from this direction were almost as likely to occur at any time of day. However, for all seasons there was also evidence to suggest that the sea breeze could not be easily isolated from synoptic winds; instead the sea breeze formed a complex interaction with synoptic winds from approximately 45-120°. The average magnitude and frequency of the sea breeze was also found to be seasonally dependent. For example, the sea breeze occurred most frequently in summer, followed by autumn and then spring. The average magnitude of the sea breeze (when it is at its maximum for a given day) was greatest for summer and spring, where wind speeds were on average approximately 5 ms\(^{-1}\), which is above the cut-in wind speed of most modern day wind turbines (3 ms\(^{-1}\)). In contrast, the average magnitude of the sea breeze in autumn was observed to be only marginally above cut-in wind speed. While a local nocturnal feature was clearly pronounced over the case study days presented earlier in Figure 5.2, this feature was much less discernible over all seasons in the observations (Figure 5.8). This suggests that while localized nocturnal circulation features might sometimes be important to the wind resource, they occurred only under certain conditions and, given the limited frequency of occurrence, did not make an important average contribution to the wind climatology or wind resource quantity.

TAPM was found to perform reasonably well in terms of simulating key aspects of the observed changes in the sea breeze circulation between seasons (right panels, Figure 5.8). In all seasons, when comparing TAPM to observations, similar patterns are observed in terms of the time of onset and offset of the sea breeze, and the direction of the sea breeze. As found in observations (left panels, Figure 5.8), TAPM predicted a more discernible sea breeze in summer (compared to other seasons), with winds from this direction becoming more frequent and stronger in the afternoon. The summer sea breeze, as predicted by TAPM, was also of similar frequency occurrence and magnitude to observations. In all other seasons, the magnitude of the sea breeze was slightly under predicted by TAPM, compared to observations. In autumn and spring seasons, the sea breeze occurrence frequency was slightly under predicted by TAPM also. As found in observations, the nocturnal circulation features simulated by TAPM did not appear to make an important average contribution to the simulated wind climatology.
Figure 5.8: As for Figure 5.2 but here for comparisons between MCP (left panels) and TAPM (right panels) under different seasons: summer (JJA), autumn (MAM), winter (JJA), spring (SON).

5.4 Sea breeze contribution to wind resource quantity

It was found earlier, based on model experiments, that under certain conditions the strength of the synoptic westerly wind could be reduced by the development of a counter acting sea breeze (Figure 5.6). In contrast, in a separate experiment, it was found that under certain conditions the strength of the synoptic north-easterly could be enhanced by the development of a sea
Of further interest is the net contribution of the sea breeze to the wind resource quantity, considered under all conditions. In an attempt to examine this, TAPM was rerun from September 2011 – September 2013 with the surrounding ocean removed from all domains in the model setup, as described in Section 3.5.2.

The removal of water over the model domain resulted in a reduction of the monthly mean power density, calculated from TAPM simulated wind speed at 30m, in 22 out of 24 of the months examined (Figure 5.9). This suggests that for 22 out of 24 months examined, the sea breeze (or at least the presence of water) provided a positive contribution to the wind resource quantity. Furthermore, when averaged over all months, this contribution was approximately +10% in terms of the power density contribution (Figure 5.9). The two other months of 24, where the removal of water from the model domain resulted in an increase in the monthly mean power density, were both December months (Figure 5.9). Discussion of why these directional changes could occur in model simulations are presented in Chapter 7, related to simulated diurnal changes in temperature and the subsequent enhancement of drainage winds which preferentially occur in certain months.
Figure 5.9: Changes in monthly mean power density associated with the removal of water from TAPM in a simulation experiment run over a two year period. Dotted red line indicates percent difference; horizontal line indicates zero percent difference (no difference in power density between 'TAPM with water' and 'TAPM without water').
Chapter 6 - Microscale results

In this chapter results are presented describing the variability in ridge top wind shear and how this appears to be linked with other meteorological variables and conditions. Results describing wind shear variability within the context of the JH linear theory are presented by calculating geometric properties of Porteous Hill. Results are also presented concerning the possible applicability of MOST in this terrain setting and the relative performance of using MOST versus the more simple 1/7th power law as a tool for extrapolating wind speed with height.

6.1 Geometric properties of Porteous Hill

Various geometric properties of Porteous Hill were calculated for different wind direction sectors (Table 6.1), in the context of the JH linear theory framework (introduced in Section 2.5.4). The largest inner length scale height values ($l$) were calculated for the N-NE and NW-N sectors, however this is largely due to the large $L_H$ values found under these sectors, which should be treated with caution given that the concept of $L_H$ is not strictly valid in these cases due to the influence of surrounding topography to the north. Considering only sectors where the concept of $L_H$ is theoretically more reasonable, the biggest difference in $l$ occurred comparing the S-SW sector and the NE-E sector, where under near-neutral stability the height of $l$ was considerably higher for the S-SW sector (compared to the NE-E sector). The largest $\Delta S_{max}$ values were calculated for the NE-E sector, due to the lowest $L_H$ (greatest average slope) in this sector. The height at which $\Delta S_{max}$ occurs ($h(\Delta S_{max})$) was also found to be lowest for the NE-E sector, due to this sector reporting the lowest $l$. The physical interpretation of this being that, for the NE-E sector, at a height of approximately 9m (on the ridge top) the wind speed (associated with near-neutral stability) is estimated to be approximately 75% greater than the wind speed at 9m height upwind where the flow is unimpeded.
Table 6.1: Geometric measures on Porteous Hill for different wind direction bins. Variables \( l, \Delta S_{\text{max}} \) and \( h(\Delta S_{\text{max}}) \) are calculated based on the JH linear theory under near-neutral conditions. * indicates where the \( L_H \) concept is not strictly valid due to the influence of nearby topography.

<table>
<thead>
<tr>
<th>Wind direction bin</th>
<th>( L_H ) (km)</th>
<th>( z_o ) (m)</th>
<th>( l ) (m)</th>
<th>( +\Delta S_{\text{max}} ) (%)</th>
<th>( h(\Delta S_{\text{max}}) ) (m)</th>
</tr>
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<tr>
<td>N-NE*</td>
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<td>75.3</td>
<td>9.04</td>
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<td>0.023</td>
<td>42.96</td>
<td>64.0</td>
<td>14.32</td>
</tr>
<tr>
<td>SE-S</td>
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<td>&lt;0.001</td>
<td>34.21</td>
<td>58.2</td>
<td>11.40</td>
</tr>
<tr>
<td>S-SW</td>
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<td>0.149</td>
<td>66.48</td>
<td>48.5</td>
<td>22.16</td>
</tr>
<tr>
<td>SW-W</td>
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<td>&lt;0.001</td>
<td>38.38</td>
<td>51.2</td>
<td>12.80</td>
</tr>
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<td>0.003</td>
<td>28.99</td>
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<td>0.055</td>
<td>84.71</td>
<td>33.2</td>
<td>29.24</td>
</tr>
</tbody>
</table>

6.2 Controls on ridge top wind shear

In this section the observed variability in wind shear between 15m and 30m is investigated, as are the controls on this variability. Observed variability in ridge top wind shear about the 1/7th power law is presented for day and night separately in Figure 6.1. Only wind speeds greater than 3 ms\(^{-1}\) were considered for reasons discussed in Chapter 3. The mean observed ridge top wind shear was found to be greater for night (0.085) than for day (0.055), influenced by the higher frequency of negative wind shear values occurring during the day. Furthermore, the differences in mean wind shear between day and night were found to be statistically significant \((p < 0.05)\) (Appendix B.1). As shown in Figure 6.1, for both day and night, the 1/7th power law overestimated the mean observed wind shear, with this overestimation more pronounced for day compared to night.

The impaired performance of the 1/7th law, as a method for extrapolating wind speed with height on Porteous Hill, is shown in Figure 6.2. In particular, the 1/7th law resulted in an average overestimation of 30m wind speeds, as indicated by the reduced gradient of the best fit line compared to the 1:1 gradient line (left panel, Figure 6.2). Furthermore, while there was an average overestimation of wind speeds by the 1/7th law, the extent of this overestimation was dependent on the hour of day (right panel, Figure 6.2). In particular, the overestimation was most pronounced in the afternoon (approximately 8% overestimation) and least pronounced in the morning (approximately 4% overestimation).
Figure 6.1: Probability density functions of wind shear at 15-30m for day and night. Solid vertical line displays the ‘1/7th’ power law assumed wind shear.

Figure 6.2: Left panel - comparisons of the 15m to 30m 1/7th power law extrapolation against 30m observations at 10 minute average time scale. Solid line shows line of best fit; Dotted line shows 1:1 relationship. Right panel - ratio bias in the 15m to 30m 1/7th power law extrapolation as a function of hour of day. Vertical bars display ±1 standard deviation in the ratio bias for a given hour.

The hypothesis that wind speed, time of day and wind direction all contribute to observed variability in wind shear is explored in detail. As shown in Figure 6.3, large variability was observed in terms of wind shear between different times of day, different wind directions and different wind speeds, however complexity in these associations exists. Based on the findings presented earlier in Chapter 5, there is strong evidence to suggest wind speed, wind direction
and time of day exert multicollinearity. Therefore, this must be taken into account when considering the relationship between wind shear and each of these independent variables.

Figure 6.3: As for Figure 5.2 but here showing dependence of wind shear on hour of day and wind direction (top panel), and dependence of wind speed on hour of day and wind direction over the same time period for reference (bottom panel). Wind shear is displayed as a factor of 100 here to emphasize variability.

When considering diurnal changes in wind shear, wind shear decreased during the day time across all wind direction sectors and reached an average local minimum at approximately 1300 hours (Figure 6.3). By comparing magnitudes (colours) of wind shear pertaining to a particular hour and wind direction against wind speed pertaining to the same hour and wind direction, during the night (2000 – 0800 hours) lower average wind speed was generally associated with higher average wind shear (Figure 6.3). This negative relationship between wind speed and wind shear during the night is also shown in Figure 6.4. During day time (0800 – 2000 hours), the relationship between wind shear and wind speed was generally negative also, but with a less negative slope (Figure 6.4), which was found to be dependent on wind direction also. For example, in Figure 6.3, the wind direction sector 45-135° appears to be an anomaly (compared
to other wind direction sectors) in that lower day time wind speeds were also associated with lower day time wind shear over this sector. This anomalous positive relationship for day time wind shear and wind speed over the sea breeze sector (45-120°) is also illustrated in Figure 6.5.

Figure 6.4: Relationship between wind speed and wind shear for all wind directions, comparisons shown between day (red) and night (black). Wind speed is binned at 1 m/s intervals. Bars represent the 95% confidence interval in the mean for a given wind speed.

Figure 6.5: Relationship between wind speed and wind shear for wind directions 45-120°, comparisons shown between day (red) and night (black). Wind speed is binned at 1 m/s intervals. Bars represent the 95% confidence interval in the mean for a given wind speed.

Certain wind direction sectors in Figure 6.3 appear to display different average wind shear values, unexplained by the time of day and the wind speed in that sector. The biggest difference in average wind shear was observed between wind direction sector 180-225° and
wind direction sector 45-135° (Figure 6.3). As shown in Table 6.1, the wind direction sector 180-225° (S-SW) and the wind direction sector 45-135° (NE-E and E-SE) also displayed large differences in terms of the estimated \( h(\Delta S_{\text{max}}) \). In particular, \( h(\Delta S_{\text{max}}) \) was closer to 15m for the wind direction sector 45-135°, therefore the increase in wind speed induced by the slope of the hill was estimated to reach a maximum (in neutral conditions) at a height near to where the lower level wind speed (15m) was used in the calculation of wind shear. The possible implications of this result, in terms of a contribution to variability in wind shear observed between wind direction sectors, are discussed in Chapter 7.

To explore the possibility that differences in wind shear observed between wind direction sectors was simply due to confounding factors, such as lower average wind speeds or nocturnal winds (both shown earlier to generally enhance shear) being more common in a particular sector, comparisons were made between sectors after isolating the effects of these factors. As shown in Figure 6.6, for a given wind speed, the mean wind shear was found to be higher across the 180-225° sector compared to the sea breeze sector (45-120°). The higher mean wind shear observed across the 180-225° sector was also statistically significant at the 95% confidence interval (confidence intervals between directions do not overlap for a given wind speed bin), except for very high wind speeds (>12 ms\(^{-1}\)). This result was generally still observed when only nocturnal winds were considered (Figure 6.7), with the exception for one further wind speed bin considered (for wind speeds 4-5 ms\(^{-1}\)) where confidence intervals overlap between 45-120° and 180-225° sectors. This suggests that the enhanced wind shear observed across the 180-225° sector (compared to the 45-120° sector) can be largely attributed to differences in terrain or surface type factors associated with this sector, as opposed to being statistical artifacts of multicollinearity.
Figure 6.6: Relationship between wind speed and wind shear without separating night from day, comparisons shown between wind direction sectors 45-120° (blue) and 180-225° (green). Wind speed is binned at 1 ms\(^{-1}\) intervals. Bars represent the 95% confidence in the mean for a given wind speed.

Figure 6.7: Relationship between night time wind speed and wind shear, comparisons shown between wind direction sectors 45-120° (blue) and 180-225° (green). Wind speed is binned at 1 ms\(^{-1}\) intervals. Bars represent the 95% confidence in the mean for a given wind speed.
6.3 Utility of MOST

In this section the utility of MOST is explored. If the utility of MOST can be confirmed in this setting, and if a large amount of variability in wind shear can be explained by MOST, in the absence of upper level wind speed measurements, this could: (1) provide wind resource assessors with a relatively easy way to infer or parameterize wind resource quality; (2) provide wind resource assessors with a more accurate way to extrapolate near surface measurements of wind speed to wind turbine hub height.

Stability was found to display a distinctive diurnal signal (Figure 6.8). In particular, values of $z/L$ on average transitioned from stable ($z/L > 0$) to unstable ($z/L < 0$) at approximately 0900 hours and transitioned back to stable again at approximately 1800 hours, associated with the change in direction of the sensible heat flux over this time. For wind speeds greater than 3 ms$^{-1}$, diurnal changes in $z/L$ were less pronounced, compared to diurnal changes in $z/L$ for wind speeds less than 3 ms$^{-1}$. For a given hour, less variability (lower standard deviation) in the distribution of $z/L$ was found under wind speeds greater than 3 ms$^{-1}$.

![Figure 6.8: Diurnal variation in mean stability ($z/L$) under lower (black) and higher (red) wind speeds. Vertical bars display ±1 standard deviation for a given hour.](image)

The use of MOST, as a tool for extrapolating wind speed measurements with height, was shown to generally perform less well compared to the simple $1/7$ power law (Figure 6.9). While both the $1/7$ power law and MOST on average overestimated extrapolated wind speeds, the extent of this overestimation was greater for MOST (average overestimation of 14.9%).
compared to the 1/7th power law (average overestimation of 5.7%). Furthermore, MOST was shown to substantially overestimate extrapolated wind speed during stable conditions (night) by approximately 20%. In contrast, during convective conditions (day), the performance of MOST improved and generally performed slightly better than the 1/7th power law.

Figure 6.9: Ratio bias in extrapolation (15m to 30m) as a function of hour of day for the 1/7th power law method (blue) and the MOST method (red). Dashed horizontal lines display the average bias (averaged across all hours) for each method. Vertical bars display ±1 standard deviation for a given hour.

### 6.3.1 Relationships under all conditions

The utility of MOST in this ridge top setting was explored by statistically comparing relationships between normalized vertical ($\bar{w}$) and horizontal ($u, \bar{w}$) standard deviations in velocity fluctuations and stability at this site, against those found in other studies where the utility of MOST has been examined. The implications of auto-correlation in these relationships is not considered explicitly here but is discussed in Chapter 7.

Standard deviations in the normalized vertical velocity ($\frac{\bar{w}}{u^*}$) in the unstable range were found to approximately follow the relationship with $z/L$ presented by Kaimal and Finnigan (1994) (hereafter KF94) over flat terrain, as indicated by the closeness of the fitted lines (Figure 6.10). Observational data fitted the relationship proposed by KF94 with $R^2 = 0.30$; with adjustable parameters this relationship increased slightly with $R^2 = 0.33$ (Table 6.2).
In the stable range $\frac{\sigma_w}{u^*}$ did not adhere to the original relationship proposed by KF94 with $R^2 < 0.1$ (Table 6.2), and with the KF94 relationship clearly under predicting the slope of the fit to the observed data (Figure 6.10); however, with adjustable parameters this relationship was found to increase with $R^2 = 0.38$. Standard deviations in the normalized horizontal velocities ($\frac{\sigma_u}{u^*}$ and $\frac{\sigma_v}{u^*}$), in both the stable and unstable range, did not follow the relationship proposed by Nadeau et al. (2012) well, nor did they follow this relationship when adjustable parameters are introduced. This is evident in the high degree of scatter observed in Figure 6.10 and the low $R^2$ values presented in Table 6.3 under these relationships.

By comparing near-neutral moment ratios ($\sigma_u: \sigma_v: \sigma_w: u ~$) observed at this site against those found in other studies (under different surface types) insight can be gained into the organization of the turbulence structure here. As shown in Table 6.4, the magnitude order of the moment ratios was preserved here with $\frac{\sigma_u}{u^*} > \frac{\sigma_v}{u^*} > \frac{\sigma_w}{u^*}$ being in line with other studies. However, both the vertical and horizontal moments were found to exhibit higher ratios compared to those found in other studies presented in Table 6.4. For example, the near-neutral asymptotic limit of $\frac{\sigma_w}{u^*}$ here more closely resembled that of urban surface types in other studies compared to flat terrain. Furthermore, in the cases of $\frac{\sigma_u}{u^*}$ and $\frac{\sigma_v}{u^*}$ the near-neutral asymptotic limits found here were 43% and 56% higher, respectively, than commonly observed over flat terrain. It should also be noted that there is some uncertainty associated with the values presented in Table 6.4 (for this study), as considerable scatter was observed in the near-neutral range.
Figure 6.10: Relationship between normalized vertical ($w$) and horizontal ($u, v$) standard deviations in velocity fluctuations and MOST stability. Blue line is relationship based on KF94 for $\frac{\sigma w}{u^*}$ and based on Nadeau et al. (2012) for $\frac{\sigma u}{u^*}$ and $\frac{\sigma v}{u^*}$; red line is observed best fit under the same formulation but with iterations performed on parameters.

Table 6.2: Relationship between normalized vertical standard deviations in velocity and MOST stability, comparisons made between the formulations used by other authors.

<table>
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<tr>
<th>Variable; stability</th>
<th>Formulation</th>
<th>Parameter values</th>
<th>adj. $R^2$</th>
</tr>
</thead>
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<tr>
<td>$\frac{\sigma w}{u^*}; \frac{z}{L} &gt; 0$</td>
<td>KF94</td>
<td>$\alpha = 1.25$, $\beta = 1$</td>
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<td>$\alpha = 1.362$, $\beta = 0.573$</td>
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<td>$\frac{\sigma w}{u^*}; \frac{z}{L} &lt; 0$</td>
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<td>$\alpha = 1.299$, $\beta = 0.231$, $\gamma = 0.532$</td>
<td><strong>0.33</strong></td>
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Table 6.3: Relationship between normalized horizontal standard deviations in velocity and MOST stability, comparisons made between the formulations used by other authors.

<table>
<thead>
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<th>Variable; stability</th>
<th>Formulation</th>
<th>Parameter values</th>
<th>adj. $R^2$</th>
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<td></td>
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<td></td>
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<td></td>
<td></td>
<td>$\gamma = 3$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>This study</td>
<td>$\alpha = 3.058$</td>
<td>$&lt;0.1$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$\beta = 3.415$</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>$\gamma = 2.407$</td>
<td></td>
</tr>
</tbody>
</table>
Table 6.4: Comparisons between asymptotic limits of near-neutral velocity fluctuations between studies of different surface types and this study. Table adapted from Nadeau et al. (2012).

<table>
<thead>
<tr>
<th>$\frac{\sigma_u}{u^*}$</th>
<th>$\frac{\sigma_v}{u^*}$</th>
<th>$\frac{\sigma_w}{u^*}$</th>
<th>Surface type</th>
<th>Author(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.4</td>
<td>1.9</td>
<td>1.25</td>
<td>Flat terrain</td>
<td>Garratt (1994), Kaimal and Finnigan (1994), and others</td>
</tr>
<tr>
<td>2.3</td>
<td>1.85</td>
<td>1.35</td>
<td>Urban</td>
<td>Wood et al. (2010)</td>
</tr>
<tr>
<td>2.5</td>
<td>2.2</td>
<td>1.3</td>
<td>Urban</td>
<td>Hogstrom et al. (1982)</td>
</tr>
<tr>
<td>1.76</td>
<td>1.6</td>
<td>1.22</td>
<td>Urban</td>
<td>Al-Jiboori et al. (2002)</td>
</tr>
<tr>
<td>2.35</td>
<td>2.1</td>
<td>1.35</td>
<td>Urban</td>
<td>Xu et al. (1997)</td>
</tr>
<tr>
<td>-</td>
<td>2</td>
<td>1</td>
<td>Coastal</td>
<td>Shao and Hacker (1990)</td>
</tr>
<tr>
<td>2.85</td>
<td>2.24</td>
<td>0.98</td>
<td>Steep alpine slope</td>
<td>Nadeau et al. (2012)</td>
</tr>
<tr>
<td>3.43</td>
<td>2.96</td>
<td>1.36</td>
<td>Hill ridge top</td>
<td>This study</td>
</tr>
</tbody>
</table>

6.3.2 Dependency on wind speed and direction

While $\frac{\sigma_u}{u^*}$ and $\frac{\sigma_v}{u^*}$ did not appear to follow MOST in this setting, of interest is whether the reported statistical relationship between $\frac{\sigma_w}{u^*}$ and $z/L$ might be sensitive to different meteorological conditions. To explore this, relationships were statistically examined under different wind speeds and directions along with the associated change in the $R^2$ values found under these conditions (Figure 6.11; Figure 6.12; Table 6.5; Table 6.6). Under the various wind speeds and directions considered, changes in these conditions were accompanied by changes to the reported $R^2$ values of less than ±0.1 (Table 6.5; Table 6.6). That is to say, changes in the wind speed and direction considered here changed the percentage of variability in $\frac{\sigma_w}{u^*}$ explained by $z/L$ by less than 10%. While changes in wind direction had more of an influence than changes in wind speed, these changes were relatively small and likely insignificant for reasons discussed in Chapter 7.
Figure 6.11: Relationship between normalized vertical standard deviation in velocity and MOST stability for wind speeds < 3 ms⁻¹ (top panels) and wind speed > 3 ms⁻¹ (bottom panels). Red line is observed best fit, blue line is relations based on formulations commonly reported over flat homogenous terrain.

Figure 6.12: As in Figure 6.11 but here for comparisons between wind direction sectors 45 – 120° (top panel) and 180 - 225° (bottom panel).
Table 6.5: Relationship between normalized vertical standard deviation in velocity and MOST stability under different stability and wind speed conditions and the associated change (relative to all conditions) in \( R^2 \) statistic.

<table>
<thead>
<tr>
<th>Conditional filter</th>
<th>Formulation</th>
<th>Parameter values</th>
<th>adj. ( R^2 ) (change in adj. ( R^2 ) relative to all conditions)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \frac{z}{L} &lt; 0 ) wind speed &lt; 3 ms(^{-1})</td>
<td>KF94</td>
<td>( \alpha = 1.25 ) ( \beta = 3 ) ( \gamma = 3 ) ( \text{This study} ) ( \alpha = 1.258 ) ( \beta = 0.242 ) ( \gamma = 0.564 )</td>
<td>0.3 (0) 0.36 (+0.03)</td>
</tr>
<tr>
<td>( \frac{z}{L} &lt; 0 ) wind speed &gt; 3 ms(^{-1})</td>
<td>KF94</td>
<td>( \alpha = 1.25 ) ( \beta = 3 ) ( \gamma = 3 ) ( \text{This study} ) ( \alpha = 1.295 ) ( \beta = 0.054 ) ( \gamma = 0.116 )</td>
<td>0.27 (-0.03) 0.30 (-0.03)</td>
</tr>
<tr>
<td>( \frac{z}{L} &gt; 0 ) wind speed &lt; 3 ms(^{-1})</td>
<td>KF94</td>
<td>( \alpha = 1.25 ) ( \beta = 0.2 ) ( \text{This study} ) ( \alpha = 1.326 ) ( \beta = 0.554 )</td>
<td>&lt;0.1 (0) 0.34 (-0.04)</td>
</tr>
<tr>
<td>( \frac{z}{L} &gt; 0 ) wind speed &gt; 3 ms(^{-1})</td>
<td>KF94</td>
<td>( \alpha = 1.25 ) ( \beta = 0.2 ) ( \text{This study} ) ( \alpha = 1.360 ) ( \beta = 0.628 )</td>
<td>&lt;0.1 (0) 0.36 (-0.02)</td>
</tr>
</tbody>
</table>
Table 6.6: Relationship between normalized vertical standard deviation in velocity and MOST stability under different stability and wind direction conditions and the associated change (relative to all conditions) in adj. $R^2$ statistic.

<table>
<thead>
<tr>
<th>Conditional filter</th>
<th>Formulation</th>
<th>Parameter values</th>
<th>adj. $R^2$ (change in adj. $R^2$ relative to all conditions)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \frac{z}{\bar{L}} &lt; 0 ) 45 – 120°</td>
<td>KF94</td>
<td>( \alpha = 1.25 )  ( \beta = 3 )  ( \gamma = 3 )</td>
<td>0.33 (+0.03)</td>
</tr>
<tr>
<td></td>
<td>This study</td>
<td>( \alpha = 1.27 )  ( \beta = 0.002 )  ( \gamma = 0.005 )</td>
<td>0.42 (+0.09)</td>
</tr>
<tr>
<td>( \frac{z}{\bar{L}} &gt; 0 ) 45 – 120°</td>
<td>KF94</td>
<td>( \alpha = 1.25 )  ( \beta = 0.2 )  ( \gamma = 0.1 )  ( \gamma = 0 )</td>
<td>&lt;0.1 (0)</td>
</tr>
<tr>
<td></td>
<td>This study</td>
<td>( \alpha = 1.423 )  ( \beta = 0.633 )</td>
<td>0.36 (-0.02)</td>
</tr>
<tr>
<td>( \frac{z}{\bar{L}} &gt; 0 ) 180 – 225°</td>
<td>KF94</td>
<td>( \alpha = 1.25 )  ( \beta = 0.2 )  ( \gamma = 0.596 )</td>
<td>&lt;0.1 (0)</td>
</tr>
<tr>
<td></td>
<td>This study</td>
<td>( \alpha = 1.367 )  ( \beta = 0.596 )</td>
<td>0.45 (+0.07)</td>
</tr>
</tbody>
</table>
Chapter 7 - Discussion

The following research questions were introduced in Chapter 1 and subsequently form the basis of each section presented in this chapter, these were:

- How does the observed wind power density at the site vary on monthly and seasonal scales? Can the reorganization of synoptic scale circulation features be linked to this variability?

- At the sub-synoptic scale, to what extent do thermally generated winds appear to contribute to the quantity of the wind resource?

- At the microscale, what variables appear to exert control on wind shear? If the complexity of the terrain contributes to variability in wind shear, might this violate the usefulness of the 1/7th power law or MOST in wind resource assessments?

By discussing each of these questions in detail, this chapter also builds on the results presented in Chapters 4, 5, and 6. This Chapter is again divided on the basis of scale with Section 7.1 and Section 7.2 focusing on synoptic and sub-synoptic (local scale to mesoscale) contributions to the wind resource quantity and variability. However, as previously noted, difficulty exists in separating these processes in complex terrain, therefore some implications of scale interaction are also discussed. Section 7.3 focuses on the microscale processes that appear to control ridge top wind shear on Porteous Hill; an assessment of MOST is also presented in this terrain setting and in the context of the wind resource assessment.

7.1 Synoptic scale contributions

7.1.1 Inter-monthly and inter-seasonal variability

This subsection focuses on how wind resource quantity varies on Porteous Hill between months and seasons. While studies such as Bowden (2011) and Cullen et al. (2012) have focused on spatial variability in the wind resource across the broader Blueskin Bay region, the focus of this study was to comprehensively examine causes for temporal variability at one point in space (the ridge top of Porteous Hill). Particular focus is given to discussing the tools implemented to reconstruct the necessary time series, and the applicability of these tools in the wider context of wind resource assessments.
Reconstruction using MCP method

The use of the linear regression MCP model at Porteous Hill was found to be a relatively robust and accurate tool for reconstructing wind speed used in the assessment of resource quantity on a monthly average scale. The performance of the linear regression model, tested under different training periods (70 days versus 112 days), revealed only slight increases in model performance under the longer training period. Some commentators (e.g. Dinler, 2013) have suggested the use of $r > 0.7$ as an initial critical value when assessing the suitability of a target site in wind resource assessments. In this study, for the shorter and longer training periods the linear regression coefficients were $r = 0.96$ and $r = 0.97$ respectively, providing initial confidence in the use of this model here. In a more comprehensive validation process, the performance of the MCP model was assessed considering a number of measures, based on the recommendations of Rogers et al. (2005), including: ability to reproduce monthly mean wind speed, ability to reproduce monthly Weibull parameters and ability to reproduce monthly mean power density. Over the five months available to test these considerations (where wind speed measurements were concurrently made at T1 and T2), the bias in monthly mean wind speed and monthly mean power density was less than 3% and 13% respectively, over all months. The Weibull distributions of wind speeds, produced by the MCP method, were also found to closely match the Weibull distributions of wind speed from observations, over all months considered.

In other studies, the use of the linear regression MCP model has given less satisfactory results (Rogers et al., 2005; Carta et al., 2013). A number of commentators have also criticized certain aspects of such an approach, despite the approach still being that most commonly used in wind resource assessments. According to Rogers et al. (2005) the main limitation of the linear regression approach is the effect caused by the variance of the calculated wind speed being less than the variance of the observed wind speed, inherent in linear regression models. Subsequently, while the calculated monthly mean wind speed is unaffected, the wind speed distributions can often be erroneous. Despite the concerns raised by Rogers et al. (2005), there is little evidence to suggest that this effect was having a major bias on monthly mean power density estimates here, given that the Weibull distributions predicted by the MCP method were very similar to those calculated from observations. Other alternatives to the linear regression MCP approach involve a binning method, whereby different regression equations are formed for wind speed under different wind direction bins (Beltran et al., 2010). It has been proposed (e.g. Craine et al., 2004; Beltran et al., 2010) that this method is particularly advantageous (over the traditional linear regression method) in complex terrain because of the different influences of orography on wind speed under different wind directions between reference and target sites. However, the benefit of such an approach was thought to be of little advantage in
the context of this study, with the reference and target sites both positioned on Porteous Hill and exposed to very similar orographic influences.

Based on the finding that the highest bias (least accurate) monthly mean power density was 13% over the five month validation period, it was assumed that this was a reasonable upper estimate of the monthly mean power density uncertainty over the two year reconstructed time period. However, it is possible that the regression model may produce a higher bias (i.e. >13%) in a substantially different ‘climatic’ season outside of that which the model was trained in (Carta et al., 2013). Unfortunately, the limited overlap period of T1 and T2 data in this study limited the potential to extensively explore the time variant properties of this bias; however, some evidence exists to suggest that this might not be so important here. For example, the month of August 2013 was outside of the model training period (and in a different climatic season to that at the start of the training period) yet reported a lower bias in monthly mean wind speed and monthly mean power density than other months that were inside of the training period.

Reconstruction using TAPM

The numerical model TAPM was found to perform well in terms of simulating wind speed over the calibration period. Over the calibration period, the skill of TAPM (determined by the IOA statistic) was found to increase as higher spatial resolution and more nested domains were employed. According to Hurley et al. (2002), an IOA value greater than 0.5 indicates model skill for a range of meteorological variables including wind speed. Therefore, the IOA of 0.72 found here, over the initial calibration period and with the optimized model setup, suggests adequate model performance. This result, with the same optimal model setup, was also found in Bowden (2011) in a similar terrain setting, but over a different time period. In other studies, using different mesoscale numerical models (e.g. McKendry and Steyn, 1988; Seaman et al., 1995; Lyons et al., 1995) IOA statistics for wind speed are often lower (less than 0.6) than that reported here for TAPM. Hurley et al. (2008) provided a comprehensive review of TAPM performance in terms of wind speed simulated by TAPM in different terrain conditions across Australia and the U.S. The authors found that, over a range of geographic settings, the IOA for TAPM simulated wind speed was between 0.67 and 0.86, with the lower values generally reported for wind speed measurements in more complex terrain sites and the higher values reported for wind speed measurements at higher elevations in the ABL (e.g. 100m). Therefore, given the complexity of the terrain here, the IOA values obtained over the calibration period of this study appear to be in broad agreement with those reported from TAPM in other studies.
While the IOA is a commonly used measure to examine the skill of model simulated meteorological parameters, the ability of TAPM to simulate monthly mean power density (as a direct measure of wind resource quantity) was considered to be a more relevant measure of model performance. The ability of TAPM to simulate the observed monthly mean power density varied between months, but was often poor. The mean power density was under predicted by 60% in August 2013, while better performance (lower absolute value in the percentage bias) was reported for March – May 2013 where the percentage bias varied between -20% to +12%. The months that performed better were inside the calibration period of the model (14 March – 23 May 2013); however this was deemed coincidental as no physical explanation could be provided as to why the calibration process (involving optimizing the number of domains and grid resolution) would favour performance in particular months. Other measures of performance, such as ability to group monthly mean power density into the classification bands presented by Mostafaeipour et al. (2011), tested over the entire two year period against the MCP method, also suggested that TAPM was only capable of adequately simulating monthly mean power density approximately 50% of the time. The impaired performance of TAPM in certain months appears to be due to a combination of both poorly predicting mean wind speeds and the wind speed distribution (in terms of Weibull parameters) in these months.

This study appears to be the first of its kind to investigate the performance of TAPM in terms of its ability to simulate monthly mean power density, at this site or elsewhere. However, based on the limited performance of TAPM, it was deemed inappropriate to use TAPM in this setting to infer wind resource quantity outside of a time period where field based measurements of wind speed were available (prior to September 2011). The idea that a relatively high IOA for TAPM simulated wind speeds over a short period of model calibration (70 days) can be accompanied by poor performance to simulate monthly mean power density at other times of the year is an important finding. For example, the magnitude of temporal variability in model performance implies that model validation against field based wind speed measurements should be carried out over at least several months before relying on the output of model simulations in this context.

While explicitly untangling the causes of TAPM’s inability to adequately simulate the wind resource quantity was outside of the aims of this study, some consideration is given to this here. According to Cullen et al. (2012) TAPM has a tendency to under predict the wind resource quantity at Porteous Hill due to the relatively coarse representation of the hill in the model causing the height of the hill to be under predicted. While this suggestion might partly explain the limited performance of TAPM here, it is not deemed to be the dominant or sole attributor, given that the monthly mean power density was also at times overestimated by TAPM.
Another, perhaps stronger, explanation is that TAPM has a tendency to under predict extreme events such as strong westerlies. For example, the assumption of incompressibility and the upper extent of non-hydrostatic effects (5000m) in TAPM, mean that meteorological variables must be ‘smoothed out’ to avoid substantial wave reflections from the top of the model (Zawar-Reza et al., 2005). As a result of this, very deep atmospheric circulation such as strong westerly winds, associated with wave motion, are often less well simulated by TAPM. Given that these strong westerly winds were shown to be linked with high wind resource quantity, it is speculated that this is an important contributor to TAPM’s impaired performance found here.

**Two year variability in wind resource quantity**

An analysis of observed wind speed distributions at 30m revealed that wind speed could be well modelled by a Weibull distribution in this terrain setting. In contrast, other studies (e.g. Jaramillo and Borja, 2004) have shown that in complex terrain, locally generated winds and orographic blocking are capable of distorting wind speeds away from the Weibull distribution and towards a bimodal distribution. The finding of this study therefore suggests that in other settings the complexity of the terrain might not necessary violate the usefulness of representing the wind speed distribution by Weibull parameters. This has important implications for wind resource assessments in complex terrain, given that the power density in the wind based on Weibull distribution parameters is a commonly used metric for wind resource quantity.

Substantial variability in the two year record of wind resource quantity was found to exist between months and seasons at this site. On average, spring months examined had the highest mean power density followed by winter months. This variability resulted in monthly classifications of wind resource quantity ranging from ‘poor’ to ‘excellent’. Furthermore, the extent of this between month variability was such that the variability in monthly power density between consecutive months could be more than 800%. In terms of the wind resource utilization, this finding highlights the intermittency of the resource quantity and suggests that in certain months or seasons wind energy generation might be substantially less reliable. Some wind resource assessment studies in other parts of the world have also found similarly large intermonthly variability in mean power density, whereas in other settings the intermonthly variability is notably less. For example, Mirhosseini et al. (2011) carried out a wind resource assessment in Iran to find substantial variability in 30m power density on monthly time scales. The biggest differences were reported between December and July where mean wind power density increased from 89 Wm$^{-2}$ to 544 Wm$^{-2}$ respectively. In contrast, Mayhoub and Azzam (1997) investigated the wind resource potential at 15 different locations across Egypt to find that while variability in the monthly mean power density between stations could be substantial,
the intermonthly variability at a particular station was notably less, and for many stations this was relatively constant between months. Although intermonthly variability in wind resource quantity is often found in wind resource assessments in the published literature (e.g. Mirhosseini et al., 2011; Keyhani et al., 2010), very rarely is any attempt made to untangle this variability or recognize that a large proportion of that variability might be explained by synoptic atmospheric circulation. Discussion of this is the focus of Section 7.1.2.

7.1.2 Linking wind resource quantity to atmospheric circulation

This subsection examines the extent to which the above described temporal variability in wind resource quantity can be linked to the reorganization of synoptic scale circulation over different temporal scales. Through establishing probabilistic linkages, it is also inferred how larger scale climate oscillations (ENSO and SAM) and change (21st century climate change) also influence variability.

Monthly MSLP linkages

To initially explore the idea that wind resource quantity in this setting could be linked with synoptic scale atmospheric circulation, links between the spatial patterns in monthly average MSLP (from NCEP/NCAR reanalysis) and observed wind roses (frequency distributions of wind speed and wind direction at 30m) were (semi) qualitatively examined. This analysis revealed that average changes in the synoptic circulation were most pronounced between spring months examined compared to summer months, with these seasonal changes linked to changes in the observed wind speed and direction at the site. For example, in spring months examined the synoptic westerly belt on average extended across the country, with large average meridional gradients in synoptic pressure linked to observed strong and frequent westerly winds. In contrast, in the summer months examined, on average the synoptic westerly belt and associated meridional synoptic pressure gradients were located south of New Zealand; this was accompanied by more frequent and less strong (compared to spring months) winds across the NE-SE sector. The more frequent winds observed across the NE-SE sector in the summer months is partially attributable to a thermally generated sea breeze, often occurring in the absence of strong synoptic pressure gradients, which is discussed further in Section 7.2.

A composite analysis of MSLP between the five highest generation potential months and the five lowest generation potential months revealed that differences in generation potential could be linked to spatial differences in the average latitudinal position of high pressure centres, with these differences found to be strongly statistically significant ($p < 0.01$). In particular, months with the highest generation potential occurred when monthly average high pressure centres
were situated further north of New Zealand at 20-25°S; in contrast the five lowest generation potential months occurred when monthly average high pressure centres were located SE of New Zealand at 50-55°S. This finding reinforces the idea that the average position of high pressure centres between 20-25°S, associated enhanced meridonal synoptic pressure gradients over New Zealand, is a large determinant of high wind resource quantity.

It is well established that the wind regime of the Otago region in a particular season can be influenced by either a strong belt of westerly winds or a dominant high pressure belt, as these features on average shift latitudinally between seasons (Sturman and Tapper, 2006; Cullen et al., 2012). However, the findings presented here are novel in demonstrating that changes in the monthly average atmospheric circulation can be linked to changes in the monthly average wind resource quantity. The finding that this link could be established in a complex terrain setting is also important. For example, the influence of orographic blocking of the Southern Alps and the influence of local-mesoscale generated winds (whilst pronounced) do not appear to substantially mask the synoptic scale signal here. The implications of this being that synoptic scale linkages to the wind resource might also be attainable in other parts of New Zealand and even in very complex terrain, where wind turbines are often selectively placed.

**Kidson type linkages**

The analysis presented above, in terms of linking MSLP to wind resource quantity, was conducted over monthly average time periods under which some important variability might be lost in this somewhat arbitrary chosen averaging period. Therefore, the Kidson synoptic classification types were employed to explore synoptic scale linkages with wind resource quantity over shorter time periods and in a more quantitative manner. The employment of a logistic regression model here proved to be a useful statistical tool for linking a particular Kidson type to the odds of a maximum or minimum 12 hour generation event. The changes in the odds of an event (under a certain Kidson type or month of year) discussed hereon were all shown to be statistically significant ($p < 0.05$) providing further confidence in these linkages.

The probability of a minimum generation 12 hour event occurrence was highest for the HSE Kidson type followed by the H Kidson type, relative to the other Kidson types. These findings are in broad agreement with the monthly average MSLP linkages presented earlier where it was found that monthly average high pressure centres over New Zealand, or to the southeast of New Zealand, were associated with the poorest generation months. Minimum generation 12 hour events were also more likely to occur in February, April, June and August months examined, compared to December. The findings for February and April reflect the relatively low mean power density observed at the monthly mean time scale. However, June and August months
examined were observed to have relatively large mean power density across the two year period examined (compared to December), suggesting that these months exhibited large amounts of variability with a greater tendency for extreme events (both high and low).

The probability of a maximum generation event occurrence was greater for a number of Kidson types compared to the H Kidson types. The probability of maximum generation event occurrence was generally greatest for the Kidson types associated with relatively strong west or south-west synoptic circulation over the South Island (SW, W, T, HW and HNW Kidson types), and lowest for the HSE Kidson type, associated with very weak synoptic gradients over the South Island. A similar finding was observed by Mullan et al. (2008) whereby the same five Kidson types produced the highest occurrence of extreme winds when analysed across the Otago region. This finding is also in broad agreement with the monthly average MSLP linkages, where it was found that monthly average high pressure centres positioned further north of New Zealand, with the average westerly belt positioned over New Zealand, were associated with the highest generation months. Six months were found to have a higher probability of a maximum generation 12 hour event occurrence relative to December. All of these months, with the exception of May, were spring or winter months, which is broadly in agreement with the monthly mean power density observed as being higher in these months (compared to December). Included in these months were June and August, associated with a higher probability of a maximum 12 hour event occurrence. Interestingly, June and August were also found earlier to be associated with a higher probability of a minimum 12 hour event occurrence (compared to December), which again strengthens the idea that the wind resource quantity in these months was highly variable.

The employment of the logistic regression model to link Kidson type classifications to wind resource quantity over a certain 12 hour period was considered successful for a number of reasons. First, the model confirmed the earlier found linkages between the synoptic state of the atmosphere and the wind resource quantity over a different (shorter) averaging period, suggesting that the analysis here is robust in that regard. Second, the model not only confirmed the results found earlier over longer averaging periods, but provided new insights into these linkages. For example, there is evidence to suggest that certain months examined (June and August) tended to exhibit larger intramonthly variability in wind resource quantity.

The logistic regression model analysis also has important practical applications. Since the synoptic state of the atmosphere can be forecasted a few days ahead by current generation numerical weather prediction (NWP) models, the linkages established could permit real-time predictions of the probability of generation event extremes on Porteous Hill, a few days ahead. Another advantage of this probabilistic type analysis lies in the potential to infer how large
scale climate oscillations might affect aspects of the wind resource. Other studies (e.g. Kidson and Renwick, 2002; Renwick, 2011) have found that the occurrence of particular Kidson types and regime groups is influenced by larger scale climate oscillations (e.g. IPO, ENSO and SAM). Therefore, since probabilistic links have been established between Kidson types and wind resource quantity here, the employment of the logistic regression model allows inference as to how wind resource quantity on Porteous Hill might change under longer term considerations, as discussed in the following section.

**Longer term considerations and future wind resource quantity**

Of interest is whether the monthly and seasonal variability in wind resource quantity observed between September 2011 – September 2013 is anomalous in the long term climatology. While no field based measurements of wind speed are available at the site prior to September 2011 to directly assess past wind resource quantity, given that links between Kidson types and wind resource quantity have been established, and given that Kidson type classifications exist since 1948, inferences can be made regarding typical seasonal variability over longer time periods.

A number of similarities were found to exist between this study period (2011 – 2013) and the long term record (1948 – 2013) in terms of seasonal frequencies of Kidson types. For example, as found in this study period, SW and W Kidson types were found to be most pronounced in spring in the long term record. Therefore, the finding that spring months exhibited a higher power density than other months in this study period is not likely anomalous, given that these Kidson types were strongly linked to a greater probability of maximum generation event occurrence on Porteous Hill. However, the frequency of the SW Kidson types, and to a lesser extent the W Kidson types, was found to be higher for spring over this study period compared to the long term record, suggesting that the magnitude of the seasonal differences in power density might have been less pronounced in the longer term climatology. In terms of Kidson types that were shown to increase the probability of minimum generation event occurrence on Porteous Hill, H and HSE Kidson types were more common in summer over this study period compared to the long term record, suggesting that the often low mean power densities observed here in summer months might be unusual and specific to this time period.

In winter and autumn, the distribution of Kidson types, shown to have the largest influence on wind resource quantity on Porteous Hill, displayed more variability in terms of directional change when comparing this study period to the long term record. For example, in these seasons some of the Kidson types, shown to increase the probability of maximum generation event occurrence, occurred more persistently in this study period whereas others occurred more persistently in the long term climatology. Similar changes in winter and autumn were also
observed for Kidson types shown to increase the probability of minimum generation event occurrence, when comparing this study period to the longer term climatology. In conclusion, there is some evidence to suggest that the magnitude of the differences in wind quantity between spring (generally high quantity) and summer months (generally low quantity) observed over this study period might be unusual in terms of the longer term climatology; whereas the wind resource quantity in winter and autumn months observed over this study period might be more similar to the longer term climatology.

Large scale climate oscillations such as ENSO and SAM have been shown to be responsible for favouring certain Kidson regime groups (Kidson and Renwick, 2002; Renwick, 2011). Such studies found that, somewhat independent of the season, under El Niño (positive SOI) there is a tendency for an increase in the zonal types (H, HNW and W Kidson types) while under La Niña (negative SOI) there is a tendency for an increase in blocking type (HSE, HE, NE, HW and R Kidson types). These changes can be further amplified under the specific phase of the IPO, with a positive IPO generally favouring an El Niño state and a negative IPO generally favouring a La Niña state. Based on the logistic regression model linking Kidson regime groups to maximum generation day events, it can be inferred that under El Niño events the increase in prevalence of zonal regime groups is likely to result in an increase in the probability of maximum generation day occurrence, compared to La Niña events where blocking types are more prevalent. Furthermore, there is some evidence to suggest that under El Niño events, the increase in zonal regime groups might result in a decrease in the probability of minimum generation day occurrence, compared to La Niña events where blocking regime groups are more prevalent. However, less confidence can be placed in the linkage with minimum generation day occurrence given that the difference is not statically significant in the model. Based on these findings, it appears that the wind resource quantity on Porteous Hill might on average increase under El Niño compared to La Niña. The studies of Kidson and Renwick (2002) and Renwick (2011) also indicated that the positive phase of SAM is associated with more frequent blocking types while the negative phase of SAM is associated with more frequent trough types. Under the negative phase of SAM, the increase in trough regime group prevalence is likely to result in an increase in the probability of maximum generation events and a decrease in the prevalence of minimum generation events, compared to the positive phase of SAM. Therefore it appears the wind resource quantity on Porteous Hill would on average increase under a negative SAM phase, compared to a positive SAM phase.

Given these inferences, the state of large scale climate oscillations observed over this study period might partly explain some of the observed inter seasonal variability in wind resource quantity on Porteous Hill. A relatively strong and persistent El Niño event occurred between approximately September 2011 and January 2012 (Appendix C.1) accompanied by an on
average negative SAM phase between September 2011 and November 2011 (Appendix C.2). Given that the El Niño phase and negative SAM phase were inferred above to contribute to, on average, an increase in wind resource quantity (compared to the respective opposite phase of these indices), it is likely that this contributed to the September 2011 - November 2011 period recording the highest three month mean wind resource quantity. In contrast, the lowest three month mean power density was recorded between February 2013 – April 2013. In part this might have been amplified by a relatively strong positive SAM phase over this period (Appendix C.2), accompanied by an increase in blocking types resulting in a negative contribution to wind resource quantity. The IPO has been in a negative phase since approximately the year 2000 and therefore cannot explain the prevalence of El Niño events over this period, given that negative IPO state is usually associated with more prevalent La Niña events. In conclusion, it appears that while seasonal variability in the latitudinal position of the westerly belt over New Zealand is a major driver of inter seasonal variability in wind resource quantity on Porteous Hill, there is some evidence to suggest that these divers are enhanced (or dampened) by the particular state of large scale climate oscillations such as ENSO and the polarity of the SAM.

Model simulations suggest that climate change might be capable of significantly altering aspects of the regional wind regimes over New Zealand (Mullan et al., 2008; Mullan et al., 2011), and subsequently the wind resource over much of New Zealand (Renwick et al., 2010). Model simulations carried out by Mullan et al. (2008) found that, under the IPCC A2 emission scenario (“high emissions”), there is likely to be an average increase in the annual mean westerly wind speed across New Zealand. Seasonal variability in these projections also exist and by 2090 the strength of the westerly wind component is projected to increase by about 50% in winter and 20% in spring, and decrease by about 20% in summer and autumn. However, Mullan et al. (2008) point out that while “confidence” can be placed in the prediction that the westerly wind speed will on average increase, “low confidence” accompanies the projections regarding the seasonal variability in the increase and in the magnitude of the increase. Based on these considerations, and given that west to south-west winds have been shown here to be the most important contributor to wind quantity on Porteous Hill, it might be expected that the wind resource quantity on Porteous Hill will, on average, increase throughout the 21st century. The seasonal variability accompanying the projections of Mullan et al. (2008) might also lead to enhanced inter-seasonal variability in the wind resource quantity on Porteous Hill, with the gap between high generation seasons (spring and winter) and low generation seasons (autumn and summer) becoming more pronounced. To some extent, the findings of Mullan et al. (2008) mirror the projected changes of Kidson types under climate change presented by Mullan et al. (2011), when analysed over shorter (daily as opposed to monthly) time scales and through
considering changes to MSLP simulated by general circulation models (GCMs). Specifically, while Mullan et al. (2011) found no signal in the annual statistics, it was generally observed that for winter (summer) trough and zonal regime groups were predicted to increase (decrease) and blocking regimes predicted to decrease (increase). Projections also suggested that spring closely resembled winter, while summer closely resembled autumn, in terms of frequency changes. Applying the seasonal frequency changes of Mullan et al. (2011) in the context of the findings of the observed probabilistic linkages between Kidson regimes in this study, suggests and strengthens the idea that the amplification of the seasonal reorganization of Kidson types under climate change might amplify the seasonal variability of the wind resource quantity on Porteous Hill.

The climate change signal over the 21st century might also be enhanced or dampened depending on the direction of future trends in large scale climate oscillations, to which uncertainty still remains (Renwick et al., 2010). For example, some authors (e.g. Meehl and Washington, 1996; Trenberth and Hoar, 1997) suggest that anthropogenic greenhouse emissions may already have been responsible for a recent increase in prevalence of strong El Niño events. Given that El Niño events are, on average, likely associated with higher generation events on Porteous Hill, such an occurrence would likely enhance the climate change signal. However, it should be noted that there is some debate regarding the future of ENSO, with Harrison and Larkin (1997) suggesting that observed changes in the prevalence of El Niño events might be more due to natural variability of the tropical Pacific. The SAM has also been noted to be trending towards a positive state recently, with GCMs generally predicting continuation of this under a range of emission scenarios throughout the 21st century, although this might be offset somewhat through Antarctic ozone recovery (Arblaster and Meehl, 2006). Given that the positive SAM phase is, on average, associated with a reduced probability of maximum generation events on Porteous Hill, such an occurrence would likely dampen the climate change signal.

7.1.3 Limitations and areas for future research

The aim of this section was to link variability in the observed wind resource potential to large scale atmospheric circulation, which has received relatively limited consideration in the wind resource assessment literature. The report by Schreck et al. (2008) highlighted that linkages between wind resource characteristics and synoptic climatology and climate oscillations are particularly necessary in the context of studying climate change impacts on the wind resource, but also that possibilities to do so are limited given the scarcity of available long term data sets. Similarly, the two year time frame of this study was too short to directly assess the linkages between large scale climate oscillations (e.g. IPO, ENSO and SAM) and wind resource potential. Furthermore, the numerical model TAPM was not found to be capable of adequately
simulating the wind resource quantity when compared against observations; in turn the model could not be used reliably to simulate wind resource quantity over a period of time before measurements were made. While untangling the causes of TAPM’s inability to adequately simulate the wind resource quantity was outside of the aims of this study, such an assessment would be beneficial. For example, future research could be directed towards incorporating a higher resolution and more realistic DEM into the model, or towards comparing the relative performance of TAPM against a more sophisticated higher resolution numerical model such as WRF. However, it should be noted that even more sophisticated models (such as WRF) are also potentially limited in terms of simulating deep atmospheric circulation events associated with the wave motion of strong westerlies over New Zealand, with the extent of this limit not yet fully understood (Zawar-Reza, pers. comm.).

The limited time frame where 30m wind speeds were measured directly in this study also meant that seasonal variability and linkages with synoptic Kidson types were established based on wind speed data calculated under the MCP method. As discussed earlier, the accuracy of the regression model used in the MCP method appeared relatively robust over the available test period; however, further confidence could be placed in the conclusions drawn from this analysis if the time variant properties of the uncertainty in the MCP method were tested extensively, which could be a topic of future research. Furthermore, the maximum height of tower wind speed and direction measurements (30m) potentially restrict the (direct) relevance of some of these findings to relatively small wind turbines; subsequently, the findings could potentially be extended to tall wind turbines through the employment of SODAR (Sonic Detection and ranging equipment) to make more complete vertical profile measurements.

The use of the logistic regression model in this study proved to be a powerful tool to establish probabilistic links between Kidson types and wind resource quantity. Given that the complexity of the terrain and subsequent influence of orographic blocking is highly variable across much of New Zealand, it seems probable that the linkages established here are site specific to some extent. Therefore, future research could be aimed at applying a similar methodology to datasets from different climatic regions of New Zealand to investigate different spatial patterns in the synoptic scale control on wind resource potential. The influence of large scale climate oscillations on wind resource quantity was inferred based on the probabilistic linkages between Kidson types and wind resource potential, and how the frequency of Kidson types have been shown to be ‘rearranged’ under large scale climate oscillations in other studies. The conclusions drawn are therefore subject to both the uncertainty associated with the logistic regression model employed in this study and also to the uncertainty (and variability) associated with how these Kidson types are rearranged under climate oscillations. Subsequently, the inferences should be regarded as first order approximations of directional changes to the wind
resource quantity, and future research could be aimed at investigating more direct statistical linkages using a suitably long dataset, where available.

7.2 Sub-synoptic contributions

This section discusses the extent to which sub-synoptic thermally generated winds affect the wind regime and wind resource quantity. The analysis is presented based on observations and modelled simulations, both over selected case study days and under all other conditions. Idealized model simulations were also carried out in an attempt to untangle some of the complexity associated with the thermally generated circulation and to quantify the contribution to the wind resource.

7.2.1 Case study days

In a case study of ten select days deemed most favourable for the development of thermally generated circulation features, an afternoon sea breeze and nocturnal wind were clearly discernible in the observational data. Aspects of these circulation features including: frequency, timing of onset, duration and wind direction were largely unchanged between 3.3m and 30m on the ridge top of Porteous Hill. This finding suggests that thermally generated circulation features were not limited to only a very shallow depth in the ridge top boundary layer but instead occurred to a depth sufficient to provide momentum for at least small wind turbines.

The onset of the sea breeze occurred relatively early in the day (between 1000 and 1100 hours), and while the sea breeze onset has been shown to be dependent on the month of the year and on the ambient synoptic wind in other studies (e.g. Khan, 2010), it is also possible that the presence of the hilly terrain surrounding the coast is partially responsible for an earlier onset. For example, in a similar terrain setting Charabi et al. (2011) attributed the early onset of a sea breeze to the preferential heating of sloped terrain which caused the differences in land-sea temperature to become pronounced earlier in the day. Other competing mechanisms over a range of scales may also have complicated the influence of the sea breeze on the locally observed wind regime (and subsequently on the wind resource quantity), as discussed later in this section.

Differences in wind speed associated with the sea breeze were observed between different measurement heights, with the highest measurement height (30m) corresponding to the highest wind speed. This is as expected, with the 30m measurement height a greater distance away from surface roughness and friction elements that reduce wind speeds. Importantly, the wind speeds associated with the sea breeze was often above cut-in wind speeds (3 ms⁻¹), particularly
at 15m and 30m heights. This suggests that the sea breeze can make a positive contribution to the wind resource on certain days with very weak synoptic gradients associated with very low and inadequate wind speeds. This is also important in the context of findings presented earlier, whereby it was found that Kidson types with very weak synoptic gradients over New Zealand (HSE and H Kidson types) were generally associated with the lowest generation potential (linked to the lowest probability of maximum generation events and highest probability of minimum generation events). For example, the findings presented here suggest that these Kidson types would be associated with even lower generation potential were it not for the influence of the above mentioned thermally induced circulation features capable of enhancing wind speeds under such conditions.

Over the same case study period, TAPM was found to be broadly capable of simulating aspects of the sea breeze at 30m, but not capable of simulating the observed nocturnal wind. The timing of onset of the sea breeze (approximately 1100 hours), the average wind speed of the sea breeze, the timing of the offset of the sea breeze (approximately 2000 hours), and the direction of the sea breeze were all considered to be well simulated by TAPM. The frequency of the sea breeze occurrence was somewhat under predicted by TAPM, however this was found to be due to TAPM simulating a strong synoptic westerly on three of the case study days, which limited the potential for sea breeze development on these days in the model. In light of these findings, TAPM was considered suitable for simulating aspects of the sea breeze circulation, in accordance with the findings of some other studies (e.g. Luhar and Hurley, 2004). In contrast, other studies (e.g. Soriano et al., 2003; Mocioaca et al., 2009) have found that TAPM tends to overestimate the magnitude of the sea breeze; therefore it appears the skill of TAPM in simulating the sea breeze is site specific to some extent.

TAPM was not capable of simulating the observed nocturnal wind from the north. Instead, TAPM simulated an early morning wind from approximately the west which appeared to be the result of a drainage wind from the surrounding terrain. It is hypothesized that the inability of TAPM to correctly resolve the nocturnal thermal wind is partly due to the spatial heterogeneity of the topography in this setting, occurring at subgrid scales. However, TAPM has also exhibited limited skill in terms of simulating nocturnal winds in a number of settings (Zawar-Reza et al., 2005), which is perhaps due to unrealistic boundary-layer model parameterizations in the stable boundary-layer regime.

### 7.2.2 Idealized model experiments

In idealized simulations carried out by TAPM, a number of aspects of the sea breeze circulation were shown to be dependent on the strength and direction of the ambient synoptic wind. For an
ambient synoptic westerly (of a range of magnitudes) the sea breeze was capable of developing and reducing the strength of the simulated wind speed on Porteous Hill, with the magnitude of the reduction often critical to generation. For synoptic wind speeds of 3 ms\(^{-1}\) and 5 ms\(^{-1}\) magnitude the sea breeze developed at approximately 0900 hours, compared to the 10 ms\(^{-1}\) synoptic case where the sea breeze developed later at approximately 1100 hours. For the 3 ms\(^{-1}\) and 5 ms\(^{-1}\) cases, the development of the sea breeze front resulted in a strong reduction of wind speeds from approximately 4 ms\(^{-1}\) to below turbine cut-in wind speed between approximately 0900 and 1100 hours. In contrast, for the 10 ms\(^{-1}\) case, the development of the sea breeze front resulted in a gradual reduction of wind speed from approximately 6 ms\(^{-1}\) at 0900 hours to being sustained at below turbine cut-in wind speed between approximately 1200 and 2100 hours. Further evidence of this occurrence is shown in Figure 7.1 based on model simulations at this site, with blue shading indicating the convergence of the synoptic westerly with the afternoon sea breeze over Porteous Hill, resulting in wind speeds less than 3 ms\(^{-1}\). These findings suggest that the presence of the sea breeze under certain conditions might be capable of reducing (as opposed to enhancing) the potential for generation, and that these reductions are greatest when the counteracting synoptic westerly is stronger (10 ms\(^{-1}\)). However, this result needs to be considered in the context of earlier findings whereby the synoptic westerly was still statistically linked to the highest generation potential (compared to other synoptic wind directions). This suggests that the influence of ‘calm zones’ might occur rarely enough so to not substantially reduce the average strength of the westerly (at least relative to that of other synoptic wind directions).

The idea that a sea breeze can counteract the ambient synoptic wind result to produce ‘calm zones’ is not new (e.g. Segal et al., 1982; Gahnberg et al., 2010), and has been attributed to the dynamic pressure effect induced under the collision of the two opposing air masses at the convergence zone of the sea breeze front (Gahnberg et al., 2010). The implications of this finding present a challenge for coastal wind resource assessments. However, the idea that a sea breeze can produce ‘calm zones’ that can negatively affect wind resource quantity over certain time periods has not been explored in onshore coastal wind resource assessments in the published literature. For example, Cullen et al. (2012) concluded that harnessing the sea breeze over the Blueskin Bay region would be particularly crucial for generation in summer months, without giving any consideration to the possible complicating effects of the sea breeze on the wind regime.

In contrast to the finding that the offshore synoptic wind could interact with the sea breeze to result in reduced generation potential over certain hours of the day, it was found (also based on model simulations) that the synoptic wind from the north-east resulted in an interaction with the sea breeze to increase wind speed. For example, for all synoptic wind speeds simulated, the
wind speed was shown to increase in the afternoon, with the afternoon sea breeze intensifying the ambient synoptic wind. Again, this finding is important for coastal wind resource assessments. At similar sites, it appears that the contribution of the sea breeze to the wind resource depends somewhat on the prevailing synoptic wind direction (and the strength of this wind) with respect to the orientation of the coast. In particular, the contribution of the sea breeze to the wind resource quantity might be greatest at sites where the prevailing wind direction is onshore.

Figure 7.1: TAPM simulation of sea breeze front (dark blue) at 1400 hours moving right (east) to left (west) in the model domain and causing reduction of wind speeds over Porteous Hill (red star). Black lines are terrain contours and also indicate the land-sea boundary; simulated wind speed and direction (white vectors) is for the inner most nested domain of the model at a 25m elevation.

7.2.3 Seasonal variability in the sea breeze

Based on the reconstructed data obtained from the MCP method, seasonal variability in certain aspects of the sea breeze was observed. Most notably, the sea breeze was not as clearly discernible from the synoptic north-easterly in winter, as little diurnal change in wind direction occurred across the NE-SE wind direction sector. In contrast, the diurnal change in wind direction was more apparent in all other seasons, suggesting that the sea breeze made a more important average contribution to the wind climatology in these seasons. The finding that the sea breeze was less pronounced in winter is likely largely attributable to a less pronounced land
sea temperature difference in the winter months. The sea breeze was found to make the largest average contribution (in terms of magnitude and frequency) to the locally observed wind climate in summer months. This is likely attributable to the most pronounced land sea temperature differences occurring in these months. However, additional factors are also likely important, including the idea that conditions favourable for the occurrence of sea breezes, such as Kidson types with weak synoptic pressure gradients, frequently occur in summer months.

In summer months and spring months, the magnitude of the sea breeze was shown to be largest, reaching an average mid-afternoon maximum wind speed of approximately 5 ms\(^{-1}\), above wind turbine cut-in speed. Similarly in Perth, Western Australia, Masselink and Pattiaratchi (2001) observed that the average mid-afternoon sea breeze magnitude was approximately 5.7 ms\(^{-1}\). Given that the sea breeze in Perth, Western Australia is considered to be one of the strongest sea breeze systems in the world (Masselink and Pattiaratchi, 2001); the average observed mid-afternoon sea breeze strength observed in this study is considerably large.

In this study, sea breeze ‘events’ were not strictly defined by a simple set of criteria, which is often done in other studies examining the sea breeze circulation (e.g. Masselink and Pattiaratchi, 2001; Khan, 2010). Justification for this was that such a strict demarcation of a ‘true’ sea breeze is likely less appropriate in this geographic context, given the complex interaction of multi-scale mechanisms on the east coast of the South Island discussed in McKendy et al. (1986). In particular, some complexity exists in isolating the exact cause of the locally observed flow regime due to complications induced by a number of competing mechanisms which vary diurnally including: the lee trough north-easterly, slope heating and cooling rates and land-sea temperature differences (McKendy et al., 1986). Subsequently, it is likely that, to some extent, the influence of the sea breeze on the locally observed wind climate has also been affected by these other mechanisms. Therefore, the finding that the sea breeze was less pronounced in winter months does not necessarily imply that the sea breeze is not capable of developing in winter, but only that its average influence on the wind climate was less pronounced, and with the signal perhaps distorted by other competing mechanisms. Following this line of reasoning, it is also possible that the relatively strong mid-afternoon ‘sea breeze’ wind speed, observed in summer and spring months, was elevated, or at least complicated, by the above mentioned competing mechanisms.

7.2.4 Sea breeze contribution to wind resource quantity

In a model experiment where water was removed from all model domains, the monthly mean power density decreased by approximately 10% over the two year simulation period. On the basis of this experiment, it is proposed that the presence of the site being near to the coast
contributes to an on average 10% increase in monthly mean power density. However, two of the months (December 2011 and December 2012) over the two year simulation period, showed an increase in monthly mean power density after the removal of water. Furthermore, clear seasonal variability was observed in terms of the percentage difference in the power density between water present and water absent simulations. In particular, the removal of water resulted in larger negative changes to power density in winter (especially in August months), and smaller negative or even positive changes to power density in summer (especially in summer months).

These findings were not as expected. Earlier it was found that the sea breeze generally made a positive contribution to the wind resource under weak synoptic gradients and under north-easterly synoptic winds, while making a negative contribution to the wind resource over certain hours (‘calm zone’ hours) under strong westerly synoptic winds. Given that weak synoptic gradients were generally found to be most pronounced in summer, and strong westerly synoptic winds were generally found to be most pronounced in spring, it was expected that the removal of water would have the largest negative effect in summer months and the largest positive effect in spring months, contrary to the analysis presented here. However, it appears that the removal of water from TAPM not only removed the influence of the sea breeze, but also operated to change the climate towards a more continental climate with an enhanced diurnal extent of temperature change, with these differences most pronounced in summer months (Figure 7.2). As such, the removal of water from the model induced a secondary effect of enhancing the diurnal rates of temperature resulting in an enhanced drainage wind which is most pronounced in summer months. This is evident in Figure 7.3, as indicated by red circles, where changes to the drainage wind simulated by TAPM substantially affect nocturnal wind speeds. In summer months, the removal of water appears to make a more important positive average contribution to the wind regime (associated with the addition of the drainage wind) than the negative average contribution induced from the removal of water (associated with the removal of the sea breeze), resulting in the increased power density in summer months. In other months (outside of summer) the removal of water did not greatly enhance the average contribution of the drainage wind to the wind climate (not shown). In spring months, the inclusion of water in the model still resulted in increases in the monthly mean power density (compared to the removal of water); subsequently this suggests that the influence of ‘calm zones’, expected to be most pronounced in spring where strong synoptic westerly winds were most pronounced, does not substantially reduce the positive contribution of the sea breeze to the wind resource quantity.

These findings, while based purely on model simulations, highlight the interconnectedness of the mechanisms that affect the local wind regime in this complex, coastal terrain setting. The
The sea breeze cannot easily be isolated from other mechanisms that also potentially affect the wind resource, thereby making it difficult to precisely quantify the overall contribution of the sea breeze to the wind resource quantity. However, it is speculated that the average monthly contribution of the sea breeze to the wind resource could be greater than the 10% estimate proposed earlier, especially given that this estimate is affected by negative contributions in summer months associated with changes to drainage winds which complicate the sea breeze signal. These findings carry a number of implications for wind turbine sitting in coastal regions. A comprehensive examination of aspects of the sea breeze and the interaction with ambient synoptic winds seems necessary, given that the effect on the wind resource could be pronounced, seasonally variable, and either positive or negative in some settings.

Figure 7.2: Diurnal changes in mean 10m temperature on Porteous Hill simulated by TAPM for August and December months. Comparisons made between the default model setup (‘water’) and the removal of water from the model domain (‘no water’). Vertical bars represent ±1 standard deviation for a given hour.
7.2.5 Limitations and areas for future research

The case study period, comprised of days deemed most suitable for the development of thermally induced circulation features, only included days between 14 March and 23 May 2013. This period was limited to days where incoming shortwave radiation was measured on Porteous Hill, as this was considered an important determinant for the occurrence of a sea breeze. Given this, it is possible that certain aspects of the circulation induced under ideal conditions (clear skies and weak pressure gradients) might have changed between seasons which were unaccounted for in this study. This presents an opportunity for future research in the context of the wind resource assessment at this site, in which measurements of radiation should be made over an entire year.

Over the case study days analysed, a nocturnal thermally induced circulation feature was observed, with a wind speed magnitude comparable to that of the observed sea breeze and above wind turbine cut-in speed. However, no attempt was made to untangle the dynamics of this nocturnal northerly wind, and questions remain whether this observed wind was the result of a drainage wind or a nocturnal LLJ. TAPM is not adequate to explore such questions, given that TAPM did not simulate these observed wind events correctly over the case study period.
Furthermore, the limited measurements made with height in the ABL in this study also make such an examination difficult from an observational point of view. Therefore, future research could focus on employing a higher resolution numerical model such as WRF in combination with more measurements made with height in the ABL using a SODAR.

The finding that relatively strong synoptic winds could interact with the sea breeze to potentially limit generation over certain hours of the day was based solely on TAPM simulations. As such, this finding is largely dependent on the ability of TAPM to realistically simulate the sea breeze and its interaction with synoptic winds. Although TAPM was shown to be capable of simulating a number of aspects of the sea breeze on idealized days, no thorough assessment was made in terms of validating the ability of TAPM to simulate the interaction of synoptic winds with the sea breeze. Such an assessment would be useful in terms of further validating some of the conclusions reached here, and could be the focus of future research. Similarly, the experiment designed to quantify the overall contribution of the sea breeze to the wind resource quantity was also subject to the reliability of TAPM. Given that the performance of TAPM was often limited in terms of its ability to simulate the monthly mean power density earlier; such quantifications should be treated only as initial estimates of directional changes in monthly mean power density. Again, comparing these estimates of TAPM against a higher resolution and more sophisticated numerical model such as WRF could be useful to infer the level of confidence associated with the estimates provided by TAPM.

7.3 Microscale considerations

7.3.1 Controls on ridge top wind shear

This subsection focuses on characterizing the controls on ridge top wind shear, and discusses the implications of these findings. Characterizing wind shear variability is important in wind resource assessments for several reasons. Wind resource assessments in the published literature often assume a constant wind shear value when extrapolating near surface wind speeds to hub heights, therefore average deviation from, or variability about, the constant value used can adversely affect estimates of the wind resource quantity at hub height (Storm and Basu, 2010). Beyond this, wind shear has been shown to affect the quality of the wind resource, such that for a given wind speed changes in wind shear can change the amount of energy extractable by wind turbines and also change the load and lifetime of wind turbines (e.g. Wharton and Lundquist, 2010; Clifton et al., 2013).

Wind shear values on the ridge top of Porteous Hill, calculated based on profile measurements of wind speed between 15m and 30m, deviated substantially from those assumed by the $1/7^{th}$
law wind shear (average shear = 0.143). This deviation was found to be more pronounced during the day (average shear = 0.055) than for night (average shear = 0.085). As a consequence of this deviation, it was shown that an extrapolation of wind speeds from 15m to 30m, under the 1/7th power law, overestimated observed wind speeds at 30m. As expected, this overestimation was most pronounced during daytime compared to night time. The performance of the 1/7th power law was found vary diurnally due to diurnal changes in stability that are unaccounted for in the simplistic adiabatic extrapolation. In particular, during the day time when the ABL is statically unstable, the thermally generated turbulence is likely to reduce wind shear; therefore the overestimation of wind speed by the 1/7th power law is enhanced under such conditions. This was also observed in Focken and Lange (2006) when examining the bias in the 1/7th power law extrapolated wind speeds as a function of ABL stability. The study of Focken and Lange (2006) also found that during statically unstable conditions (night time) the 1/7th power law underestimated wind speeds substantially. In contrast, here it was found than even during statically unstable conditions the 1/7th power law still overestimated wind speeds. This contrast can be attributed to the idea that the average wind shear on Porteous Hill is sufficiently less than that predicted by the 1/7th law, such that even under statically unstable conditions extrapolated wind speeds remain overestimated.

It is generally assumed that average wind shear is greater at sites where the terrain is considered more complex (Elkinton et al., 2006). But this general assumption lacks precision and has not always been observed in the published literature. For example, Elkinton et al. (2006) found lower average wind shear for a hilly site with complex terrain compared to that of a number of flat terrain sites. The findings presented here are also in agreement with that of Elkinton et al. (2006) with the observed mean wind shear for Porteous Hill substantially lower than the 1/7th power law, expected to be a better estimate of wind shear over flat terrain. However, substantial variability in wind shear about the mean observed wind shear was found here, with this variability shown to be controlled by the time of day and the wind speed and direction. Therefore, by investigating the controls on wind shear variability in detail, inferences can be made as to why the mean wind shear was found to be substantially lower than that assumed through 1/7th power law.

Wind shear was shown to decrease as the wind speed increased, however this relationship was also dependent on the time of day. For example, during night time wind shear decreased rapidly with increasing wind speed, whereas during the day time the decrease in wind shear with increasing wind speed was less pronounced. This is attributable to the ‘nature’ of turbulence changing between night and day. In particular, during night time turbulence is controlled only by dynamic effects such as frictional drag over the surface which increases with increasing wind speed to reduce wind shear. In contrast, during the daytime turbulence is
influenced also by thermal effects with this addition observed to dampen the wind speed – wind shear signal here. Wind shear was also observed to vary between certain directional sectors, presumably due to the different upwind terrain factors modifying aspects of the flow. The most notable differences in wind shear were found to be occurring between direction sectors 45 - 120° (lowest shear) and 180 - 225° (highest shear). After isolating the effects of wind speed and time of day on wind shear (which could also complicate the wind shear signal between these directional sectors); the 180 - 225° sector exhibited a higher average wind shear.

It is proposed that differences in the upwind terrain between these sectors is a large determinant of observed differences in wind shear between these sectors. Most notable of the terrain differences is the upwind forest block over the 180 - 225° sector compared to the upwind coastal sector over the 45 – 120° sector. The low roughness lengths reported over the 45 - 120° sector and the highest roughness lengths reported over the 180 - 225° sector are also attributed to the differences in the forest block compared to the more “smooth” water affecting the flow downwind of the obstacle. It is typically expected that more “smooth” terrain with lower surface roughness lengths correspond to lower shear values (Table 7.1). Evidence of this was found here with the forest block sector reporting higher shear values (generally 0.1 - 0.15) than the coastal sector (generally 0.05 - 0.07).

It is also apparent that the values for wind shear found in this study under different upwind terrain sectors are notably smaller than those typically observed (Table 7.1). For example, wind shear values found for the upwind forest block sector are more typical of smooth ground or ocean, whereas the wind shear values for the coastal sector are below any classification level reported in Table 7.1. It is speculated that the smaller wind shear values reported here are partially the result of the ‘speed up’ of the hill occurring at a height favourable for the reduction of wind shear under certain wind direction sectors. There was evidence to suggest this was occurring at times based on calculations of the maximum speed-up height from geometric properties of Porteous Hill in the context of the JH linear theory. For example, under near neutral conditions maximum speed up was predicted to occur at a height between approximately 9m and 14m for the 45-120° sector with a percentage speedup of approximately 64-75% (relative to undisturbed flow upwind at the same height). Since the maximum speedup height was estimated to occur near to a height of 15m (where the lower level height used to calculate wind shear) one speculates that this might have resulted in a reduction of shear by enhancing the 15m wind speed and decreasing the vertical change in wind speed between 15m and 30m, under near neutral conditions. In the context of the JH linear theory, whether the ridge top wind shear is enhanced or reduced by the presence of the speedup of the hill depends both on the geometric properties of the hill and the height over which shear is measured. Given these considerations, it is likely that wind shear is more variable with height in the ridge
top setting (compared to flat terrain), with the vertical height range over which wind shear is
calculated being a large determinant of the magnitude of wind shear values obtained. The idea
that the speedup of the hill can modify typical wind shear values appears to be an overlooked
area of research in the wind resource assessment literature. In particular, while wind turbines
are often placed in hilly terrain, generalized wind shear tables do not specify how the ‘typical’
wind shear values corresponding to a certain terrain type might be conditionally dependent on
the presence of a hill and the geometric properties of the hill.

Table 7.1: Typically observed wind shear under different terrain conditions in other studies (from
Bechrakis and Sparis, 2000).

<table>
<thead>
<tr>
<th>Description of terrain</th>
<th>Wind shear</th>
</tr>
</thead>
<tbody>
<tr>
<td>Smooth ground, lake or ocean</td>
<td>0.1</td>
</tr>
<tr>
<td>Short grass</td>
<td>0.14</td>
</tr>
<tr>
<td>Level country with foot-high grass and occasional tree</td>
<td>0.16</td>
</tr>
<tr>
<td>Tall row crops or hedges</td>
<td>0.2</td>
</tr>
<tr>
<td>Many trees and buildings</td>
<td>0.22-0.24</td>
</tr>
<tr>
<td>Wooded country, suburban areas</td>
<td>0.28-0.30</td>
</tr>
<tr>
<td>Urban areas</td>
<td>0.40</td>
</tr>
</tbody>
</table>

The idea that average ridge top wind shear can be enhanced or reduced by different upwind
terrain conditions is important in the context of wind turbine sitting. In other studies, higher
wind shear values were found to have a positive effect on power production for wind speeds
greater than 5 m s\(^{-1}\), while wind shear had little effect on power production for wind speeds less
than 5 m s\(^{-1}\) (Wharton and Lundquist 2012; Clifton et al., 2013). Therefore, the finding here
that an upwind forest block is capable of enhancing wind shear for a given wind speed implies
that power production over this wind direction sector could be enhanced for certain wind
speeds. Subsequently, this suggests that careful selection (or modification) of upwind terrain
could affect the quality of the wind resource at a particular site. However, a critical balance
likely exists in terms of whether upwind terrain conditions increase or decrease the quality of
the wind resource. For example, trees of sufficient height can also create shelter belts, acting to
reduce wind speeds over a height range important for extraction by turbines, as discussed in
Bowden (2011).

The finding that average wind shear, over a range of directional sectors, was generally lower
than reported elsewhere might also be partly due to the occurrence of negative wind shear
values reducing the mean wind shear. However, there is evidence to suggest this was not the
most dominant contributor. For example, negative wind shear values were found to occur
considerably less during night time (compared to day time), while the mean wind shear levels at
night time still remained greatly underestimated by the $1/7^{th}$ power law. The occurrence of negative wind shear values is often not reported in the wind resource assessment literature, suggesting that a unique aspect of the terrain here might be preferential to the development of negative wind shear. While it was outside the scope of this study to explicitly investigate causes of negative wind shear, such occurrences were considerably more pronounced during day time but were not found to be limited to any particular directional sector (not shown). Negative wind shear was shown to reduce turbine power output in Wharton and Lundquist (2012), especially under strong wind speeds, suggesting that such occurrences could carry negative consequences for wind resource quality in this setting somewhat.

7.3.2 Utility of MOST

This subsection focuses on examining the utility of MOST in this complex terrain ridge top setting. The applicability of MOST in the context of wind resource assessments is important for characterizing atmospheric stability (e.g. Wharton and Lundquist, 2010; Clifton et al., 2013) and as a physically derived tool for extrapolating near-surface wind speeds to wind turbine hub height (Focken and Lange, 2006). Examination of near-neutral convergence of turbulence intensities was carried out to compare the organization of the turbulence structure to that found in other studies in different terrain. A statistical examination of whether turbulence intensities could be collapsed as functions of stability within the MOST framework, as found in other studies, was carried out to examine the applicability of MOST in this setting. Some of the broader implications of these findings for wind resource assessments in such terrain are also discussed.

Near-neutral behaviour

The similarity of scaled standard deviations were analysed in the context of MOST, based on near-surface (2m) eddy-covariance measurements made on the ridge top of Porteous Hill. When near-neutral moment ratios were analysed, the order of these ratios were aligned with other studies such that $\frac{\sigma u}{u^*} > \frac{\sigma v}{u^*} > \frac{\sigma w}{u^*}$, highlighting the anisotropy of the flow. However, in terms of the magnitude of these ratios, pronounced differences were found when compared to those commonly found in other studies for different terrain types. In particular, the near neutral asymptotic limits found for the horizontal fluctuations were higher here than reported in other studies (Table 6.4) while the vertical fluctuations more closely resembled those commonly found in urban studies. Comparisons against other studies were however limited given the considerable scatter of these moment ratios found under near-neutral stability in this study. For example, most other studies in complex terrain (e.g. Nadeau et al., 2012; Pegahfar and
Bidokhti, 2013) report that in near-neutral conditions scaled standard deviations become independent of $z/L$ and tend towards a constant value; in contrast the extent of the scatter was found here to increase approaching near-neutral conditions.

Similar studies carried out over ridge top settings have been limited (Kaimal and Finnigan, 1994); however the findings presented here also appear to differ from those that do exist (e.g. Mason and King, 1985; Taylor and Teunissen, 1987). For example, in other ridge top studies it was found that horizontal fluctuations were reduced near the surface of the ridge top compared to over upwind flat terrain, while the vertical fluctuations were essentially unchanged (Kaimal and Finnigan, 1994). In contrast, all moment ratios were found to be greater in this study compared to those commonly found in flat terrain (Table 6.4). However, the increases found here might simply be attributable to the scatter found in the near neutral stability range in this study. Another possible explanation might be related to the idea that changing the distance in which eddy-covariance measurements are made from the ridge top centre ($x/L_{hi}$) can change moment ratios greatly (Kaimal and Finnigan, 1994). Therefore, the scatter of these moment ratios might be partly attributable to the idea that the non-axisymmetric geometry of Porteous Hill is essentially capable of changing $x/L_{hi}$ for different wind directions. It should also be noted that it is inherently difficult to compare these results obtained in a ridge top setting to those of other studies, given that the moment ratios change dramatically depending on the height at which measurements are made within the inner layer height, and because the inner layer height will differ between hills considered between experimental studies (Kaimal and Finnigan, 1994).

**Normalized standard deviations of velocity components**

Vertical velocity fluctuations were found to be in best agreement with other studies in the unstable domain, however relatively large scatter was still observed. When relationships for vertical velocity fluctuations were assessed statistically, the agreement with those found in other studies (e.g. Kaimal and Finnigan, 1994) was limited, with the best agreement of $R^2 = 0.3$ occurring in the unstable domain. Furthermore, it is likely that statistical agreement of such magnitude is largely due to self-correlation inherent in the relationship being analysed, as opposed to being physically meaningful. For example, when analysing relationships between standard deviations in velocity scaled by friction velocity and $z/L$, autocorrelation is inherent because the scaling variable (friction velocity) is also correlated with Obukhov Length ($L$) (Klipp and Mahrt, 2004). Nadeau *et al.* (2012) carried out a comprehensive examination of the extent of autocorrelation between these variables, to find that vertical velocity fluctuations can be auto-correlated with $z/L$ by as much as $R^2 = 0.6$. Therefore, the findings of Nadeau *et al.*
(2012) imply that the already relatively low $R^2$ value found here for the relationship between vertical velocity fluctuations and $z/L$, would be even less and perhaps near zero (no statistical relationship) after adjusting for auto correlation. When parameters were adjusted to find ‘best-fit’ non-linear relationships, the statistical performance increased slightly but overall was still considered to be too low to be meaningful. Statistical performance was also relatively unchanged when different wind speed and directions were selectively considered. In contrast, the studies of Martins et al. (2009) and Moaraes et al. (2005), also carried out in complex terrain, found that adherence to MOST could be attained for certain wind speeds and directions. This suggests that the applicability of MOST here is limited for a range of conditions, as opposed to being limited for certain conditions.

It appears that the poor relationship between vertical velocity fluctuations and similarity theory limit the applicability of MOST almost all of the time in this setting. Horizontal fluctuations in velocity were also found here to be in poor agreement with similarity theory laws, although this finding is more expected given that other studies over flat terrain have also found limited adherence to MOST for the horizontal fluctuations (Kaimal and Finnigan, 1994). Theoretically, it is expected that MOST might be applicable in a ridge top setting below some critical depth within the inner layer of the hill. In this study, since eddy-covariance measurements were estimated to be well within the inner-layer depth, this suggests that the suitability of MOST might be limited even very near the surface at the ridge top in some settings.

It was also shown that MOST (with unmodified stability functions) was generally less capable of extrapolating wind speeds from 15m to 30m on the ridge top of Porteous Hill, compared to the simple 1/7th power law. The performance of MOST was found to be especially limited during stable conditions where wind speeds were substantially overestimated. In particular, the standard Businger-Dyer stability correction equations, employed in stable conditions, appear to dramatically over correct for the influence of stability on the wind profile, producing a large average overestimation of extrapolated wind speed. This suggests that the standard stability functions commonly found in flat terrain are not appropriate here, especially under stable conditions. It is suggested that the failure of flux-profile relationships in this setting is also perhaps partly due to the presence of the hill or surrounding terrain curvature affecting vertical momentum flux divergence between the surface of the ridge top and 30m, such that friction velocity might not remain an appropriate scaling variable here.

The finding that the applicability of MOST appears limited in such a setting is important in the context of wind resource assessments. This is especially important given that wind resource assessments are often selectively carried out in complex terrain and ridge top settings, but also because a number of recent studies have highlighted the importance of characterizing
atmospheric stability in wind resource assessments (e.g. Wharton and Lundquist, 2010; Clifton et al., 2013). Other commentators have also suggested that the use of MOST, as a tool for extrapolating near surface wind speeds to wind turbine hub height, should be advantageous over the use of commonly employed simple adiabatic power laws (e.g. Focken and Lange, 2006). However, before MOST can be considered a useful tool in the context of wind resource assessments, its applicability should be verified at the site under examination for the wind resource assessment, especially in complex terrain. The use of eddy-covariance measurements to parameterize stability as a tool for extrapolating wind speed with height in this ridge top setting appears limited, at least in the context of traditional MOST. In contrast, Focken and Lange (2006) found that MOST could be a useful tool for extrapolating wind speed with height, even in conditions where the theoretical validity of MOST was questionable. However, in contrast to the methods employed in this study, Focken and Lange (2006) did not use eddy-covariance measurements to parameterize stability, but instead calculated stability through profile measurements of temperature. While the method of Focken and Lange (2006) appears advantageous, the practical value of this method is limited in wind resource assessments because vertical profiles of temperature are rarely available in the absence of vertical profiles of wind speed. In other words, if vertical profiles of temperature have been made then vertical profiles of wind speed could also have been easily made, thereby making the need for extrapolating wind speed with height redundant.

7.3.3 Limitations and areas for future research

In the analysis presented here, while negative wind shear values were reported, the controls on the occurrence of such values were not examined explicitly. Given that negative wind shear values can reduce the amount of energy able to be extracted by wind turbines, future research could be carried out to assess these controls in this terrain setting. Again, the employment of a SODAR would be advantageous is such an examination, and would be useful in determining the range of heights over which negative shear was occurring and in further examining how wind shear values are related to the ‘speed up’ of the hill. The estimation of the speed up height and magnitude was carried out based on the JH linear theory, as opposed to being directly measured. Therefore, greater confidence in such estimates could be had if the speed-up of the hill was measured directly. Future research could be aligned with setting up an observational network of stations designed to measure wind speed at undisturbed upwind reference sites. However, the choice of reference sites would not be trivial in this terrain setting, given that for most upwind sectors surrounding Porteous Hill the complexity of the terrain could likely result in non-negligible flow disturbance.
In this study controls on wind shear variability were investigated, given that in other studies variability in wind shear has been shown to affect the energy extractable by turbines. However, in this study the analysis was not extended so far as estimating the extent to which changes in wind shear might change the wind resource quantity. Wind resource assessments generally fail to incorporate the effects of atmospheric stability into estimates of wind resource quantity and as yet uncertainty remains as to how best to do so. Part of this uncertainty is related to the complex and non-linear relationship between wind shear, turbulence intensity and power output from turbines, which might also be specific to a particular geographic setting or turbine model. While investigating such complex interactions is a relatively new area of research in wind resource assessments, future research could be carried out on Porteous Hill by continuing measurements of wind shear after the possible future instalment of wind turbines and exploring statistical relationships between wind shear and the actual power extracted by turbines.

A limitation of the assessment of MOST in this setting was that eddy-covariance measurements were made at a single height, and future research could be directed towards making profile measurements of fluxes used in the assessment of MOST in such a terrain setting. For example, an underlying assumption of traditional MOST is that divergence of momentum flux with height is limited, therefore testing this assumption would allow for a more comprehensive examination of MOST in this setting. Another potential extension of this assessment would be to make accompanying profile measurements of temperature to allow alternate parameterizations of stability. By doing so, estimates of stability obtained from near-surface eddy-covariance measurements could be compared and validated against other methods.
Chapter 8 - Conclusions

The main objective of this study was to use a combined modelling and field based measurement approach to assess how atmospheric and climate phenomena, over a range of spatial-temporal scales, can contribute to the quantity and quality of the wind resource in a complex terrain setting. The main findings of this research, the implications, and some avenues for future research are briefly summarised here.

Main findings and implications

- The MCP method employed was found to be a relatively accurate and robust tool for reconstructing monthly mean power density as a metric for wind resource quantity on Porteous Hill. The mesoscale model TAPM was less successful in this regard and generally could not be relied upon to reconstruct monthly mean power density. Based on the MCP reconstructions, monthly mean power density on Porteous Hill was found to exhibit substantial between month variability over the two year period examined; monthly mean power density varied by more than 800% between the highest (June 2012) and lowest (February 2013) months. The monthly mean power density averaged across the two year period was 341 Wm$^{-2}$ with a standard deviation of 202 Wm$^{-2}$ and a coefficient of variation of 0.59.

- Synoptic scale monthly averaged MSLP fields could be linked with locally observed variability in wind speed and direction in a given month, and also with the ‘quantity’ of the wind resource in a given month. Specifically, in summer months examined the synoptic westerly belt tended to lie further south of New Zealand with high pressure centres located more directly over New Zealand, resulting in the absence of strong and prevalent westerly winds and generally reduced wind resource quantity. In contrast, in spring months examined the average synoptic situation resulted in a westerly belt situated over New Zealand more often and generally enhanced wind resource quantity.

- Similar synoptic scale linkages to wind resource quantity were found through a probabilistic event analysis procedure carried out over shorter temporal scales (12 hour events). In particular, it was found that Kidson types associated with weak pressure gradients over New Zealand (H and HSE Kidson types), compared to Kidson types associated with pronounced west or south-west pressure gradients over New Zealand (SW, W, T, HW and HNW Kidson types), could be statistically linked to lower probabilities of maximum generation events and higher probabilities of minimum
generation events. The event analysis also revealed that certain months might have a
greater tendency for within month variability in wind resource quantity, including
especially June and August months over this period. Through the probabilistic event
analysis it was inferred that El Niño (compared to La Niña) can increase the frequency
of maximum generation events; whereas the negative phase of SAM (compared to
positive phase) can both increase the frequency of maximum generation events and
decrease the frequency of minimum generation events.

- Over days with clear skies and weak synoptic gradients, the occurrence of a day time
sea breeze commonly resulted in wind speeds deemed to be of sufficient magnitude for
ergy generation. Furthermore, the mesoscale model TAPM was capable of
adequately simulating a number of aspects of the sea breeze circulation over these days.
Idealized model simulations also revealed that under certain conditions, such as strong
westerly synoptic flow, the sea breeze may counteract the synoptic flow at the
detriment of afternoon energy generation on Porteous Hill. However, based on the
results from a further model experiment it was estimated that the sea breeze still
presented a positive net contribution to the wind resource; the extent of this
contribution was difficult to quantify based on multi-scale interacting mechanisms in
the model simulations.

- The average ridge top wind shear on Porteous Hill was found to be lower than assumed
by the 1/7th power law, consequently it was shown that the 1/7th power law resulted in
overestimated wind speeds, especially during day time. Variability in ridge top wind
shear was found to exhibit a complicated relationship with wind speed, time of day and
wind direction. The variable complexity of the upwind terrain with respect to wind
direction was considered to be an important control on differences in wind shear
between wind direction sectors.

- An examination of near surface ridge top turbulence revealed that horizontal and
vertical moment ratios failed to converge to a near-neutral asymptotic limit. In the
context of MOST, and after considering the possible inherent implications of auto
correlation, horizontal and vertical fluctuations, tested over a range of conditions, did
not statistically collapse well as functions of $z/L$. When MOST was applied as an
extrapolation tool, with the standard flat terrain flux-gradient relationships, the
performance of MOST was generally less than the more simple 1/7th power law
method, especially in stable conditions. Subsequently, the applicability of MOST, in
its traditional form and based on eddy-covariance measurements, appears limited in this
terrain setting.
The findings of this research have implications for the wind resource on Porteous Hill and also in a more general context for wind resource assessments elsewhere. The finding that synoptic scale circulation can be statistically linked to the potential for local wind energy generation offers opportunities, both in terms of short-term forecasting of the wind resource, and also in terms of examining longer term variability and oscillations in the wind resource. Given that this link could be established in complex terrain also suggests that it should also be possible to establish linkages over a range of terrain conditions where wind turbine sitting is common place. The finding that the sea breeze can both contribute and complicate the wind regime suggests that wind turbine sitting in coastal terrain elsewhere should give explicit regard to this. This is especially important given that contributions might be either positive or negative depending on certain conditions, such as the strength and direction of the ambient synoptic wind. The finding that different terrain complexity, under different wind directions, can substantially modify wind shear over heights representative of (small) wind turbines, also suggests that the micro sitting of turbines should be done in consideration of these effects.

From a methodological perspective, the finding that MOST appears limited in this setting suggests that a revision of MOST is needed before being applied as a tool for wind resource assessors in a complex terrain ridge top setting.

**Future research avenues**

A number of avenues for future research have been presented, sometimes in association with the limitations of methods used in this study. At the synoptic scale, research aimed at investigating how linkages between atmospheric circulation and wind resource quantity vary spatially across New Zealand is an important avenue, especially given the ruggedness of New Zealand’s terrain. Establishing such linkages could also be used to infer how the wind resource may vary or oscillate under larger scale considerations and climate change, and how regional differences may affect these linkages. The findings regarding the interaction of the sea breeze with ambient synoptic winds were based purely on model simulations and should be treated as tentative. Future research should be carried out to investigate such interactions in the context of the wind resource with a higher resolution and more sophisticated mesoscale model and in combination with a higher spatial resolution observational campaign. Given that wind shear has been shown to directly affect turbine performance in other studies, future research at this site could be dedicated to examining the extent to which actual power output from turbines (after possible future instalment) might change in response to different upwind terrain complexity modifying properties of the flow. Further research is also needed in terms of assessing the practical utility of MOST as a tool in wind resource assessments in complex
terrain; with this intention, comparing different methods of parameterizing stability within the MOST framework is suggested as an appropriate starting point.
References


Appendix A

A.1: Data logging issues at T2

An unresolved issue with the T2 data logger caused wind speed measurements at the 10m height to sporadically record as 0 ms\(^{-1}\) (‘drop out’ wind events) (GH Ltd., pers. comm.). Given that such events could not be confidently separated from ‘true’ events where the wind speed was recorded as 0 ms\(^{-1}\), the 10m wind speed data at T2 could not be reliably used.

![Evidence of ‘drop-out’ wind events in the wind speed distribution observed at the 10m measurement height at T2.](image)

Figure A.1: Evidence of ‘drop-out’ wind events in the wind speed distribution observed at the 10m measurement height at T2.

A.2: Data completeness

The completeness of data for towers T1-T4 across the time period of this study is shown in Table A.2. Note that the completeness of data reported for T2 in Table A.2 corresponds to the 6m measurement height (but not the 10m measurement height) due to the issues described in Section A.1.
Table A.2: Time periods for data acquisition and completeness of data (%) in a given month for towers T1-T4

<table>
<thead>
<tr>
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<th>11</th>
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<th>12</th>
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<tr>
<td></td>
<td>T1</td>
<td>-</td>
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<td>-</td>
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<td>100*</td>
<td>100</td>
<td>100**</td>
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<td></td>
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<td>100*</td>
<td>82.6</td>
<td>100*</td>
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</tr>
</tbody>
</table>

* reported value corresponds to after instrument setup on 14 March 2013; ** reported value corresponds to before instrument removal on 23 May 2013
B.1: Equality of mean wind shear

Formal tests of normality (e.g. the Shapiro-Wilk test) are less appropriate in this analysis, given the large sample size in each population ($N > 2000$). Therefore, the distribution was analysed visually through histograms and normal Q-Q plots. The day time wind shear population more closely resembles a normally distributed population compared to the night time wind shear population; owing to the less frequent negative wind shear occurrences at night time skewing the night time distribution.

Figure B.1: Distribution of wind shear for the day time (top panel) and night time (bottom panels) populations. Normal Q-Q plots are also shown for each population.
Based on the distributions shown in Figure B.1, it was deemed suitable to conduct a student’s t-test to assess significant differences in the mean wind shear between populations. In particular, the equal variances assumed t-test was conducted based on the Lavene’s test for equality of variances, suggesting there was no evidence for statistical difference in the variance between populations. Subsequently, the t-test provided evidence for a statistically significant difference in the mean wind shear between day and night with \( p < 0.05 \) (Table B.1). This result was statistically significant regardless of whether equal variances is assumed between populations in the test.

<table>
<thead>
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<th>t-test for equality of means</th>
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Table B.1: T-test for difference in wind shear between day and night.
Figure C. 1: Variation in the SOI index since 2011. Horizontal lines display +8(-8) SOI values indicating the transition to El Niño (La Niña) from neutral phase. Dotted line displays the 5 month moving mean in SOI. Historical SOI data are from the Australian Bureau of Meteorology (http://www.bom.gov.au/climate/current/soi2.shtml).
C.2: Monthly time series of SAM

Figure C.2: Variation in the monthly averaged SAM index since 2011. Dotted line displays the 5 month moving mean in SAM. Historical SAM data are from the British Antarctic Survey (http://www.nerc-bas.ac.uk/icd/gjma/sam.html).