Height-Dependence of the Temporal Variability of Wind Speed: A Multiscale Approach

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A Thesis Submitted to
Saint Mary's University, Halifax, Nova Scotia
in Partial Fulfillment of the Requirements for
a B.Sc. Honours of Geography

April, 2020, Halifax, Nova Scotia

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Abstract

Climate change and diminishing fossil fuel reserves have contributed to the increasing need for alternative renewable energy resources. Wind power is particularly attractive as it is both renewable and abundant. However, the spatial and temporal variability of wind makes power production intermittent, which affects the feasibility of large-scale implementation. Using statistical moments and multiscale analysis, this project intends to characterize wind speed variability as a function of height and to deepen wind variability understanding. Detrended Fluctuation Analysis (DFA) is a multiscale analysis method which is capable of assessing time series variability based on the scaling relationship between time scale and the average size of the fluctuations in the time series, thereby taking into consideration the temporal succession of time series values. By applying the coefficient of variation and DFA through three consecutive years and at 6 successive heights, a relationship can be identified between wind speed variability and height. This study found that wind speed variability consistently decreases with height up to a certain height. Beyond this height, wind speed variability was found to decrease at a more gradual rate or not at all. This was confirmed both through statistical moments and multiscale analysis. The outcomes of this project have implications for the methodology used to assess potential locations of wind turbines, as well as for studies regarding turbine design.

April, 2020

Acknowledgements

The author would like to thank the Wind Energy Institute of Canada, and in particular Ms. Marianne Rodgers, Scientific Director, for providing the wind speed data used in the research project presented in this thesis. Thanks are also given to Dr. Adel Merabet who was the Second Reader for this thesis, and to the Saint Mary's University Geography Department. Finally, it is important to express immense gratitude for the support and guidance given by Dr. Cristian Suteanu who supervised the thesis.

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1. Wind Dynamics and Power Generation

Traditional energy production has relied heavily on the extraction and combustion of fossil fuels. However, diminishing reservoirs and developing environmental issues have initiated a shift in energy sourcing (Jacobson & Delucchi, 2009). Increasing global surface temperatures, largely attributed to the combustion of fossil fuels and the release of greenhouse gases, has prompted the implementation of sustainable energy production (Jacobson & Delucchi, 2009). Further, petroleum products exist as a finite non-renewable resource, the exploitation of which have been leading to depleted supplies (Hansen et al., 2017). Due to both global climate change and the gradual diminishment of petroleum supplies, sustainable and renewable energy solutions have become not only desired but increasingly viable alternatives (Jacobson & Delucchi, 2009; Hansen et al., 2017). Renewable energy offers a sustainable alternative to conventional fossil fuel based energy sources, since production does not lead to the diminishment of resources. Examples of Earth's renewable energy include; solar, geothermal, tidal, and wind. The drawback of renewable energy, specifically of solar and wind, is the spatial and temporal intermittency at which energy production is available (Albadi and El-Saanny, 2010; Gowrisankaran et al., 2016). Despite this, wind energy represents a significant opportunity in the renewable industry, offering between 40 and 85 available terawatts with an installed capacity of approximately 600 Gigawatts (Jacobson & Delucchi, 2009; WWEA, 2019). The limitations of wind energy production are not in the supply but in the development and implementation of wind generation infrastructure.

The capturing of renewable energy poses several interesting and unique challenges, including; the development of methods and technologies to capture energy from these processes. Key challenges of wind energy involve the storage of produced power and optimization of the wind velocity range at which energy is captured (Albadi and El-Saanny, 2010; Suberu, 2014). This project will focus on the latter. Optimal generation of wind power requires an understanding of atmospheric patterns. However, given the inherent complexity and chaotic nature of the atmospheric system, a comprehensive understanding of these patterns is enormously challenging and ultimately unrealistic (Gleick, 1987; Suteanu, 2015). Instead, the accumulation of knowledge of characteristics of atmospheric patterns on a range of temporal scales can support the improvement and development of wind power infrastructure (Suteanu, 2015). The objective of this thesis is to contribute to a deeper understanding of wind patterns, and more specifically, wind speed variability, by studying the height dependence of wind speed variability.

Wind energy is captured using bladed turbines which revolve when experiencing wind currents and turn electrical generators. The wind turbines require a minimum wind speed to be able to revolve and produce electrical energy. Further, turbines can only withstand certain wind speeds, above which operation can compromise a turbine and be unsafe. The resulting power curve indicates the window of operable wind speeds (Burton et al., 2011; Busby, 2012). This wind speed window on a turbine's power curve is delineated by a lower threshold, below which wind speeds are insufficient to produce energy, and an upper threshold, above which the hazardousness of operation prevents the production of energy (Burton et al., 2011; Busby, 2012). Efficient operation of a turbine relies on wind speeds which persist in-between these thresholds and can thus constantly produce energy. As wind energy systems expand to meet energy demands, the scale of wind generation increases (Busby, 2012). Increased size of the wind turbines will facilitate more efficient energy production; however larger turbines require higher base wind speeds for energy production (Busby, 2012). This is to say, the base wind speed threshold for energy production of modern large-scale turbines is much larger than their smaller counterparts. An understanding of wind variability can inform the placement of turbines by assessing the tendency of the wind speed to vary between the thresholds of the turbine's power curve.

Larger turbines and generators, with increased energy outputs, require larger blades, which creates a larger radius around the turbine's central hub. Some turbines are so large that the blade length can be tens of meters (Busby, 2012). This means that in one revolution, a turbine's blade can travel through tens of meters of vertical distance. Given the spatial variability of wind speed it is probable that in a single rotation a turbine's blade will travel through fluctuating wind speeds. Differential variability across the diameter of the turbine will cause differences in resistance and torque affecting how the turbine operates, this will have important implications on how turbines are designed and placed (Burton et al., 2011). Further, larger generators will have increased frictions and momentums requiring more energy and time to adjust to wind speed fluctuations (Burton et al., 2011; Busby, 2012). By assessing wind speed variability at several heights, it is intended that this can inform the design and placement of wind turbines, both to optimize the power curve and accommodate variability across the turbine's rotation.

2. Wind speed Variability

Wind speeds are highly variable, both spatially and temporally (Albadi and El-Saanny, 2010; Burton et al., 2011). This inherent variability exists on a wide range of spatial and temporal scales (Burton et al., 2011). While climatic differences will have effects on regional variability, small topographic differences will affect localized variabilities (Albadi and El-Saanny, 2010; Burton et al., 2011). The influence of climate and topography make understanding of spatial variability difficult. Further, site specific temporal variability can be difficult to understand and predict. While seasonal differences are relatively predictable the development of annual trends is relatively reliable (Burton et al., 2011). However, on shorter timescales, wind speeds become increasingly chaotic and unpredictable (Burton et al., 2011).

To effectively capture wind energy, it is important for wind variability to be functionally understood and characterized. While infeasible to completely comprehend wind variability, characterization of variability can facilitate an understanding to be applied to development of wind power generation technologies. Wind variability characterization has been previously addressed using probabilistic methods, including Rayleigh distributions (Burton et al., 2011; Busby, 2012). Probability distributions give a probability curve for the site-specific mean observed wind speeds, showing the probability of a specific wind speed to be observed in any given time frame (Burton et al., 2011). For instance, the Rayleigh distribution is often used to characterize variability by showing the percentage of time represented by specific wind speeds throughout a time period (Busby, 2012). These methods of characterization allow direct application to turbine power curves, showing the amount of time at which the wind speeds exist in-between the operational thresholds of the turbine. However, to build on this characterization, consideration must also be given to the temporal succession of wind speed variability.

While distribution curves contribute to the understanding of wind speed variability, they lack information on temporal succession. Wind speed is discontinuous, and the variability of wind speeds is strong on a wide range of scales (Suteanu, 2015). The characterization of temporal wind speed fluctuations will require consideration of the time series value succession. Temporal succession of wind speeds is an important consideration as turbines will take time and energy to adjust to wind speed fluctuations (Suteanu, 2015). In this way, not only is it important how often wind speeds exist within operational thresholds but also how frequently and how strongly wind speeds fluctuate beyond these thresholds.

By implementing statistical tools which capture the temporal succession of wind speed variability, it is intended to broaden wind speed variability characterization. While mean wind speeds generally increase with height (Floors et al., 2013), how will variability change with height and how can these changes be characterized? This study will implement Detrended Fluctuation Analysis (DFA) together with mean and coefficient of variation to characterize and compare wind speed variability over height. DFA will allow characterization of variability taking into consideration time series value succession (Kantelhardt et al., 2001; Bashan et al., 2008). Using similar methods, it has been found that higher wind speeds generally correlate with lower variability (Kavanaugh, 2017). An assessment of variability as a function of height should provide further insights into the characteristics of wind speed variability.

3. Methodology

For the analysis of wind speed variability, three statistical methods will be applied, the comparison of which should allow insight into wind variability patterns. An initial assessment will be done using the mean and the coefficient of variation of the data sets. By taking the mean of the wind speeds, basic characterization of central tendency can be established. The coefficient of variation will describe the extent of wind speed value scattering in relation to the mean. In order to deepen this characterization, Detrended Fluctuation Analysis (DFA) will be applied allowing scaled variability assessment and consideration of successive wind speed values. By combining these methods of variability, the results can be compared allowing deeper understanding of variability patterns. These methods will be used in tandem to analyze the relationship between timescale, height and wind speed fluctuations.

Mean, a measure of central tendency, describes the statistical average of a data set. The Coefficient of Variation (CV) is determined by dividing the standard deviation of a data set by the mean of the data set. The coefficient of variation is thereby providing a measure of dispersion which – unlike the standard deviation – does not depend on the units used or the overall magnitude of the values. This makes CV useful when we wish to compare the variability of data with different means, in the context of evaluating wind speed values at different heights. However, CV does not take into consideration the time series succession, and this makes it incapable of capturing essential characteristics of the way in which the data fluctuate in time.

Detrended Fluctuation Analysis (DFA) performs a variability assessment by overcoming the shortcomings of conventional variability statistics. DFA is a method of time series variability characterization which allows consideration of temporal succession without being influenced by trends in the data. DFA uses moving windows, at a range of temporal scales, to delineate scaled correlation of time series variability. This is done by dividing a time series into non-overlapping windows, *m*, of length *s* (Kantelhardt et al., 2001). A best fit polynomial, *p*, is found for each window, *m* (Suteanu, 2015). The best fit polynomial values, p_m, are subtracted from the time series values, *Q(i)*:

$$Q_s(i) = Q(i) - p_m(i)$$

(Suteanu, 2015; Kantelhardt et al., 2001). The mean square of the differences, $F_s^2(m)$, between the recorded wind speeds and the interpolated wind speeds, $Q_s(i)$, is calculated:

$$F_s^{\,2}(m) = < Q_s^{\,2}(i) >$$

and the square root of the average fluctuation on time scale *s*, *F(s)*, is determined:

$$F(s) = \sqrt{\left[\frac{1}{r}\sum_{m=1}^{r} F_s^{\,2}(m)\right]}$$

where r is the number of sections length *s* in the time series, *Q(i)* (Suteanu, 2015; Kantelhardt et al., 2001). This process is repeated for a range of window lengths *s*. If a power law relationship is found between *s* and *F(s)*, then the time series can be said to have scaling properties on that temporal scale range of *s*. The proportional relationship between average fluctuation and window size can be characterized by the exponent *H*:

$$F^{(n)}(s) \propto s^H$$

where a large *H* exponent (>0.5) indicates persistence while a small *H* exponent (<0.5) indicates antipersistence and an *H* exponent value of 0.5 indicates a random time series (Suteanu, 2015). This is to say that lower *H* exponents indicate higher variability and larger *H* exponents indicate lower variability.

4. Data and Results

4.1 Data

The wind speed data were recorded at the Wind Energy Institute of Canada's Research and Development Park, which is located in North Cape, Prince Edward Island. The location is known for its high average wind speeds with low turbulence intensity (WEICan, 2020). The data consist of three successive years, 2011-2013, of high-quality wind speed data recorded at ten-minute intervals. Wind speeds values were documented at six heights, from 10 meters of elevation to 60 meters at 10-meter intervals. Each data set includes approximately 52,000 samples from January until December of each year and at each height at a sampling rate of 10 minutes. Gaps in datasets affected two of the time series: for the height of 50 metres in 2012, and for the height of 20 metres in 2013. Gaps have the potential to distort the results of the applied pattern analysis, and their removal or replacement may also affect the analysis outcomes. Since gap processing was beyond the scope of the thesis, these two time series were not included in the pattern analysis.

4.2 Wind speed dependence on height

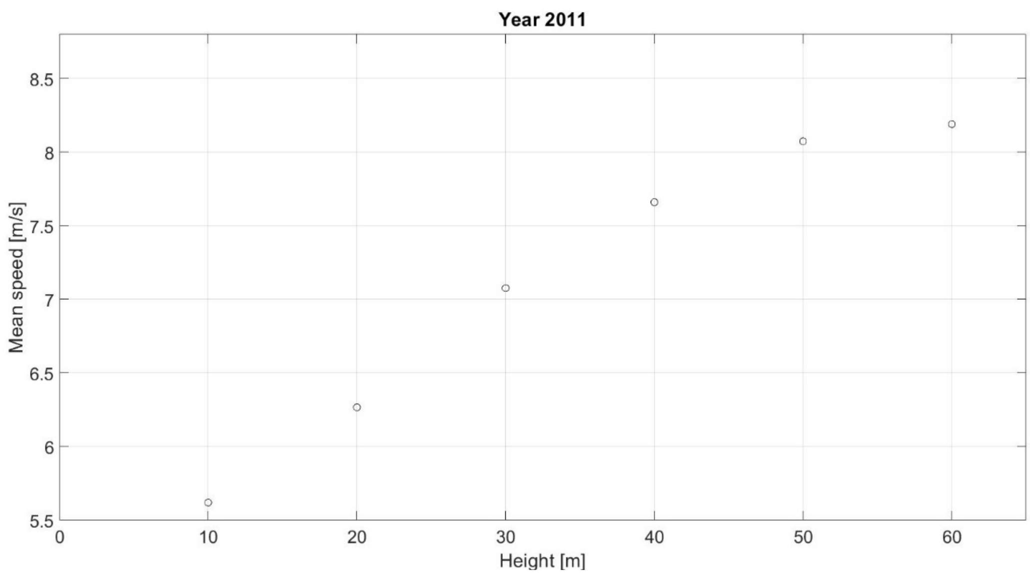

Figure 4.1: Graph of mean wind speed, in meters per second, as a function of height in 2011.

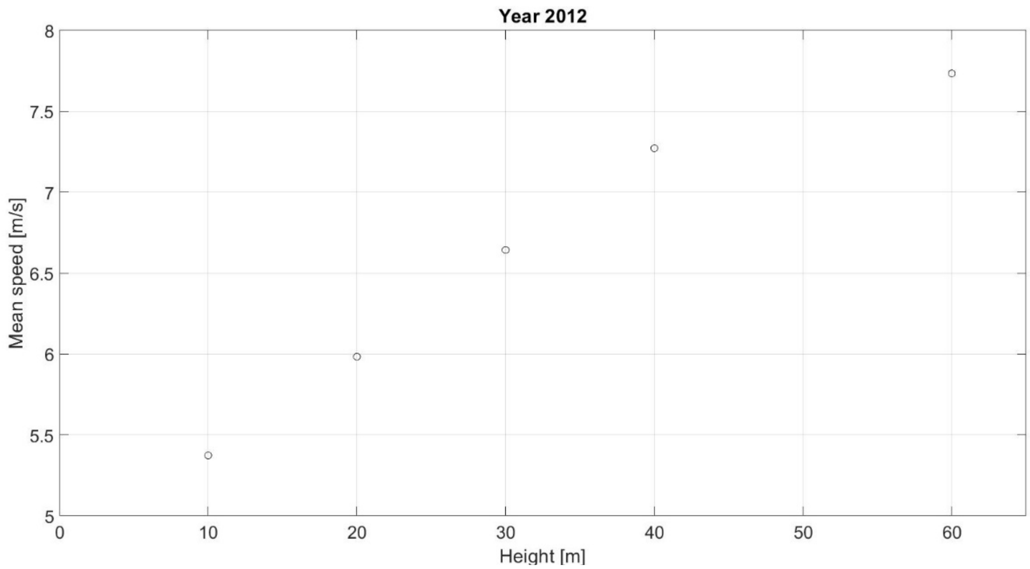

Figure 4.2: Graph of mean wind speed, in meters per second, as a function of height in 2012.

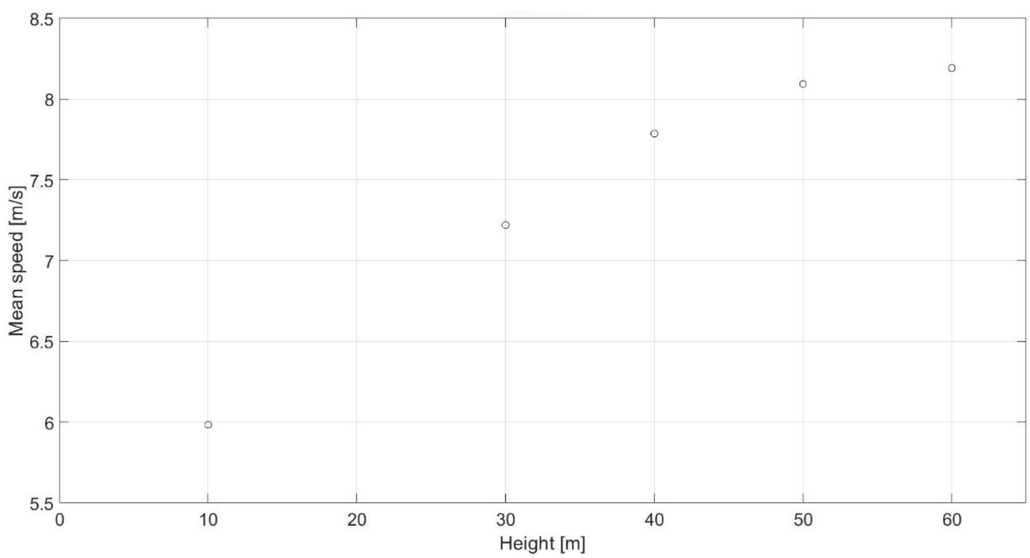

Figure 4.3: Graph of mean wind speed, in meters per second, as a function of height in 2013.

It is generally understood that wind speeds will increase with increase in height above the earth's surface (Floors et al., 2013). This is attributed to the frictional forces of the surface and surface features acting to disturb and slow wind speeds, the effect of which is diminished at increasing heights (Floors et al., 2013; Reen et al., 2014). Figures 4.1, 4.2, and 4.3 show the height dependence of mean wind speed for 2011, 2012, and 2013 respectively. They show that the mean wind speed increases, indicating higher average wind speeds with increased height. This increase in mean wind speed appears to taper beyond heights of 40 m.

4.3 Analysis of pattern variability

4.3.1 General considerations

To address the objectives of this project, which are to quantitatively evaluate the variability in wind speed data for a range of heights, and to establish the relation between variability and height, two approaches were applied: a classical statistic and a recently developed pattern analysis method. The two methods are fundamentally different from each other: they assess "variability" from distinct perspectives, as explained below.

4.3.2 Coefficient of variation

The coefficient of variation is an often applied statistic designed to establish the measure of dispersion in a set of data. It relies on the standard deviation:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N}(x_i - x_m)^2}{N}}$$

where x_i are the individual data and x_m is their mean, divided by the population size N. The coefficient of variation is determined by:

$$CV = \frac{\sigma}{x_m}$$

where σ is the standard deviation and x_m is the population mean. Compared to the standard deviation, the coefficient of variation has the advantage of evaluating data variability in a way that does not depend on the actual units or on the overall magnitude of the assessed values. For instance, if two datasets have the same amount of scattering, but set 1 has values that are overall larger than those in set 2, the standard deviation for set 1 also has a higher value. In contrast, the coefficient of variation correctly indicates the same amount of variability in both datasets.

The fact that the coefficient of variation produces results that are comparable across datasets makes it particularly useful in the context of this project: wind speed values are known to change with height. For an accurate assessment of variability as a function of height it is important to capture temporal change, without being influenced by the fact that speed values get larger and larger with increasing height.

The results of this analysis are presented in tables 4.1, 4.2, and 4.3, and in figures 4.4, 4.5, and 4.6.

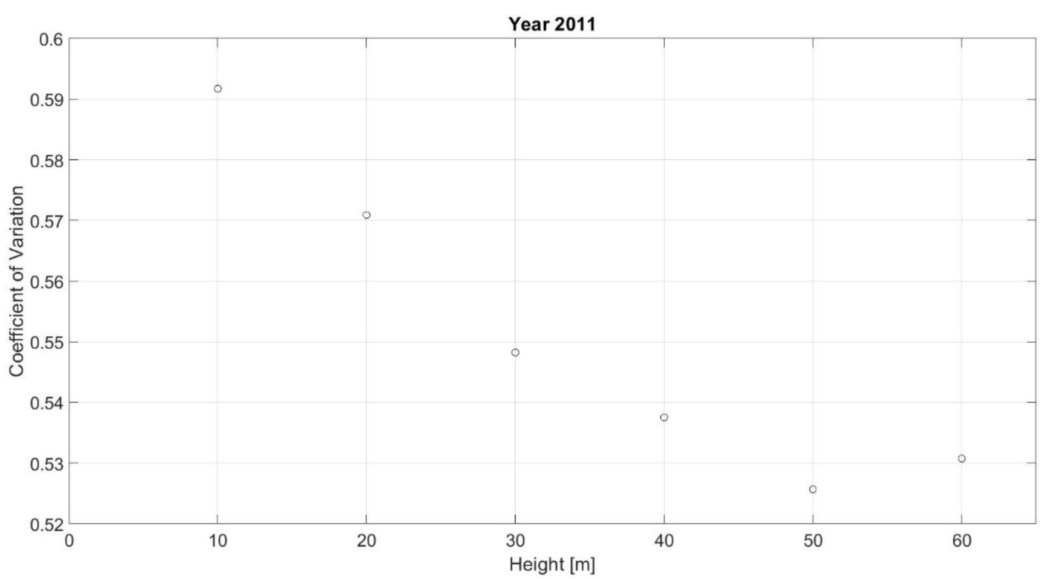

Figure 4.4: Coefficient of Variation as a function of height in 2011.

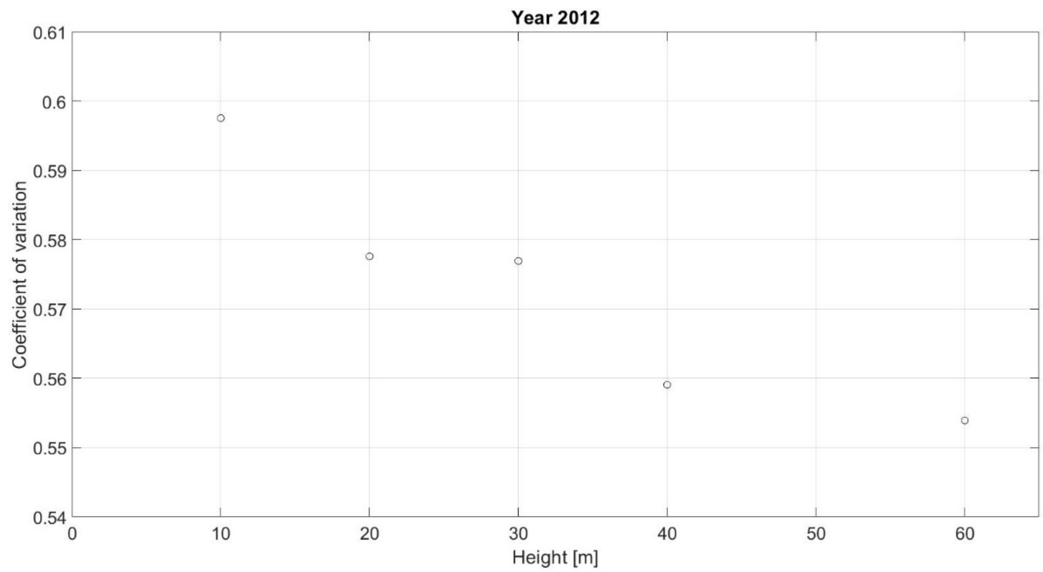

Figure 4.5: Coefficient of Variation as a function of height in 2012.

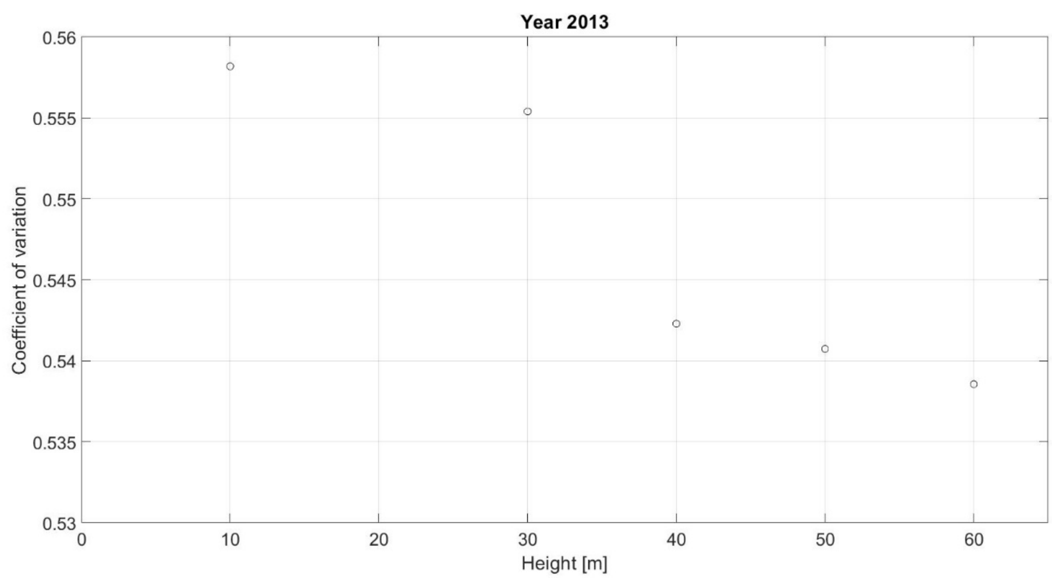

Figure 4.6: Coefficient of Variation as a function of height in 2013.

Low coefficient of variation values indicates lower variability. Figures 4.10, 4.11, and 4.12 show a decreasing coefficient of variation with increased height for each of the three analyzed years. With increasing height, the coefficient of variation is seen to decrease, however, beyond 40 m the height dependence of the CV weakens.

4.3.3 Detrended fluctuation analysis

Detrended Fluctuation Analysis (DFA) uses a polynomial of N^{th} degree (N=1,2,3…) to determine the best fit to be applied to each sample window, p_m. The fluctuation around which are taken by subtracting the best fit polynomial values, $p_m(i)$, from the actual time series values, $Q(i)$:

$$Q_s(i) = Q(i) - p_m(i)$$

The sum of the squares of the difference between the actual recorded wind speed and the interpolated wind speed via the best-fit N^{th} polynomial are taken for each sampling window, m:

$$F_s{}^2(m) = < Q_s{}^2(i) >$$

$$F(s) = \sqrt{\left[\frac{1}{r}\sum_{m=1}^{r} F_s{}^2(m)\right]}$$

The results of this formula are plotted on a window length vs. average fluctuation, in a log-log graph (figure 4.7-4.12). The exponent of the resulting power law correlation between window length (s) and fluctuation (F) is denoted by H (figures 4.7-4.12) where:

$$F(s) \sim s^H$$

This procedure is repeated for all heights in all years. The polynomial degree, p_m, used is indicated by the method's label, in this instance DFA3 indicates the application of a 3^{rd} order polynomial degree. A third-degree polynomial was used due to the low uncertainty intervals produced for the resulting H exponent when compared to the other available polynomial degrees, from 1 to 7.

DFA requires a specified sample length, *s*, to be successively applied to the time series as non-overlapping windows. Within these windows, the polynomial degree discussed above is applied. This is repeated for a scale range of window lengths on which the time series maintains scaling properties. A minimum and maximum window length determines the ranges and scaling at which DFA will be applied. This analysis found that the wind speed pattern enjoys scaling properties on a scale range from 1.7 to 53 hours. The minimum section length used was 10 samples and the maximum section length was 320 samples (Figure 4.7-4.12). A window length of 10 samples represents one hour forty minutes and a window length of 320 samples represents 53 hours and 20 minutes. At a scale of less than 10 samples, there are too few samples to establish a meaningful scale pattern, and at a more than 320 samples, there are no longer scaling properties which characterize wind variability.

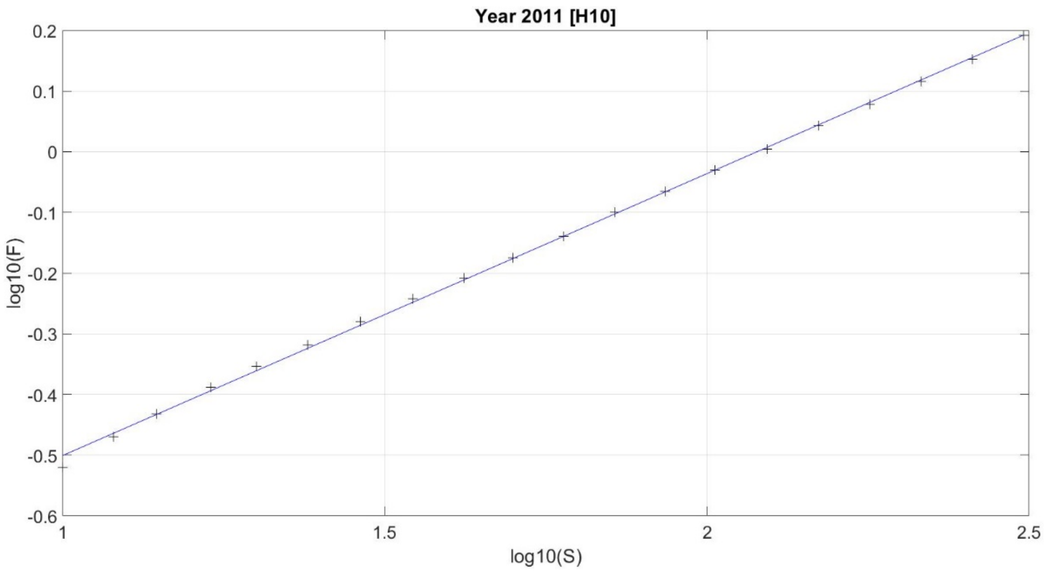

Figure 4.7: Power law correlation of window length (s) and fluctuation (F) at height 10m in 2011.

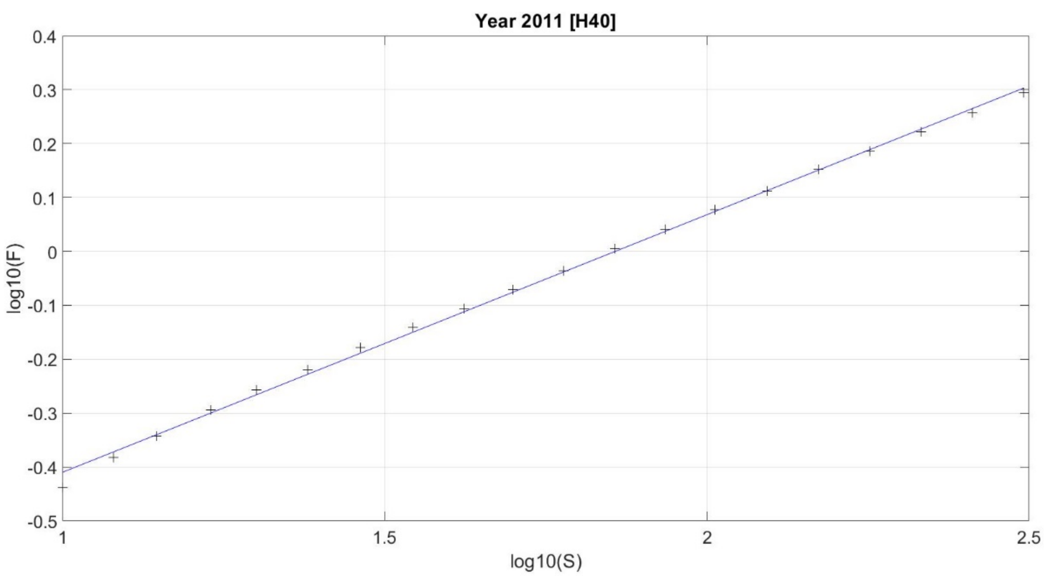

Figure 4.8: Power law correlation of window length (s) and fluctuation (F) at height 40m in 2011.

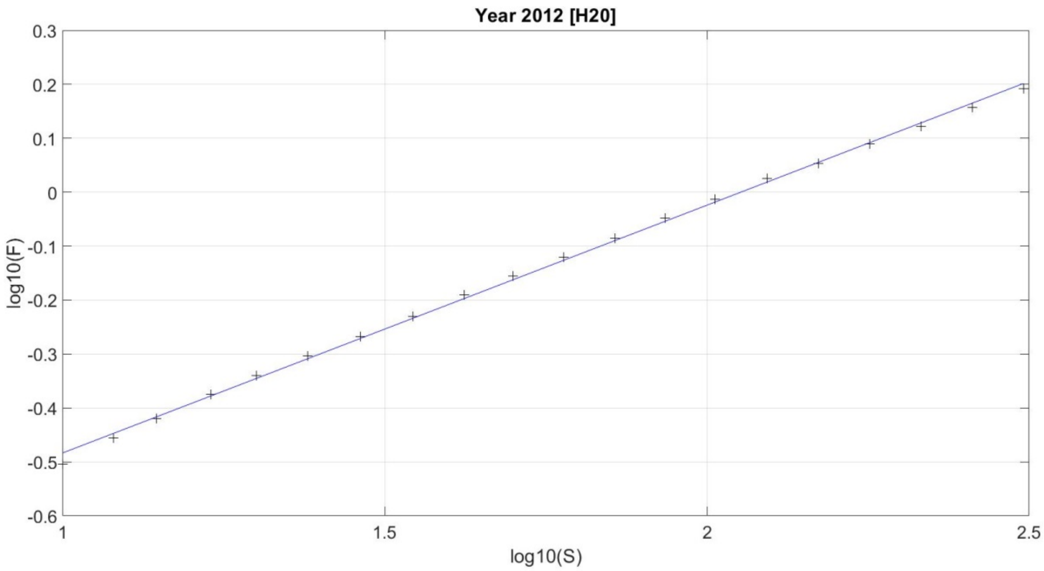

Figure 4.9: Power law correlation of window length (s) and fluctuation (F) at height 20m in 2012.

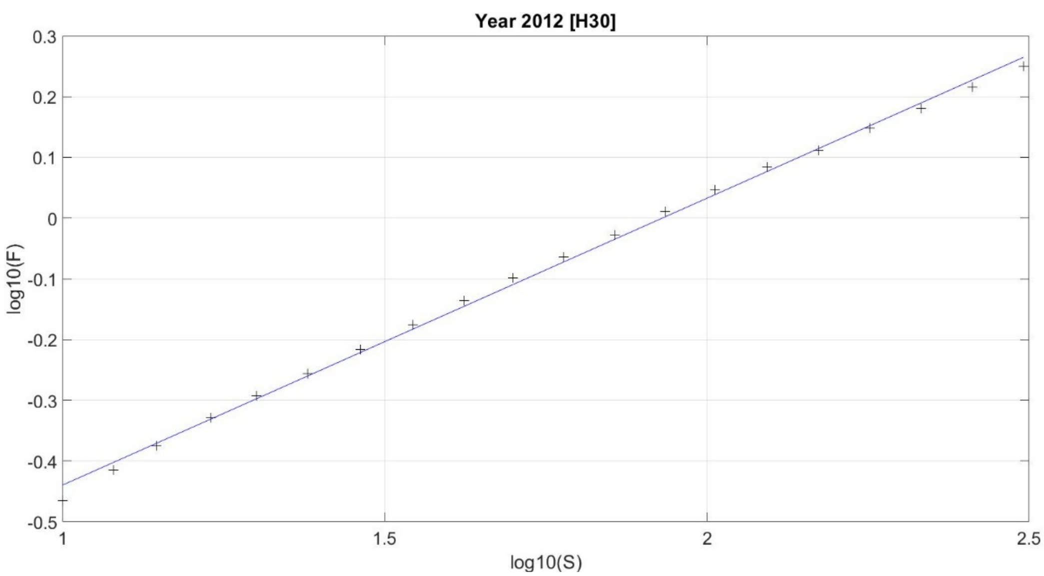

Figure 4.10: Power law correlation of window length (s) and fluctuation (F) at height 30m in 2012.

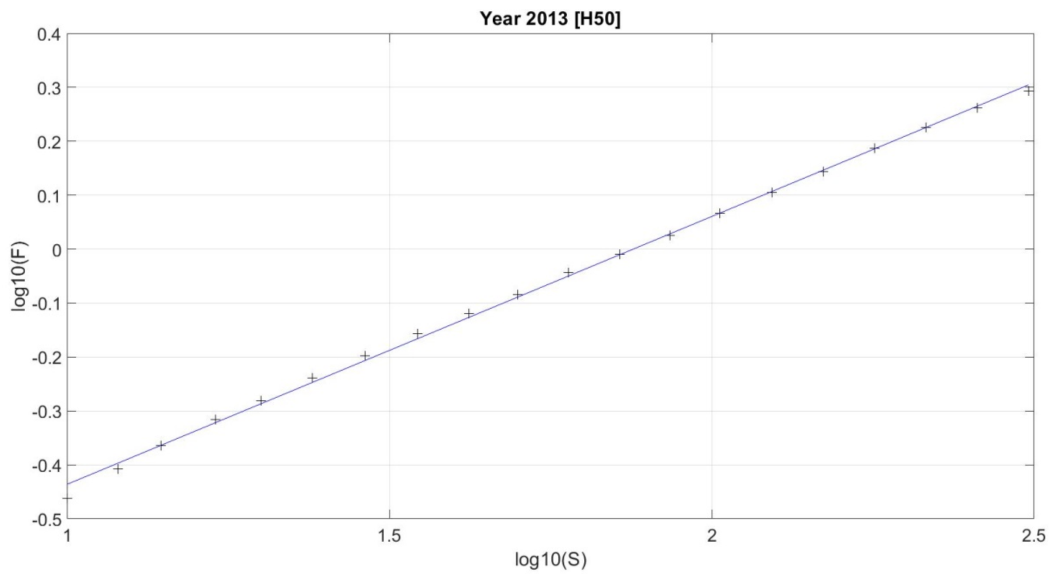

Figure 4.11: Power law correlation of window length (s) and fluctuation (F) at height 50m in 2013.

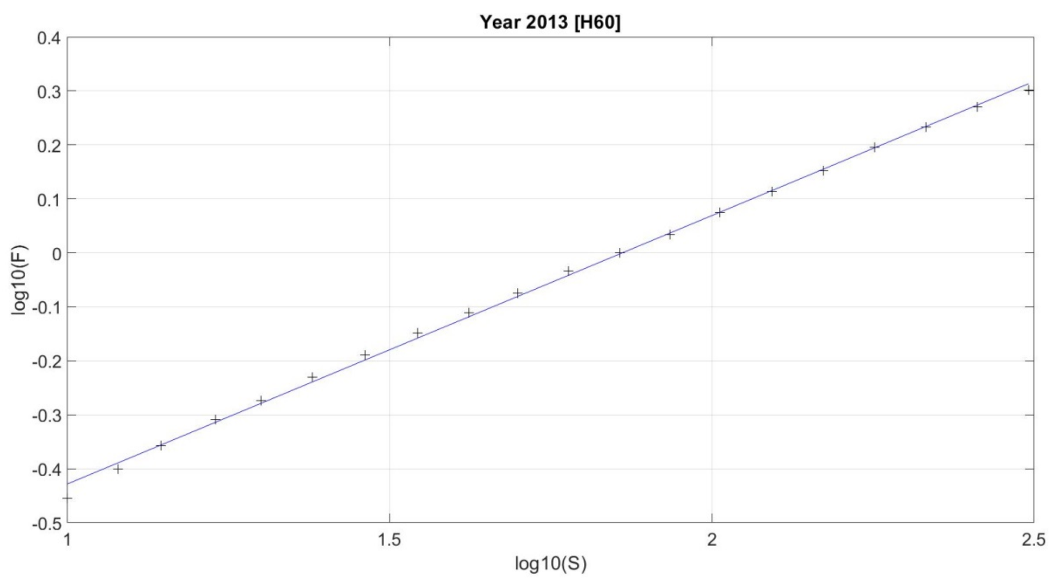

Figure 4.12: Power law correlation of window length (s) and fluctuation (F) at height 60m in 2013.

The figures 4.7 – 4.12 show the power law correlation between the fluctuation size (F) on the Y-axis and the window length (s) on the X-axis, using a third-degree polynomial. The resulting slope of the log-log graph corresponding to the power law correlation is the H exponent referring to the degree of variability in the time series. In this way, the uncertainty intervals of the resulting H exponent are dependent on the strength of the power law correlation found between the fluctuation size and the window length. Without a strong correlation, the resulting slope indicates little about the variability of the time series. In this case, the results of DFA3 had in each case a strong correlation, with all results having R^2 values of at least 99.5% (table 4.1, 4.2, 4.3). This is reflected in the power law graphs (figure 4.7-4.12) on which the points adhere very closely to a straight-line power law correlation.

For each year, and at all six heights, the mean, the coefficient of variation, and the H exponent were calculated. The mean and coefficient of variation were represented for each year as a function of height (figure 4.1 – 4.6). The H exponents were represented as a function of height for each year to create graphs directly comparable to the mean and coefficient of variation graphs produced (figure 4.13 – 4.15). These values; mean, coefficient of variation, and the H exponent as well as the correlation coefficient (R^2) are specified in tables 4.1, 4.2, and 4.3 representing these values in each year. The correlation coefficient refers to the strength of power law correlation between window length (s) and fluctuation (F) as resulting from the DFA3 function.

Height [m]	**Mean Wind Speed [m/s]**	**Coefficient of Variation**	**H-exponent***	**Correlation R^2 [%]**
10	5.62	0.59	0.465 ± 0.006	99.9
20	6.27	0.57	0.468 ± 0.006	99.9
30	7.08	0.55	0.471 ± 0.007	99.9
40	7.66	0.54	0.478 ± 0.010	99.8
50	8.07	0.53	0.481 ± 0.011	99.8
60	8.19	0.53	0.480 ± 0.011	99.8

Table 4.1: Table of results from 2011.

Height [m]	Mean Wind Speed [m/s]	Coefficient of Variation	H-exponent*	Correlation R^2 [%]
10	5.37	0.60	0.454 ± 0.007	99.9
20	5.98	0.58	0.460 ± 0.008	99.9
30	6.64	0.58	0.472 ± 0.011	99.8
40	7.27	0.56	0.478 ± 0.014	99.7
60	7.73	0.55	0.481 ± 0.016	99.6

Table 4.2: Table of results from 2012. Height 50 was omitted from the 2012 time series as per section 4.1.

Height [m]	Mean Wind Speed [m/s]	Coefficient of Variation	H-exponent*	Correlation R^2 [%]
10	5.98	0.56	0.457 ± 0.009	99.9
30	7.22	0.56	0.477 ± 0.007	99.9
40	7.79	0.54	0.488 ± 0.008	99.9
50	8.09	0.54	0.497 ± 0.009	99.9
60	8.19	0.54	0.497 ± 0.009	99.9

Table 4.3: table of results from 2013. Height 20 was omitted from the 2013 time series as per section 4.1.

The compiled results of 2011, 2012 and 2013 time series are represented in tables 4.1, 4.2, and 4.3 respectively. Height 50 was omitted from the 2012 and height 20 was omitted from 2013 as explained in section 4.1.

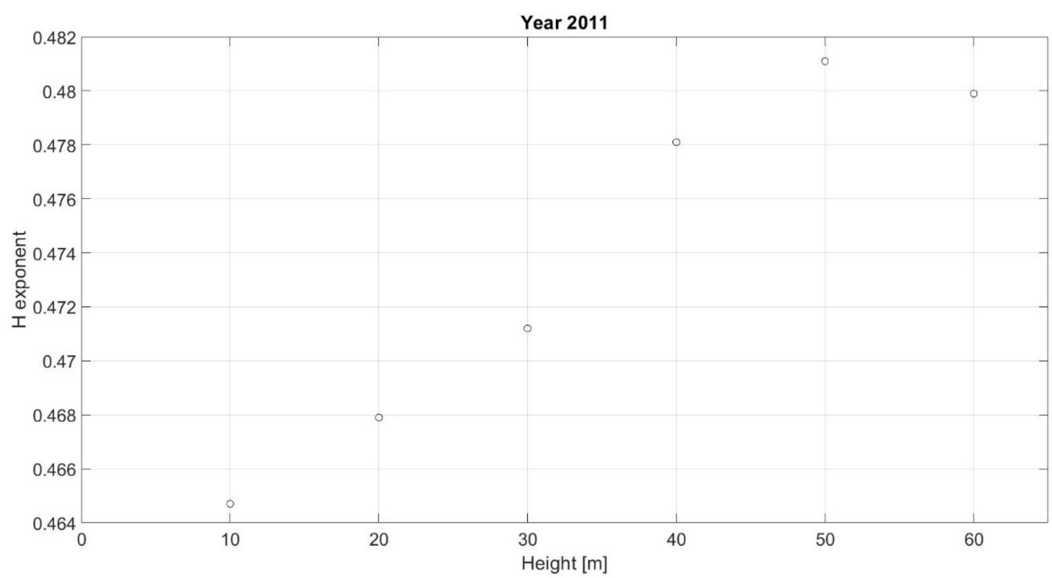

Figure 4.13: H exponent as a function of height in 2011.

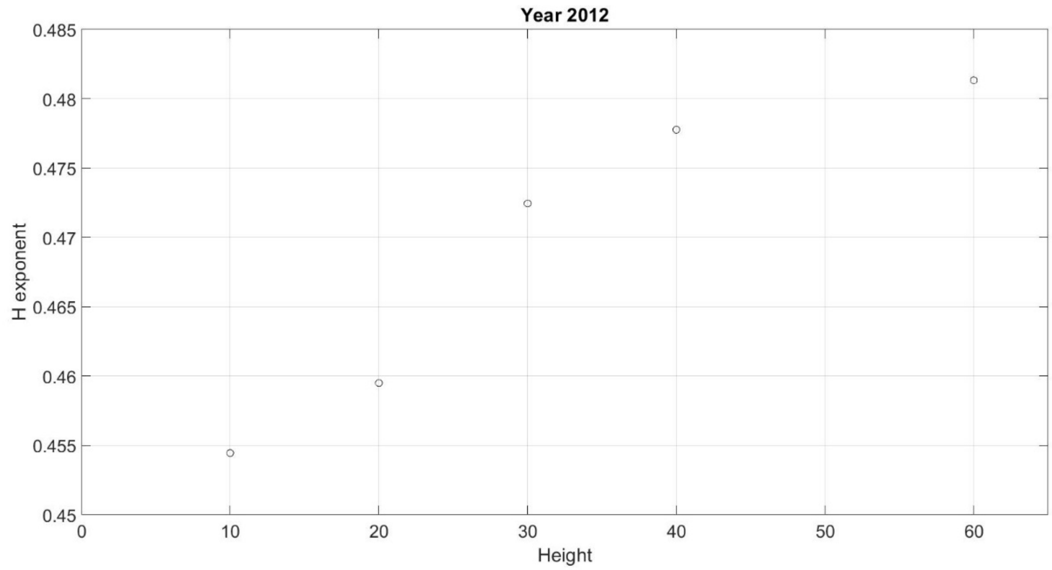

Figure 4.14: H exponent as a function of height in 2012.

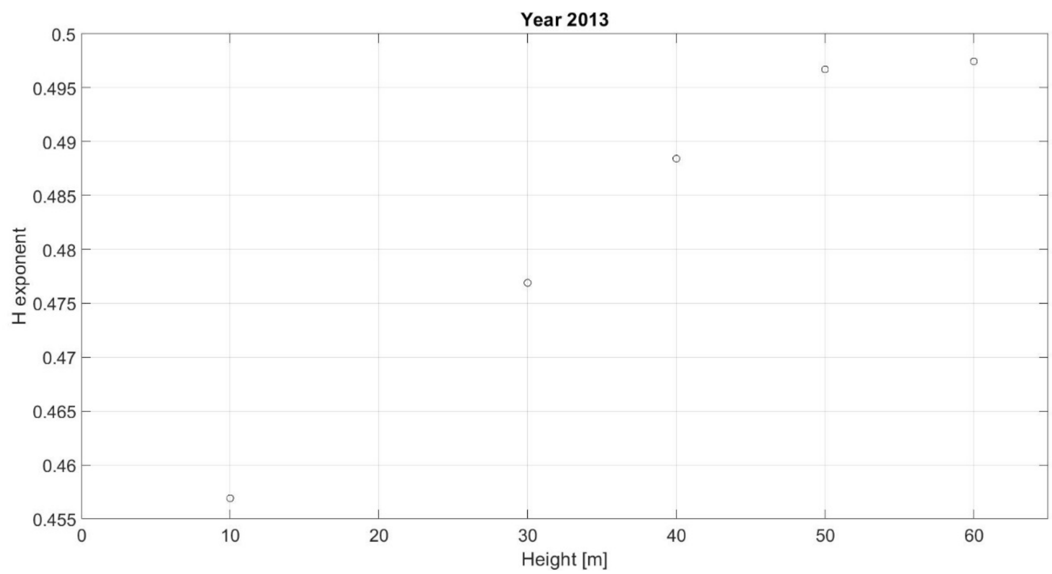

Figure 4.15: H exponent as a function of height in 2013.

In contrast to the coefficient of variation, a higher H exponent will indicate a smoother time series and a lower variability. H exponent values that are closer to 1 are indicative of greater persistence in the time series, with values closer to zero indicating a pattern which is more variable (Suteanu, 2015). Generally, the results of DFA3 show increased persistence with increasing height (figure 4.13, 4.14, 4.15). All three time series show a steadily increasing H exponent from 10m to 50m, with tapering in this increase from 50m to 60m. Figures 4.13, 4.14, and 4.15 show that persistence gets consistently higher, indicating lower and lower variability as a function of height up to around 40 meters, beyond which variability decreases less fast with height, or does not decrease at all.

4.3.4 DFA versus CV

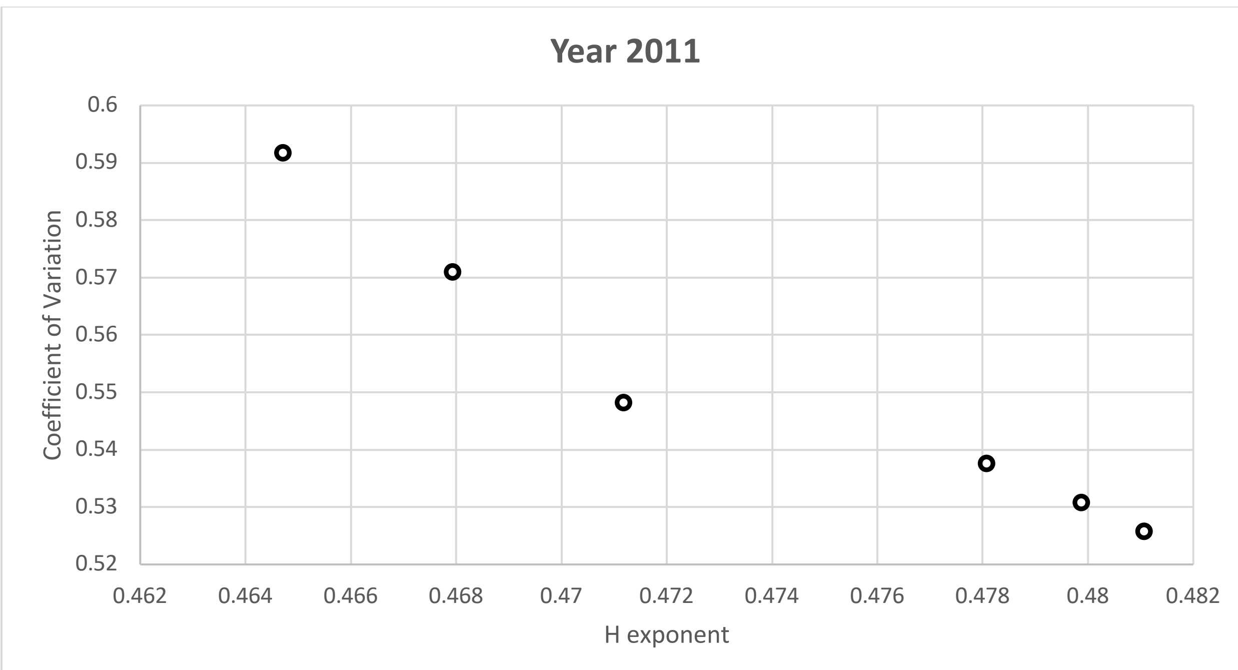

Figure 4.16: Graph of H exponent vs CV in 2011

The CV and the H exponent both indicate a decrease in variability with increase in height, especially from 10 m to 40 m for each of the studied years. Figure 4.16 shows the relation between H and CV for the year 2011, the year for which no gaps existed in any of the time series, and both CV and H could be determined (as explained in section 4.1). The fact that both CV and the H exponent values indicate a decrease in variability with height, in spite of the fact that the methods capture very different aspects of the pattern, is important and points to the presence of an intrinsic relationship between variability and height. The absence of a simple, linear relationship between the resulting H exponent and CV (figure 4.16) reflects the fact that the methods describe distinct aspects of pattern variability. While the two methods cannot be considered interchangeable in their assessment of variability, they serve to confirm and enhance the conclusion: that wind speed variability will decrease with height, up to a height of 40 m. Beyond 40 m, and at least up to the studied height of 60m, wind speed variability decreases at a more gradual rate or does not decrease.

5. Discussion and Conclusions

Wind enjoys major advantages compared to other energy sources, especially in a context of dangerous climate change. Setting up the infrastructure is less costly than for alternative sources and involves a comparatively low environmental footprint, while its functioning does not require fuel expenses or environmentally damaging waste production. Wind is a renewable resource and energy production will not diminish the supply (Jacobson & Delucchi, 2009). Further, wind energy is widely available, with atmospheric currents occurring across most land and water surfaces: – the total installed world wind power reached 600GW at the beginning of the year 2019 (WWEA, 2019). The combined effects of low environmental impact, renewability, and availability make wind energy a viable alternative resource.

However, this energy source is also affected by certain limitations. One of the most important limitations concerns the uncertainty related to energy availability due to wind intermittency (Albadi and El-Saanny, 2010; Suteanu, 2019). Wind turbines have an operational range of wind speeds, within which they are able to produce power, wind speeds outside of this range will not be able to effectively produce power (Burton et al., 2011; Busby, 2012). Therefore, an effective assessment of wind variability is crucially important for the future wind power.

In this context, the thesis is dedicated to an assessment of wind speed variability as a function of height, based on two different methods, which are meant to characterize distinct aspects of wind pattern variability. One of the methods is based on statistical moments, the other consists of multiscale analysis.

As was expected (Floors et al., 2013), mean wind speeds were found to increase with height. With the increase in height and mean wind speed, pattern variability as reflected in the coefficient of variation (CV) is seen to decrease (figures 4.4, 4.5, & 4.6). Based on the studied time intervals, the tendency of variability to decrease with height was found to be consistent between the heights of 10 m and 50 m.

Unlike the coefficient of variation, the H exponent established with Detrended Fluctuation Analysis captures variability aspects associated with (a) the succession of wind speed values in time, and (b) a range of temporal scales. The strong correlation between time scales and the average size of the fluctuations (with R^2 values over 99%), shown in figures 4.7 through 4.11, leads to narrow uncertainty intervals in H values (tables 4.1, 4.2, 4.3) and emphasizes the relevance of these values.

By comparing the H exponents obtained for the different heights, for each year, one can notice a consistent increase of H with height, again mainly between 10 m and 50 m (figures 4.13, 4.14, and 4.15). This increase in H values corresponds to an increase in pattern persistence, i.e. a decrease in variability, of wind speeds with increasing height. The relation between the H exponent and height is therefore consistent with the decrease in wind speed variability reflected in the coefficient of variation over the same height interval.

A comparison between the results obtained using the two different approaches shows that there is no simple linear relation between CV and H (figure 4.16). This result is not surprising, since the two methods applied here capture distinct aspects of wind speed values. However, the fact that in spite of the contrast between the time series aspects considered, the two approaches both point to a consistent relation between height and variability, is significant.

By applying DFA, consideration is given to the temporal succession of time series values where CV and value distributions will address only the scattering of wind speed values. For heights beyond 40m, the variability of the time series decreases faster in terms of temporal succession of wind speed values than in terms of the distribution of wind speed values. This can be observed by comparing the CV and H exponents (figure 4.16) where low CV values, corresponding to lower variability, do not change at the same rate as high CV values. This comparison indicates that changes in wind speed succession play an increasingly important role at larger heights. This change of succession variability at larger heights would not be captured by methods which address distribution variability and is an effect observed at heights with particular importance to wind generation, as turbines often stand at heights higher than 40m.

Applying the approach addressed in this thesis and quantitatively describing the relationship between height and variability could be beneficial both to the design and the positioning of future wind turbines. An effective combination of turbine placement and turbine design can be supported by a better understanding and an accurately identified variability vs. height relationship.

Future work will have to check the consistency of the identified relationship for many other sites, located in different types of geographical environment (elevation, proximity to the coast, characteristics of topography, etc.). An important objective will be to distinguish general aspects of this relation from site-specific effects. To further understand the established relationship of variability and height, it would also be interesting to assess variability at greater heights. Further, consideration can be given to the study of wind direction variability and its relation to speed, in the context of wind velocity variability with increasing height. Such an investigation would shed more light on the way in which turbines react to directional shifts in wind, contributing to the much-needed further understanding of wind speed patterns.

References

Albadi, M., & El-Saadany, E. (2010). Overview of wind power intermittency impacts on power systems. *Electric Power Systems Research, 80*(6), 627-632.

Bashan, A., Bartsch, R., Kantelhardt, J., & Havlin, S. (2008). Comparison of detrending methods for fluctuation analysis. *Physica A: Statistical Mechanics and Its Applications, 387*(21), 5080-5090.

Burton, Tony, et al. *Wind Energy Handbook*. 2nd ed., Wiley, 2011.

Busby, Rebecca L. *Wind Power: the Industry Grows Up*. PennWell Corporation, 2012.

Floors, R., Vincent, C., Gryning, L., Peña, S., & Batchvarova, -. (2013). The Wind Profile in the Coastal Boundary Layer: Wind Lidar Measurements and Numerical Modelling. *Boundary-Layer Meteorology, 147*(3), 469-491.

Gleick, J. (1988). *Chaos: Making a new science*. New York, NY: Penguin Books.

Gowrisankaran, G., Reynolds, S., & Samano, M. (2016). Intermittency and the Value of Renewable Energy. *Journal of Political Economy, 124*(4), 1187-1234.

Hansen, J., Narbel, P. A., & Aksnes, D. L. (2017). Limits to growth in the renewable energy sector. Renewable and Sustainable Energy Reviews, 70, 769-774.

Jacobson, M. Z., & Delucchi, M. A. (2009). A Path to Sustainable Energy by 2030. Scientific American, 301(5), 58-65.

Kantelhardt, J., Koscielny-Bunde, E., Rego, H., Havlin, S., & Bunde, A. (2001). Detecting long-range correlations with detrended fluctuation analysis. *Physica A: Statistical Mechanics and Its Applications, 295*(3-4), 441-454.

Kavanagh, D. S. (2018). *Enhancing the Effectiveness of Wind Power Source Assessment.* Saint Mary's University

Reen, B., Stauffer, P., & Davis, D. (2014). Land-Surface Heterogeneity Effects in the Planetary Boundary Layer. *Boundary-Layer Meteorology, 150*(1), 1-31.

Suteanu, C. (2015). A Methodology for the Time-scale-sensitive Evaluation of Wind Speed and Direction Variability. *Energy Procedia, 76*(C), 200-206.

Suteanu C. (2019), Wind pattern variability imaging: a time-scale-focused methodology, 7th EUGEO Congress, Session: Wind energy – bringing the uncertainties into focus, Galway, Ireland, 15-18 May 2019

WWEA (2019), Wind Power Capacity Worldwide Reaches 600 GW, World Wind Energy Association, 4 June 2019, Press Release, URL https://wwindea.org/blog/2019/02/25/wind-power-capacity-worldwide-reaches-600-gw-539-gw-added-in-2018/

WEICan (2020), Wind Energy Institute of Canada website, https://weican.ca/facilities, accessed April 9, 2020

Yekini Suberu, M., Wazir Mustafa, M., & Bashir, N. (2014). Energy storage systems for renewable energy power sector integration and mitigation of intermittency. *Renewable and Sustainable Energy Reviews, 35*, 499-514.