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GMS PROFIWIND

Yield Study 2015

For 16 Wind Farms

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1 Introduction

The effective operation of renewable energy systems that are dependent on ambient weather conditions such as wind energy naturally require knowledge of the near future wind conditions.

The German wind energy market has evolved from a fixed rate remuneration structure defined by the Renewable Energies Act (EEG) and its precursor, the Electricity Feed Act. In recent years, the direct marketing of electricity generated from renewables has increased and is expected to continue as new wind generation moves to the direct marketing model.

Trading in the day-ahead spot market at the Leipzig electricity exchange requires highly accurate prediction systems. A corresponding need has also arisen in the following areas:

- Effective power grid management based on realistic yield forecasts for individual wind farms. Yield forecasts are heavily dependent on wind and weather conditions at individual wind farm locations.

- Construction downtime due to unsuitable weather conditions during wind farm construction can result in considerable expense that can be avoided by using accurate wind and weather forecast.

A key difference between the requirements of a standard weather forecast and ones specially adapted for wind energy weather forecasting is the need to provide forecasts at the atmospheric boundary layer which includes accurate wind and gust data. In contrast, the lower boundary layer is secondary area of interest in a conventional weather forecast where interest is at ground level and the geostrophic atmosphere where major weather phenomena originate.

Weather forecasting methods based on mesoscale models typically have a spatial resolution of several kilometers. This resolution is too coarse, especially in areas with complex terrain, where small scale variations in wind flow may have a significant impact on predicted wind farm yields.

AL-PRO has developed a mesoscale weather forecasting model complete with self learning components for site specific forecast improvement with the GLOBAL MICROCASTING SYSTEM -GMS. GMS PROFIWIND provides forecasts specifically tailored for the wind industry.

GMS PROFIWIND provides accurate hourly or sub-hour wind, wind yield and weather forecasts for a forecast period of several days.

To validate the quality of GMS PROFI WIND forecasts, a four month study was completed in April, 2015. Data from 16 wind farms in Germany were used to validate the accuracy of GMS PROFIWIND suite of products.

2 Introduction to the Global MicroCasting System GMS

In January 2015, AL-PRO started operational implementation of the GLOBAL MICROCASTING SYSTEM-GMS, a mesoscale wind farm yield prediction model. The system operates on a company owned high performance computing system and is based on the GFS data.

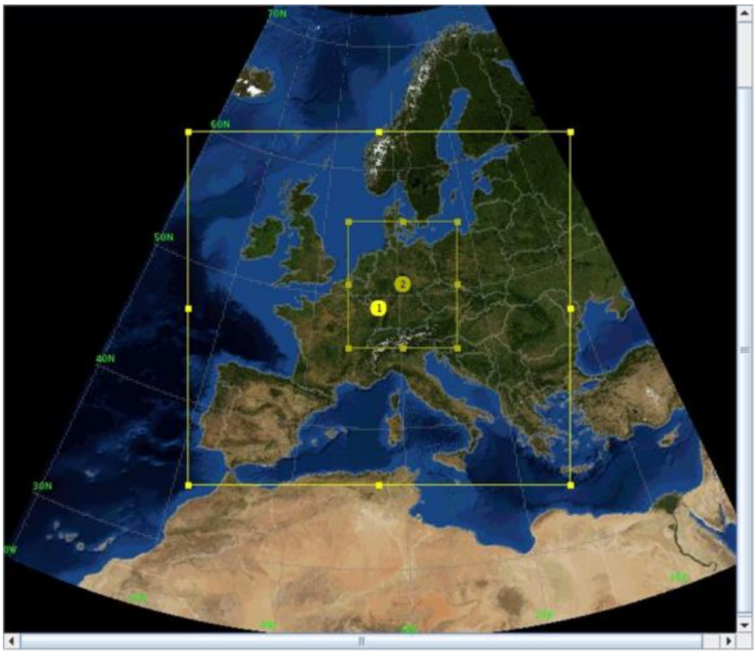

Figure 1: Study Area

Currently, the system is based on two parallel model runs, one for Germany and one for Europe with different resolutions. The German model runs with a grid spacing of 4 km and a forecast horizon of 3 days.

Figure 1 shows the extent of the model areas for Europe and Germany.

2.1 GMS PROFIWIND SMART YIELD

The GMS PROFIWIND forecast generated with the GMS Model can be optimized with GMS PROFIWIND SMART YIELD. GMS PROFIWIND SMART YIELD improves the forecast by using neural networks which are well known to recognize and solve complex, nonlinear correlations. The approach is based on the attempt to reproduce organic thinking and learning using computer-based simulations.

2.1.1 Description of neural networks

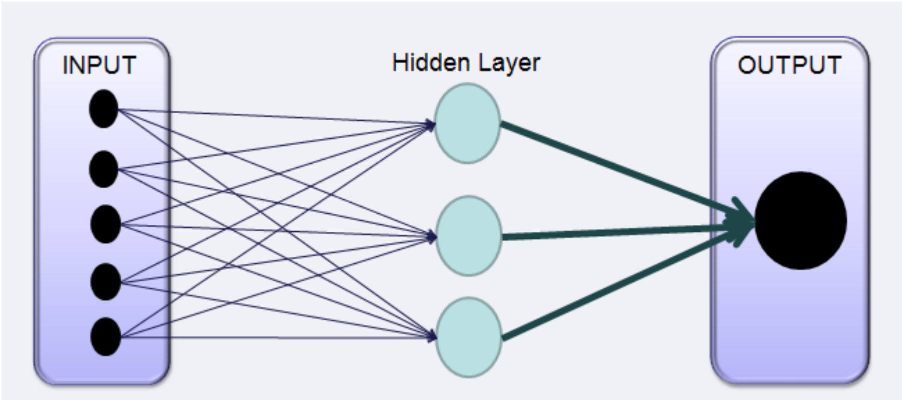

Figure 2: Illustration of a Neural Network

Figure 2 shows the schematic structure of a neural network. It typically consists of some input parameters, one or more hidden layers and one or more output parameters. The hidden layers consist of single neurons, which are represented by the turquoise circles in Figure 2. Neurons are the replica of a single organic nerve cell. They have a very simple transfer function, for example a multiplication with a constant factor, which transfers input into output. The input is typically obtained by the weighted addition of the input parameters and a bias.

The key process is the training of the neural network which is modeled like the human learning process. During training, the neural network gets a set of input parameters with the corresponding, known results. By adjusting the weights and the bias of each neuron, the so-called training, the neural network calculates the best reproduction of the output data from the input data. In the next step the trained neural network gets new input data and has to calculate the results.

In our case the input data are weather, wind and yield forecasts, and the yield production of each WEA of a wind park. The training will be performed with training data of forecasts and measured yields.

2.2 GMS PROFIWIND Products

There are three different variations of GMS PROFIWIND designed to cover different levels of market need:

1. **GMS PROFIWIND BASIC** offers detailed, hourly wind forecasts at different heights and is suited for maintenance scheduling of wind turbines.
2. **GMS PROFIWIND FARM YIELD** extents the BASIC product with the GMS YIELD PREDICTOR – a method of modeling algorithms for wind turbines of different types and/or different versions. The GMS YIELD PREDICTOR simulates wind fluctuations and turbine-induced turbulence at an hourly resolution for a wind farm. It provides detailed yield forecasts for individual turbines combined for the entire wind farm.

3. **GMS PROFIWIND PREMIUM** is available for both the wind forecast as well as for the yield forecast and includes additional GMS PROFIWIND SMART YIELD. This is a technique which significantly improves the forecasts with a neural network. The neural network is trained to recognize forecast variations and automatically correct them.

3 Participants and Wind farms

Four wind farm owners with a total of 16 wind farms participated in the GMS Yield Study 2015. The wind farms are spread over the middle and the northern areas of Germany and are mostly located in simple terrain. The wind farms Salzhemmendorf and Kuhschnappel are located in semi-complex terrain and the wind farms of the wind park owner of Westfalenwind are located in semi-complex to complex terrain. Data from each of the 100 wind turbines included the 10 minute average yield, the wind direction and the wind speed. Additionally we had access to the status codes in order to identify periods when turbines were non operational. The data period started at the beginning of April and ran to the end of July. We used 3 months (April to June) for training GMS PROFIWIND SMART YIELD and one month (July) for validation. Furthermore we also split the training data into slices of 1 month and 3 months data blocks to evaluate the improvement of using a single month of training data.

Table1: Description of Participant Wind Farms

Owner	Wind Farm Name	Turbines	Hub Height	Latitude	Longitude
eab New Energy	Pegau	2 x E-70	113 m	51,1811°	12,2372°
eab New Energy	Kuhschnappel	1 x E-48/8.48	78 m	50,8152°	12,6345°
eab New Energy	Sendenhorst	2 x GE 1.5sl & 5 x GE 2.3	100 m/93 m	51,8439°	7,7871°
eab New Energy	Wulkow	5 x V90	105 m	52,4010°	14,4414°
Landwind	Baddeckenstedt	4 x E-82 & 4 x E-66/18.70	96 m / 65 m	52,0655°	10,2997°
Landwind	Gevensleben	5 x E-66/18.70 & 5 x E-70 E4	65 m /113.5 m	52,0705°	10,7986°
Landwind	Harmshagen	3 x E-70 E4	113.5 m	53,7969°	11,2762°
Landwind	Salzhemmendorf	5 x E-82	108 m	52,0788°	9,6528°
Landwind	Söllingen	15 x GE 2.3 & 2 x E-82 E2	100 m /108 m	52,0780°	10,9484°
Landwind	Uhrsleben	13 x E-66/18.70	98 m	52,1892°	11,2754°
SL Naturenergie	Alpen-Veen	3 x E-66/18.70	98 m	51,6043°	6,4630°
SL Naturenergie	Coesfeld	1 x E-58/10.58 & 2 x E-66/18.70	70 m /86 m	51,9283°	7,2206°
SL Naturenergie	Werl	4 x E-66/18.70	98 m	51,5382°	7,9773°
Westfalenwind	Pfluglinde	4 x E-82 E2	138.4 m	51,5351°	8,6499°
Westfalenwind	Wewelsburg	11 x E-82 E2	138.4 m	51,5833°	8,6572°
Westfalenwind	Weiberg	5 x E-82 E2	138.4 m	51,5251°	8,5746°

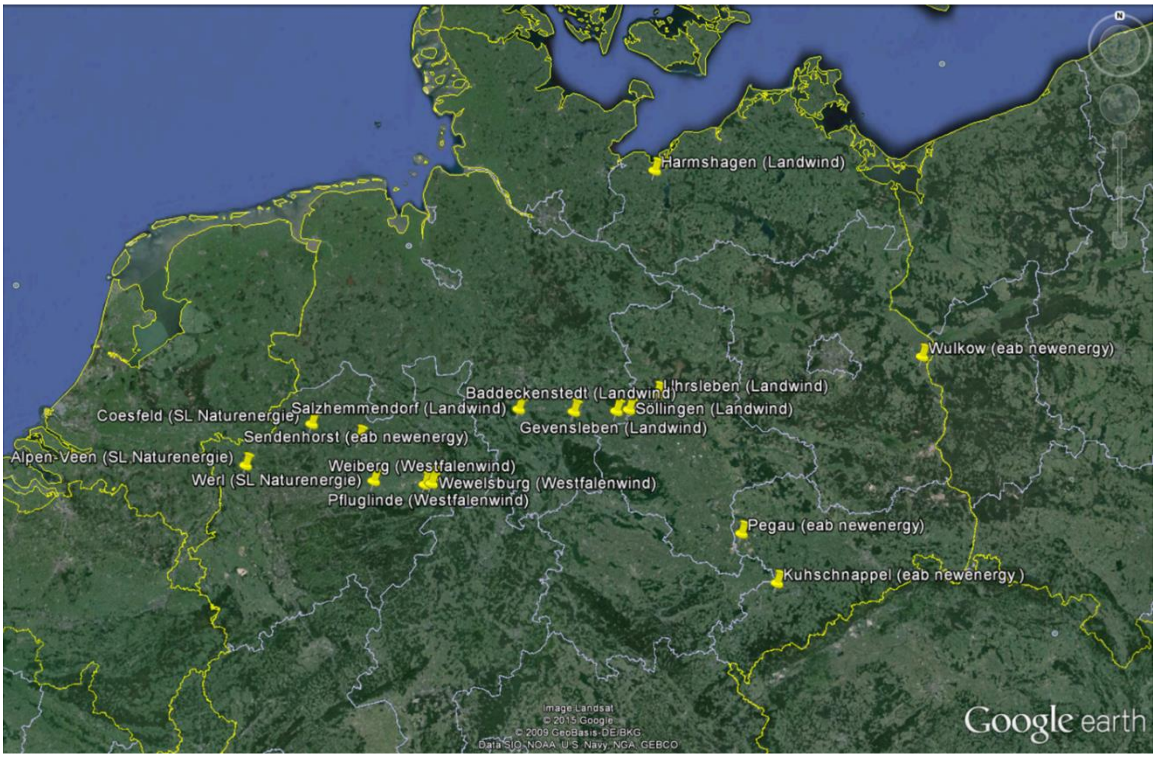

Figure 3: Location of Participant Wind Farms.

4 Methodology

4.1 Data preparation

The data delivered from the wind farms were imported into a database and subsequently filtered with a complex algorithm developed by AL-PRO. The data filtering methodology is also used for performance analysis of existing wind farms. The filtering identifies implausible values from the status codes and known operational constraints such as night time sound reductions, feed-in limitations, etc. The filtered data are used to complete a correlation analysis for each wind farm.

The data from the wind farms Söllingen, Sendenhorst, Pfluglinde, and Baddeckenstedt were rejected from further evaluation after the data filtering process because of a high number of missing or bad records.

4.2 Evaluation

Both the direct results of the GMS PROFIWIND MicroCast forecasts for each wind farm as well as the optimized GMS PROFIWIND SMART YIELD results were analyzed based on the following indicators:

For statistical analysis, the correlation or the coefficient of determination (R^2) was calculated from the measured and calculated values. These indicate how well the prediction coincides with the measured values. A value of 1 is the best score and 0 means there is no linear statistical correlation.

The mean absolute error (MAE) and root mean square error (RMSE) were also calculated. The MAE shows how big the average error is based on the following formula:

$$MAE = \frac{\sum(Xi - Yi)}{n}$$

where: X = measured values; Y = calculated values; n = number of values

In comparison to MAE, RMSE highlights larger errors more than smaller ones. RMSE is derived from the following formula:

$$RMSE = \sqrt{\frac{\sum(Xi - Yi)^2}{n}}$$

where: X = measured values; Y = calculated values; n = number of values

Furthermore, the BIAS was calculated to identify systematic deviation between measured and calculated values. (Wilks, 2006)

4.3 GMS PROFIWIMD SMART YIELD

There is no simple solution for designing a neural network. Consequently, the first essential step in GMS PROFIWIND SMART YIELD process is to determine the optimal network structure and input parameters for each turbine and wind farm. This depends on the type and amount of available training data. It is desirable to have one or two complete years worth of training data in order to recognize the often complex and seasonally dependent meteorological dependencies. Long term data was not available for this study and with 3 months of data, only simple network structures with fewer input parameters (wind speed, wind direction, calculated yield, and possibly temperature and wind shear) delivered the best results.

It is with longer periods of training data for the distinct advantage of using GMS PROFIWIIND becomes clear. Our in-house MicroCast forecast model provides access to a plethora of additional weather prediction parameters for pattern recognition and problem solving.

In this study, the optimal structured neural network for each turbine of a wind farm was used to compare the actual and forecast yields for the month of July. Both trained and untrained forecasts were evaluated with the above mentioned parameters.

In this context, the distinction between the difference forecast periods should be described. Larger forecast deviations are expected for forecast periods of several days when compared to only a few hours. Therefore, the forecast were separated in 6 hour forecast horizons. A 3 day forecast is separated into 12 horizons. This means that horizon 1 is the most current model run and the day ahead forecast is horizon 5.

5 Weather Conditions

5.1 April 2015

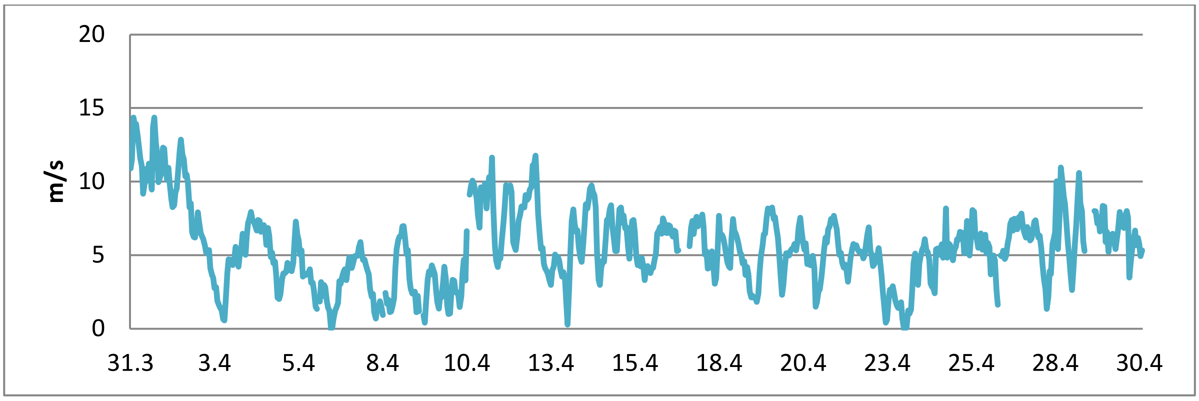

Figure 4: Wind Measurements from the Site Alpen-Veen for April 2015.

At the end of March, the storm “Niklas” tracked across Germany and caused wind related damage. Figure 4 shows the wind measurements at the wind farm Alpen-Veen. At the beginning of April, wind speeds generally slowed as a high pressure system moved across the country. However, this did not last long. From the 10th of April on, wind speeds increased for a few days before the second high pressure system caused a period of low wind. At the end of April the high pressure system diminished and wind speeds increased. Overall, the month of April was the fourth sunniest on record. It was clearly warmer than usual compared to the period from 1960 to 1991. [4]

5.2 May 2015

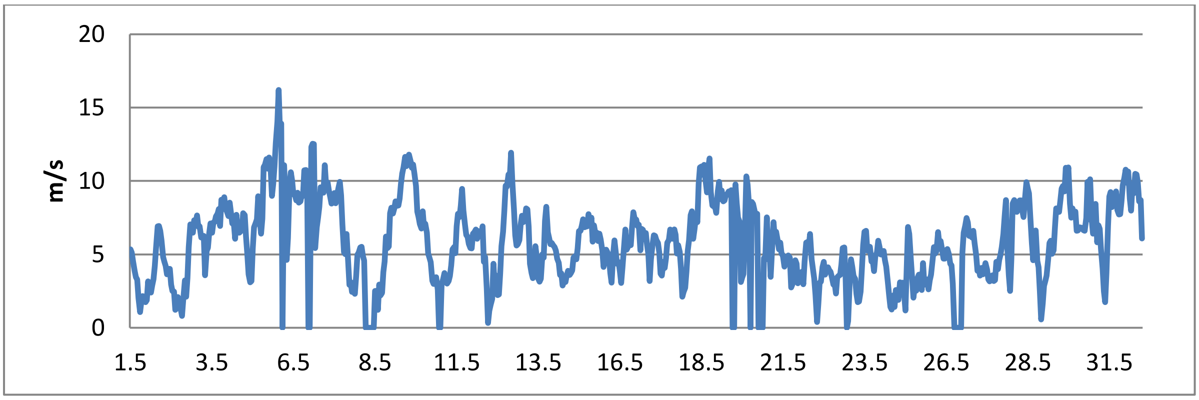

Figure 5: Wind Measurements form the Site Alpen-Veen for May 2015.

May’s weather in Germany can be described by dividing it into three parts, cloudy and cool in the north, very dry in the middle and high precipitation rates in the south. [5] The wind measurements at the wind farm Alpen-Veen (Figure 5) shows some wind peaks in the first half of the month and a weak wind resource during the later part of the month.

5.3 June 2015

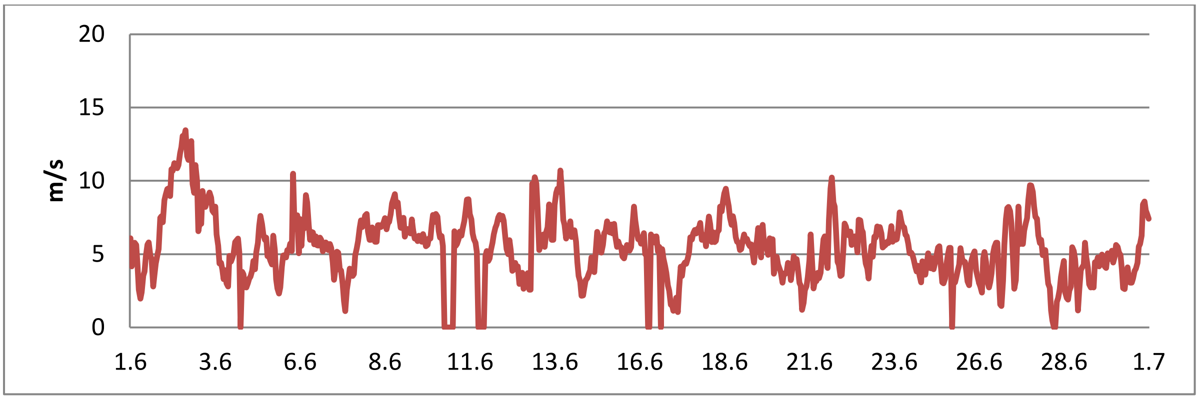

Figure 6: Wind Measurement for the Site Alpen-Veen for June 2015.

June was dominated with large drought conditions in central and northern Germany [6]. This was accompanied by very low wind conditions, as seen in Figure 6.

5.4 July 2015

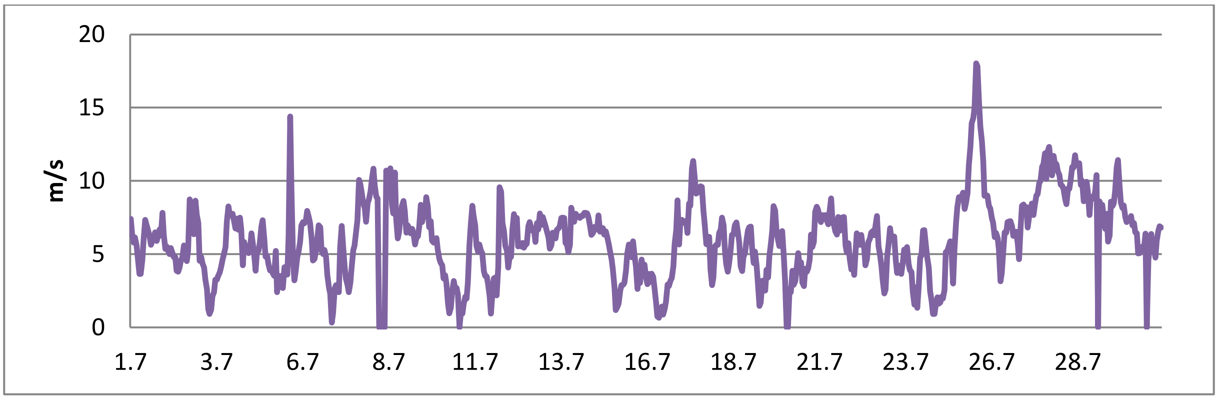

Figure 7 Wind Measurement for the Site Alpen-Veen for July 2015.

In July, high temperature records were set for many locations in Germany. Kitzingen located in central Germany, set a temperature record of 40.3^{o} C on July 5. At the end of the heat wave the Storm “Zeljko“ crossed Germany. [7]

The storm on July 25 is clearly noticeable in the wind measurement data from the site Alpen-Veen (Figure 7). On this day the highest value of 18 m/s was measured in the considered period. The remaining month shows predominantly average wind speeds.

6 Results

In the following section, GMS PROFIWIND MicroCast was validated and the quality of GMS PROFIWIND FARM YIELD is analyzed. The influence of GMS PROFIWIND SMART YIELD based on 1 and 3 months of training data were also evaluated against the GMS PROFIWIND FARM YIELD forecasts. Finally, a comparison between the yield study and the GMS yield study from 2010 is presented.

6.1 Evaluation of the GMS PROFIWIND MicroCast

In this study, the closest model run (horizon 1), the day ahead (horizon 5), the day after tomorrow (horizon 9), and day three (horizon 12) are the main components that were analyzed. Figure 8 shows the correlation coefficient (R) for the selected horizons for all wind farms. It turns out that the correlations for the 1st and 5th horizon are very high with an average of 83%. These are reduced for the other two horizons to 75% (9th horizon) and 73% (horizon 12). In addition, it can be seen that there are no major differences between the various wind farms. The best correlation of 89% for the 1st horizon was observed for Harmshagen.

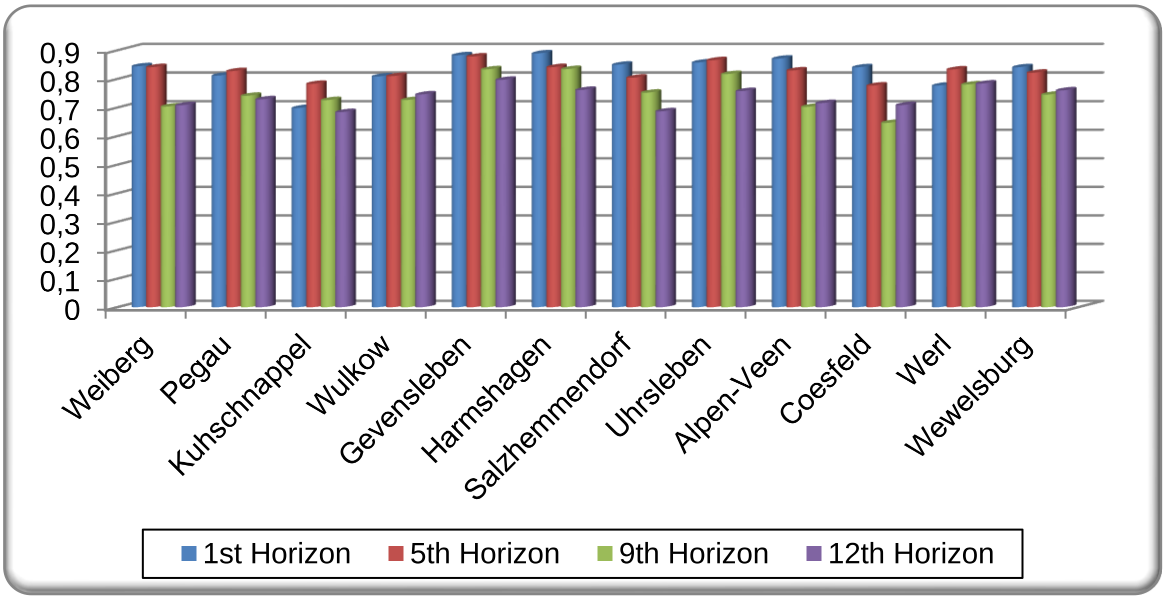

Figure 8: Correlation for the 1st, 5th, 9th and 12th Horizons.

For the 5th horizon, Gevensleben had the best correlation which is reflected in the coefficient of determination (R^2) in Figure 9 with a value of 0.7717. The worst values for the 5th horizon were observed at Coesfeld with a coefficient of determination (R^2) of 0.6037 (Figure 9). The scatter plot diagrams for the other wind farms are located in Appendix I.

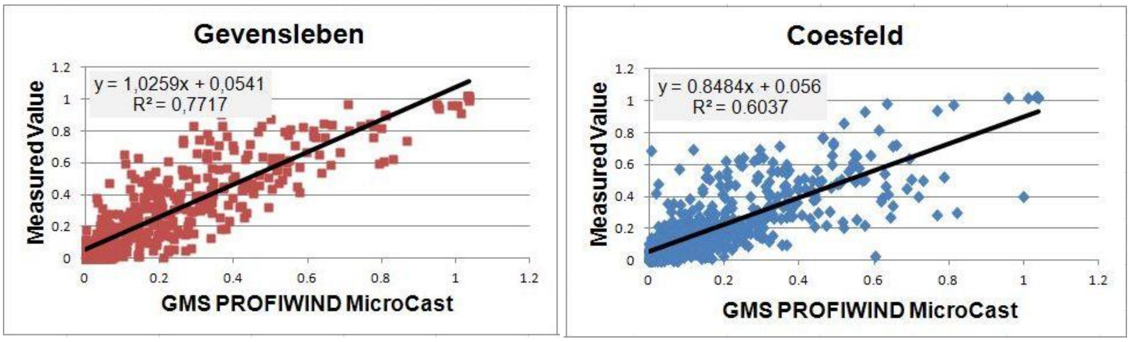

Figure 9: Scatter Plot Diagrams for Gevensleben (left) and Coesfeld (right).

The relatively strong agreement between actual and the untrained GMS PROFIWIND MicroCast for the wind farm Werl is shown in Figure 10. The results for GMS PROFIWIND SMART YIELD based on one and three month training periods are also shown in Figure 10. For the remaining wind farms, the yield curves are shown in Appendix ll.

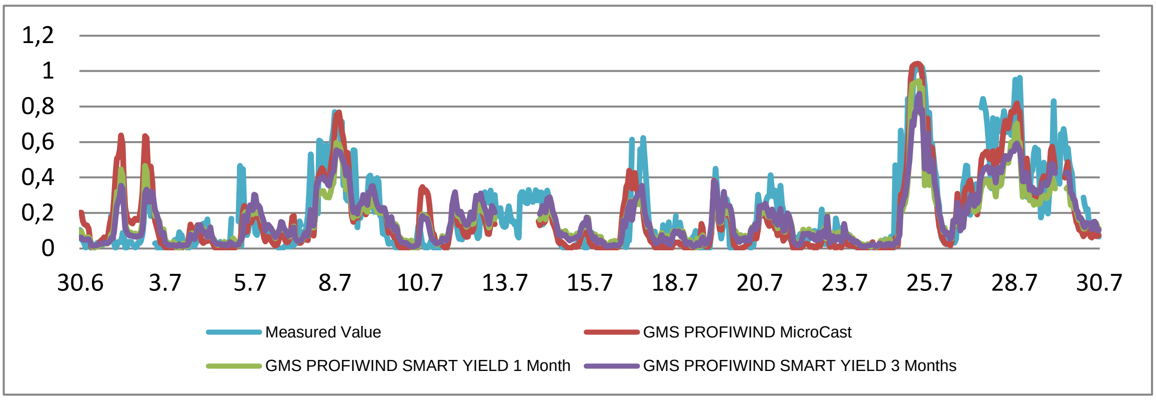

Figure 10: Yield Curves for the Site Werl for July 2015.

The good results of GMS PROFIWIND MicroCast were confirmed with the RMSE. In Figure 11 the averaged RMSE for all wind farms for all horizons are plotted. It shows that the RMSE up to the 5th horizon is very good with a RMSE of approximately 14%. After the 5th horizon, the error's between the measured and calculated values increase, mainly as a result of the duration time in relation to the present. However even the forecast horizon 3 days out (horizon 12) has a RMSE of 17 %. A summary of the RMSE for each wind farm can be found in Appendix III.

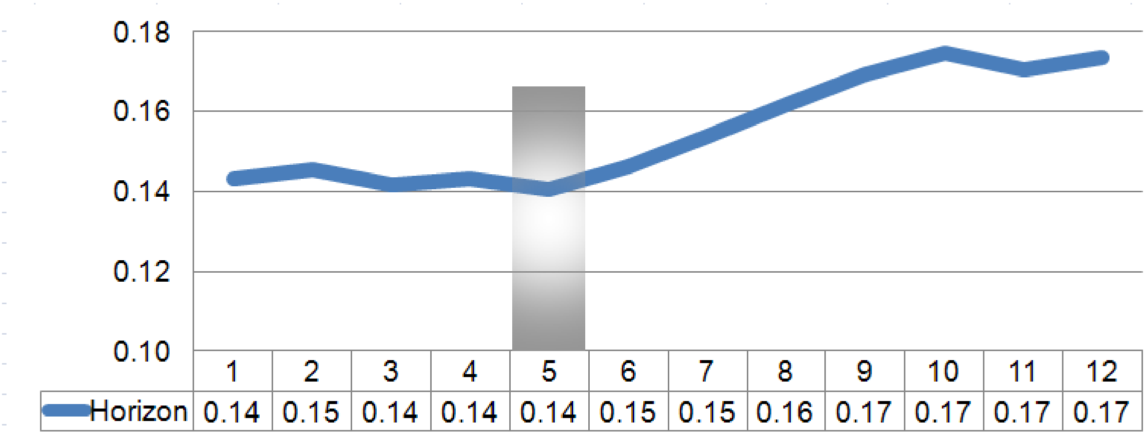

Figure 11: Average RMSE Across all Wind Farms for all Horizons.

The specific examination of the MAE for horizon 5 for all wind farms is plotted in Figure 12. It shows that the relative mean absolute error lies between 7.5 % for Alpen-Veen and 12.6 % for Wulkow. Moreover all wind farms have nearly the same results, so there is no connection to the complexity of the terrain.

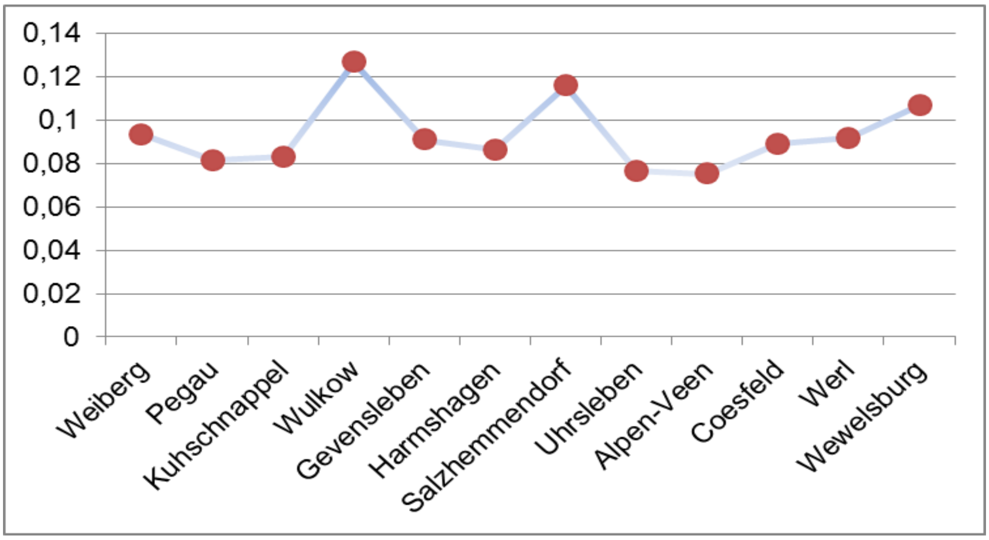

Figure 12: Relative MAE for the 5th Horizon for all Wind Farms

Figure 13 shows that the relative BIAS for all wind farms for the first horizon is negative. In principle, this means that the model underestimates the measured values but the underestimation is very low for the majority of the wind farms. The only exception is Wulkow which has a BIAS for horizon 5 that is nearly 0. For the horizons greater than 5, the BIAS's at Wulkow are slightly positive. These values are remarkably good. But other wind farms have very low values as well, like Harmshagen -0.015 for horizon 5 and Werl -0.013, also for horizon 5. It is striking that the BIAS for horizon 5 is almost always better than horizon 1. A similar behavior has been shown for the RMSE in Figure 11. Again, horizon 5 is better than the first.

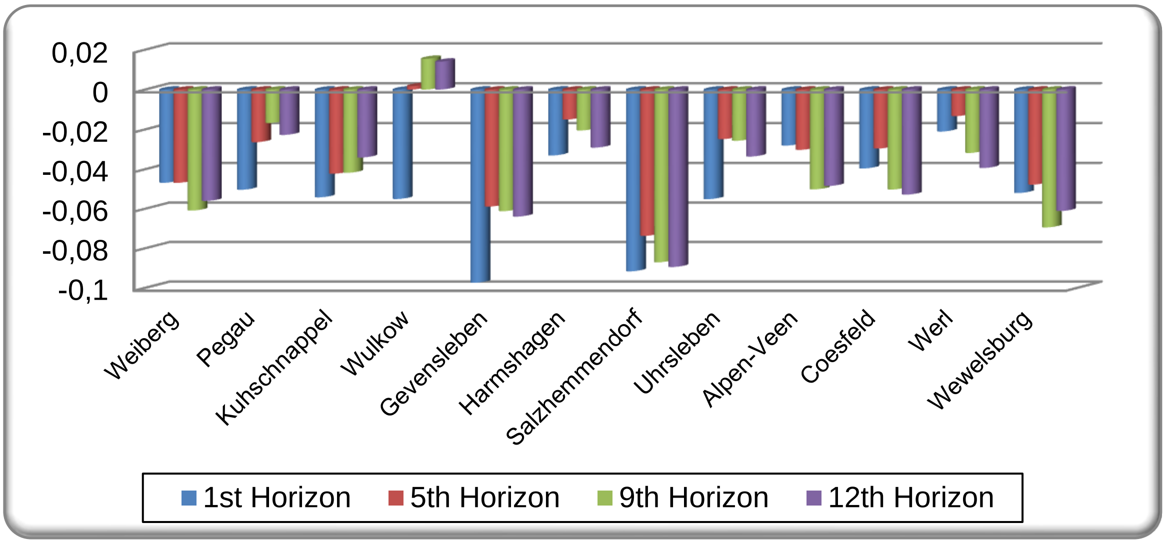

Figure 13: Relative BIAS for the 1st, 5th, 9th and 12th Horizons for all Wind Farms.

6.1.1Additional analysis for the wind measurements

Wind speed data measured with the nacelle anemometers and those predicted by GMS PROFIWIND MicroCast are similar. This is shown in Figure 14 which compares the actual versus predicted wind speeds for the Gevensleben wind farm. Wind speed comparisons for the remaining wind farms are located in Appendix IV.

Figure 15 shows the scatter plot for the 5th horizon for Gevensleben which highlights a very good coefficient of determination of 0.73.

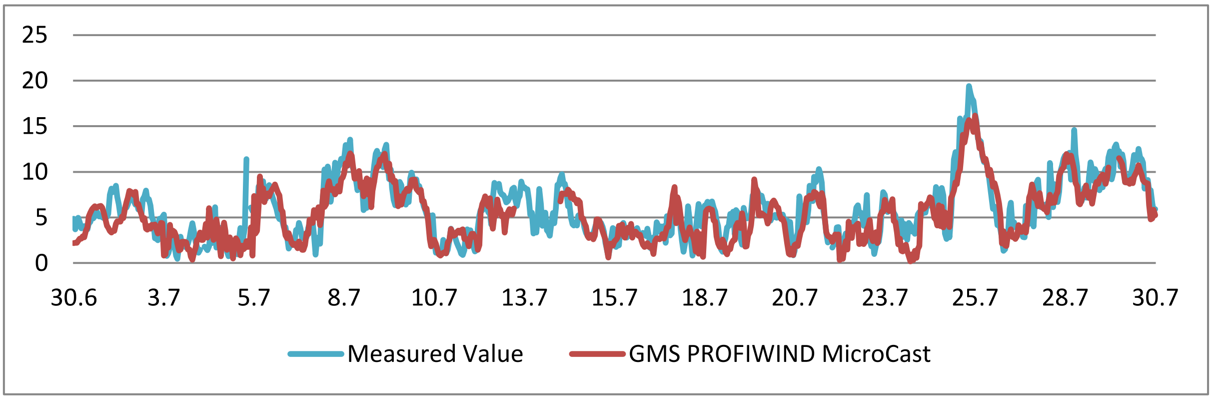

Figure 14 Meaured and Forecast Wind Speeds at Gevensleben for July, 2015.

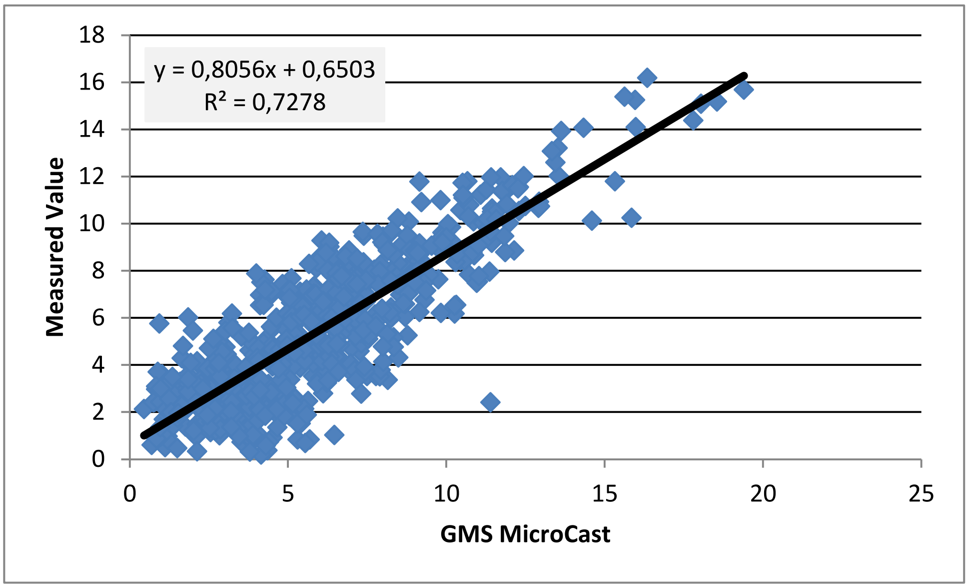

Figure 15 Scatterplot and Regression Comparing the Measured and Forecast Wind Speed for the 5th Horizon at Gevensleben.

6.1.2 Interm Conclusion on the Evaluation of GMS PROFIWIND MicroCast.

In summary, GMS PROFIWIND MicroCast provides excellent results without implementing the SMARTYIELD option. Both in the latest and day-ahead runs we achieved RMSE values of 14% for the yield forecasts. Very high correlations as high as 89% were observed with bias's close to zero. It should be noted that the prediction quality appears to be unrelated to terrain complexity. The correlations between actual and predicted wind speeds are higher than those for yield forecasts. One would expect that improving the forecast with a few months of training data and a simple neural network is difficult to achieve. A systematic bias is typical for mesoscale wind forecasts, however GMS PROFIWIND MicroCast shows a very low bias.

6.2 Evaluation of GMS PROFIWIND SMART YIELD

The network architecture for each wind farm was set up individually for all the participating wind farms by setting input parameters that provided the best results. As expected, the relatively short training period required the development of simple network structures. For neural network training of yield forecasts for GMS PROFIWIND YIELD, wind direction and wind speed were the basic parameters used. At some wind farms, temperature, wind shear, hourly and six hour pressure gradients provided better training results.

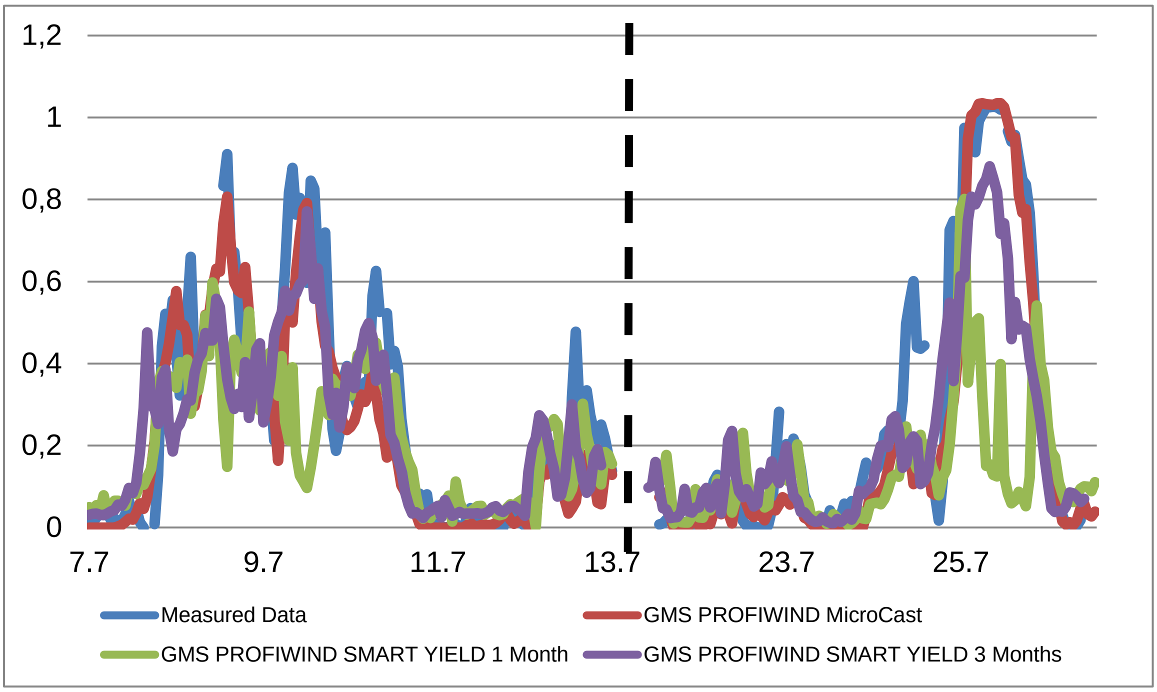

Figure 16: Measured and Modeled Profiles for Gevensleben on Selected Days in July, 2015.

Figure 16 shows the quality of the GMS PROFIWIND MicroCast is difficult to improve upon with GMS PROFIWIND SMART YIELD with relatively short training periods. At Grevensleben, the storm event on July 25 was poorly forecast with GMS PROFIWIND SMART YIELD based on a single month of training data. This is caused by the fact that there was no storm event during the training month and therefore the neural network was not able to effectively forecast the storm event. The forecast quality of GMS PROFIWIND SMART YIELD would certainly improve, if a similar storm event occurred during the training period.

This is also confirmed when the relative MAE for the 5th horizon is shown for all wind farms (Figure 17). Except for Wulkow, predictions for all wind farms using the GMS PROFIWIND SMART YIELD based on one month of training data worsened the forecast. This is presumably explained by the fact that Wulkow is the eastern most wind farm in the study and the forecast for storm on July 25 had not underestimated the yield as much as at the other wind farms. On July 26, the wind speeds reached a maximum of 13.6 m/s (Figure 18) whereas at Alpen-Veen, the maximum wind speed is 18.0 m/s (Figure 7).

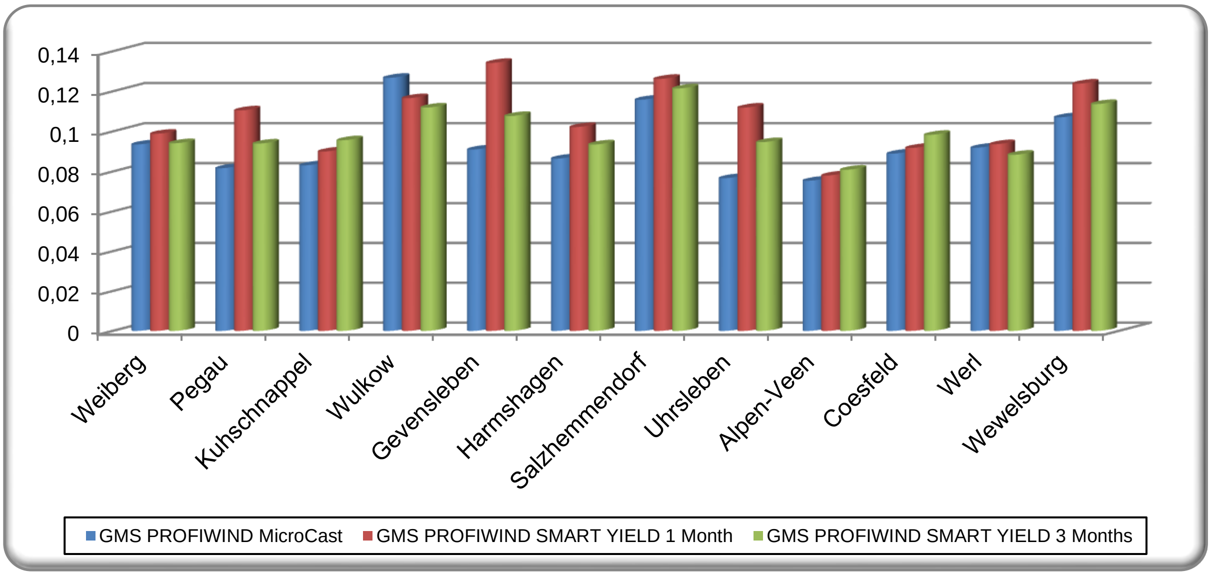

Figure 17: Relative MAE for the 5th Horizon for all Wind Farms

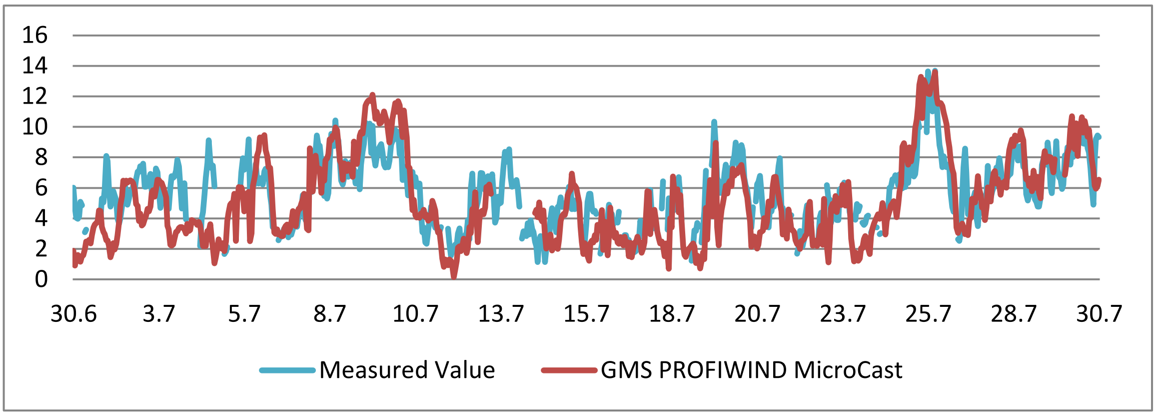

Figure 18: Measured and Foreacst Wind Speed for the Site Wulkow for July 2015

Figure 19 shows the RMSE for each of the participant wind farms. When the relative differences between the MAE (Figure 17) and RMSE (Figure 19) are compared, the GMS PROFIWIND SMART YIELD based on 1 month of training data showed a reduction in RMSE for the wind farms at Kuhschnappel and Alpen-Veen. Since the wind farm located in Kuhschnappel is located in semi-complex terrain, there may be potential for forecast improvement here.

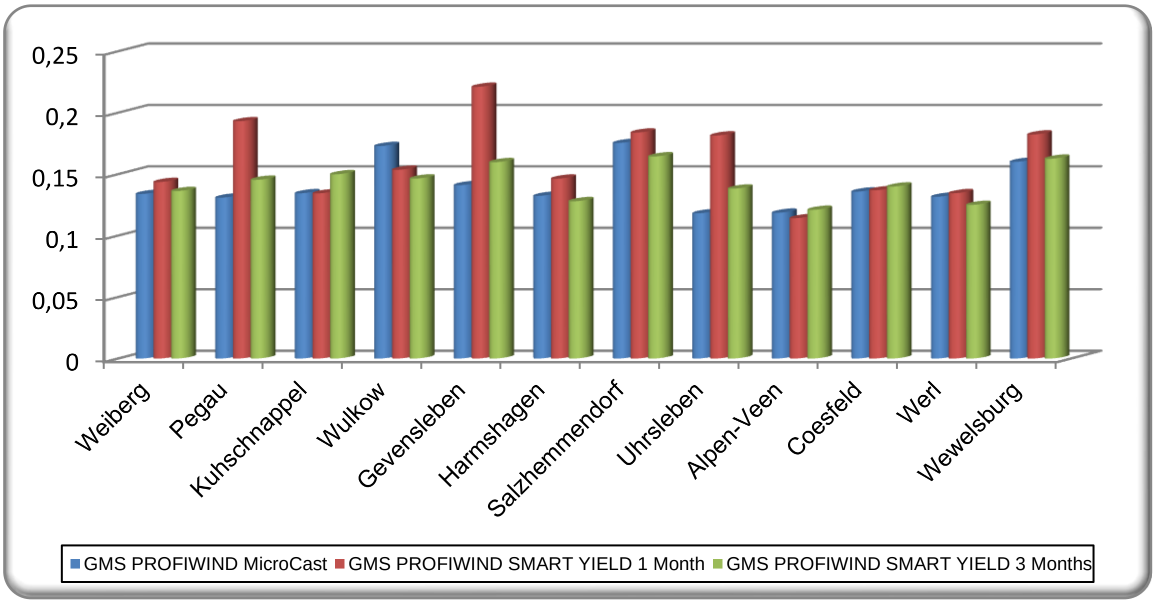

Figure 19 Relative RMSE for the 5th Horizon for all Wind Farms.

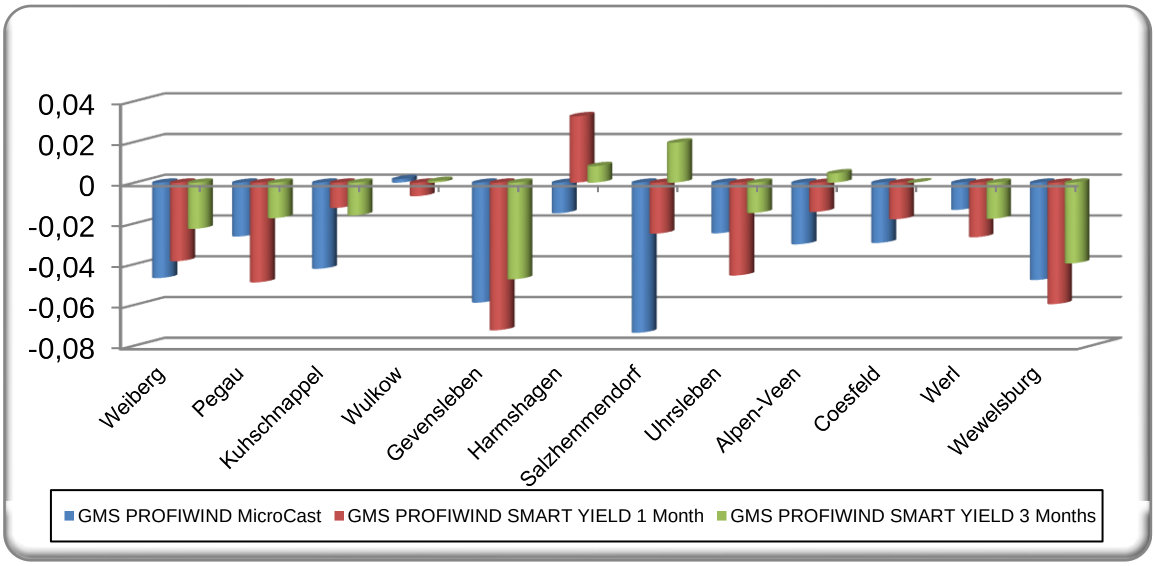

Figure 20 Relative BIAS for the 5th Horizon for all Wind Farms.

Relative BIAS, which typically is reduced by neural networks, shows some conflicting results in Figure 20. Not all wind farms exhibited improvements by reducing BIAS with the help of GMS PROFIWIND SMART YIELD based on 1 month training periods. At sites with very low BIAS''s from the GMS PROFIWIND MicroCast an increase in BIAS was observed using the 1 month training period for Pegau, Harmshagen, Uhrsleben and Werl. This deterioration of the 1 month training period is due to the strong influence of the storm event which started on July 25.

In the case of GMS PROFIWIND SMART YIELD based on a 3 month training period, the relative BIAS improves over the original GMS PROFIWIND MicroCast forecast in almost all of the wind farms. Even in Wulkow, the initially low relative BIAS of 0.0017 shows and improvement to 0.0008. BIAS is almost completely removed from the forecasts by implementing GSM PROFIWIND SMART YIELD based on 3 months of training data which is noticeable for the Coesfeld wind farm.

6.2.1Interim Conclusion on the Evaluation of GMS PROFIWIND SMART YIELD

During the evaluation of GMS PROFIWIND SMART YIELD, it became apparent that the accurate forecast results of GMS PROFIWIND MicroCast are difficult to improve upon with a short term training period of 3 months. GMS PROFIWIND SMART YIELD was challenged by the storm event on July 25, 2015. This highlights the need for long term training data to ensure a broad range of meteorological events are included in the neural network. As with GMS PROFIWIND MicroCast, the quality of the yield forecast was not related to site complexity.

6.3 Comparison with the GMS Wind Forecast Study - 2010

The current wind energy yield study builds on a previous study "Global Micro Casting Service GMS - Wind Forecast Study 2010" (Daneu & Albrecht, 2010). In the 2010 study, a weather model developed by a former partner, Weather Central was used for Mesoscale forecasts. In addition, a completely different evaluation was used, the first three months of 2010. In the 2010 study, 1 and 2 month training periods (January and February, 2010) were used and the month of March was used for the validation (Daneu & Albrecht, 2010). In Figure 21 the relative RMSE was (called RSF in the 2010 study) calculated for horizon 1, 5 and 8 based Weather Central's GMS Weather models without SMART LEARNING, and with one and two months of training for the horizons (periods).

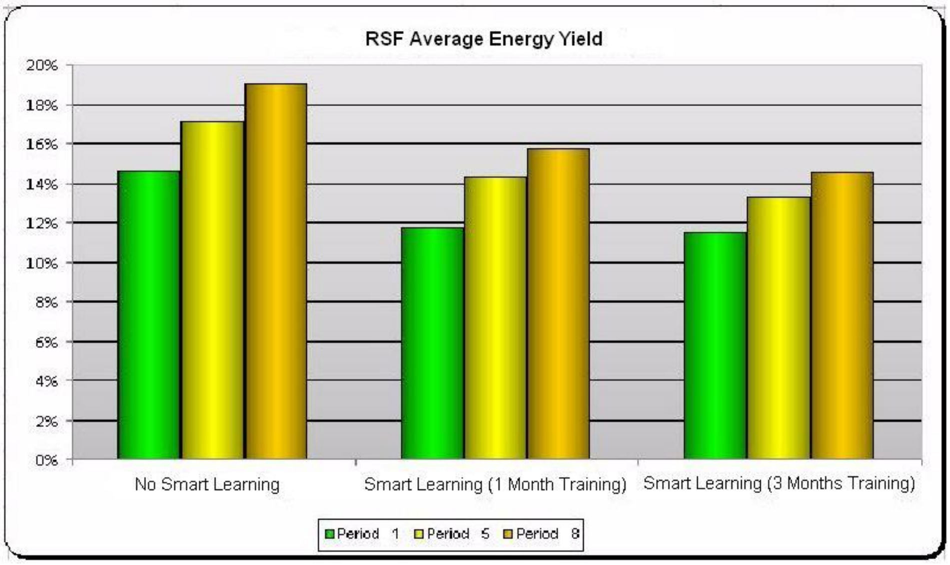

Figure 21: Figure 5.2.1.1 from the Wind Forecast Study from 2010 (Daneu & Albrech, 2010).

GMS PROFIWIND MicroCast achieved noticeably better values, when compared to the Weather Central's Mesoscale models. Especially for the day-ahead (horizon 5) data in the current study shows significantly improved RMSE values of 13.5% compared to 17.1% in the 2010 study. However, it appears that in the 2010 study, the weather prediction model results were improved by applying a neural network based on one month of training data.

In terms of the coefficient of determination for the wind speed, a mean value of 0.57 was calculated in the 2010 study (Daneu & Albrecht, 2010) for the 5th horizon without GMS SMART LEARNING. In this study, the wind speed coefficient of determination averaged across all wind farms was 0.62. In Figure 22 the coefficient of determination is shown for all wind farms for the 5th horizon.

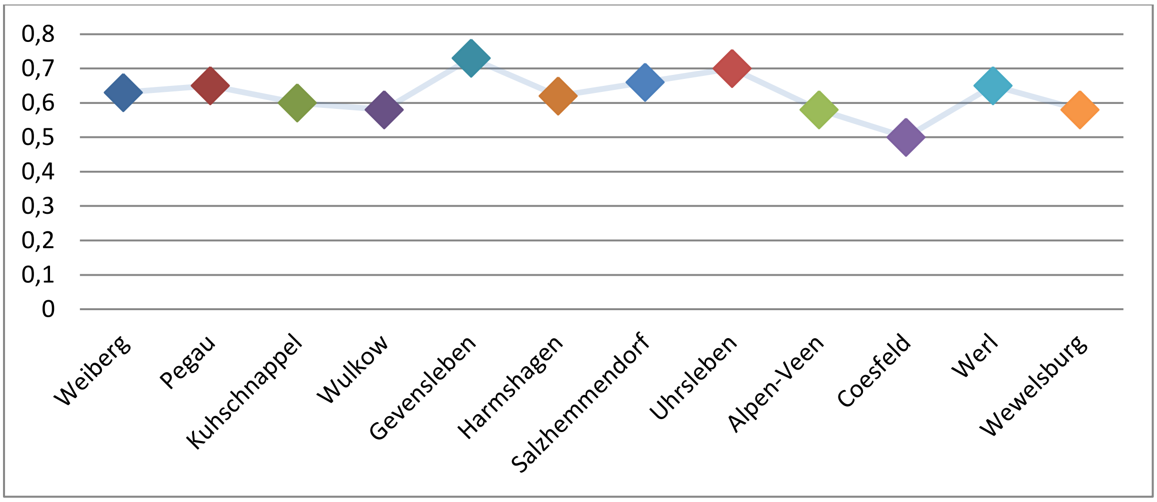

Figure 22: Coefficient of Determination for Horizon 5 for All Wind Farms.

6.3.1 Interim Conclusion compared to the 2010 Wind Forecast Study

GMS PROFIWIND MicroCast delivers a high quality forecast when compared to the Weather Central's forecasts in 2010. Furthermore, the results from the 2010 study indicate that imprecise, bias prone predictions can be easily improved by implementing simple neural networks with limited training data.

7 Summary and Discussion

This study included an evaluation of three main components which included GMS PROFIWIND MicroCast FARM YIELD forecasts, GMS PROFIWIND SMART YIELD and a comparison to the GMS-Study of 2010. In terms of GMS PROFIWIND MicroCast FARM YIELD, the results show excellent correlations between measured and forecast values as high as 89%. Also, the RMSE of the predicted yield with an average of 14% for the day-ahead shows very good results. A relationship between the yield forecasts and the terrain complexity was not observed, which may be due to the fact that GMS PROFIWIND MicroCast is modeled at a resolution of 4 km and thus can resolve complex terrain forecast issues well.

In addition, the storm on July 25, 2015 had a noticeable impact on the results of GMS PROFIWIND SMART YIELD. Since SMART YIELD had been trained on June’s weak wind resource, the lack of a significant wind event during the training period limited the ability of the neural network to predict wind speeds at high velocities. Only one wind farm showed an improvement in yield forecast using SMART YIELD based on one month of training data.

The results of implementing GMS PROFIWIND SMART YIELD based on 3 months of training data showed an improvement in forecasted yield. It should be noted that no significant storm events occurred during the training period however, there were some higher wind periods. If more diverse meteorological events occurred during the training period, the results of the SMART YIELD would have also improved. This suggests that longer training periods are required to consistently improve on the quality of GMS PROFIWIND MicroCast outputs using GMS PROFIWIND SMART YIELD. The ability of GMS PROFIWIND SMART YIELD to recognize complex meteorological patterns could not be leveraged with the short training periods. Furthermore, GMS PROFIWIND SMART YIELD can utilize time shifts to develop a stronger neural network which results in higher quality forecasts.

Finally, a comparison with the results of the 2010 wind forecast study indicate that the current weather model, GMS PROFIWINDF MicroCast is a noticeable improvement over the model used in the 2010 study. Care should be taken when interpreting results based on different forecast periods. This was demonstrated with the RMSE for the wind energy yield, as well as the coefficient of determination for wind speed. In the 2010 Study, a month in spring (March) was investigated and the GMS SMART LEARNING trained with winter data. In the current study, a summer month was studied and trained with spring and summer months.

8 Acknowledgements

AL-PRO GmbH & Co. KG would like to thank the companies that have participated in the study, particularly among their respective employees. The participants made it possible to conduct this study and allowed AL-PRO to refine the analysis routines of the PROFIWIND product suite and to evaluate the quality of the products using a scientific approach.

AL-PRO hopes that the results of this study are beneficial to participants and others.

9 Literature cited

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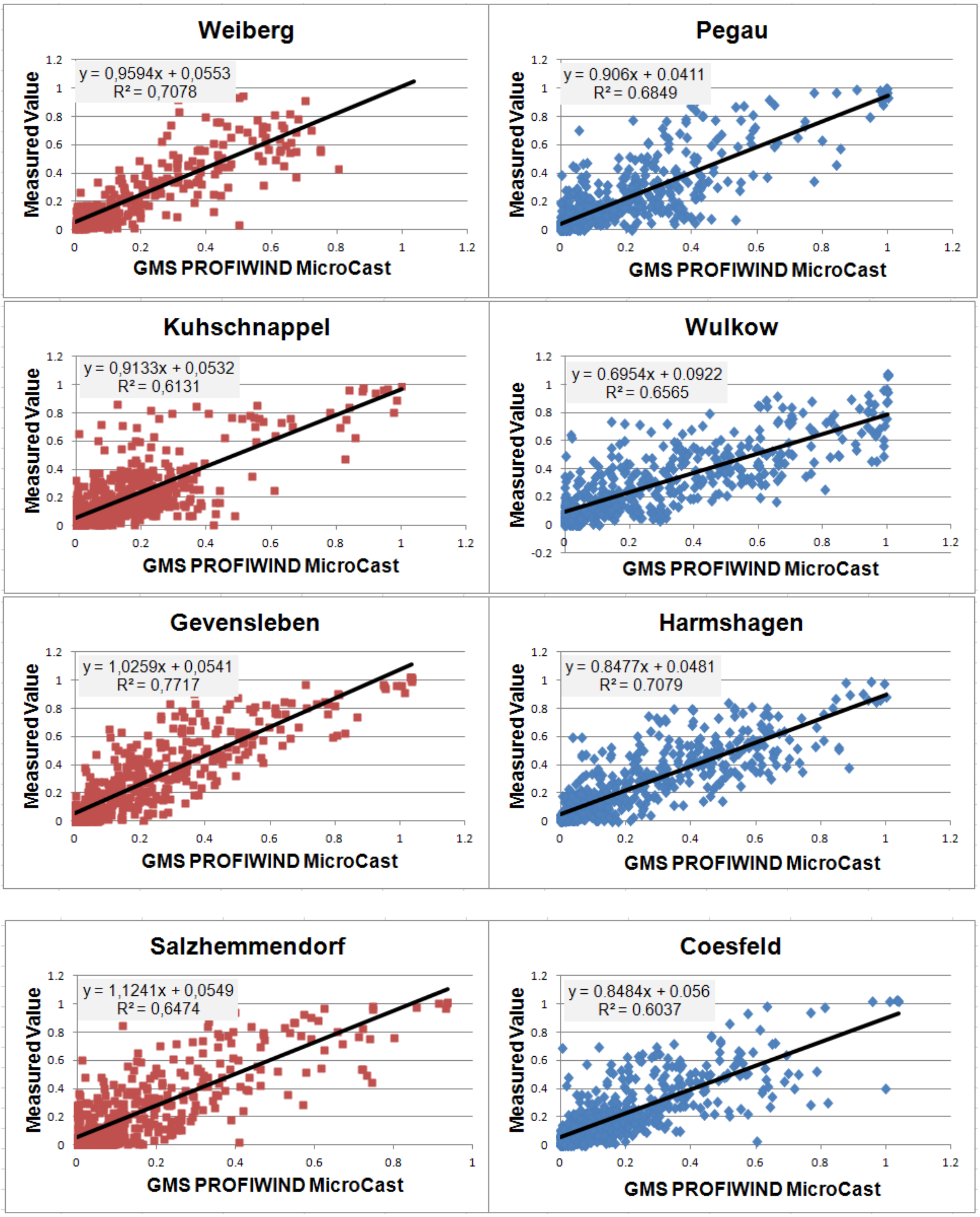
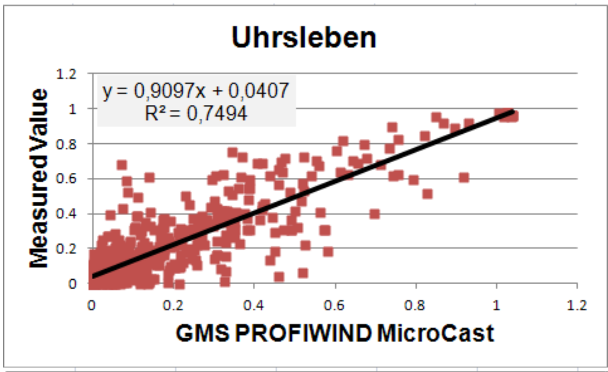
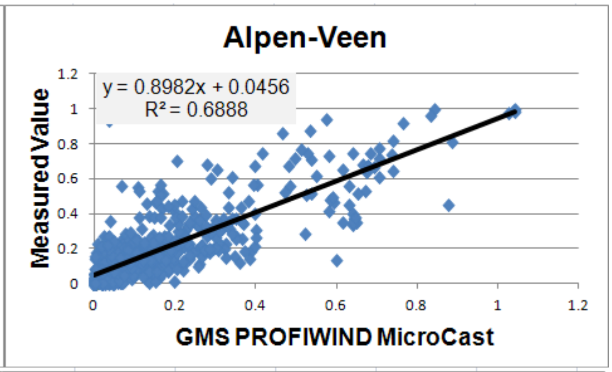
Pressestelle. (2015). *Pressemitteilung: Deutschlandwetter im Mai 2015.* Offenbach: Deutscher Wetterdienst.

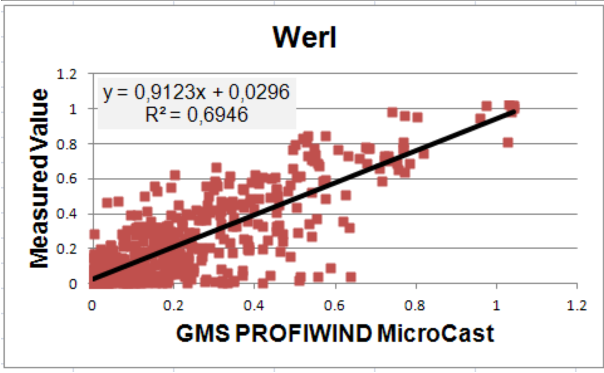
Pressestelle. (2015). *Pressemitteilung: Deutschlandwetter Juni 2015.* Offenbach: Deutscher Wetterdienst.

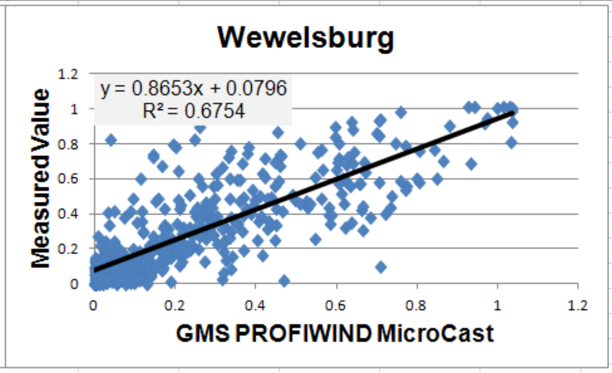
Appendix I – Scatter Plots for Each Site



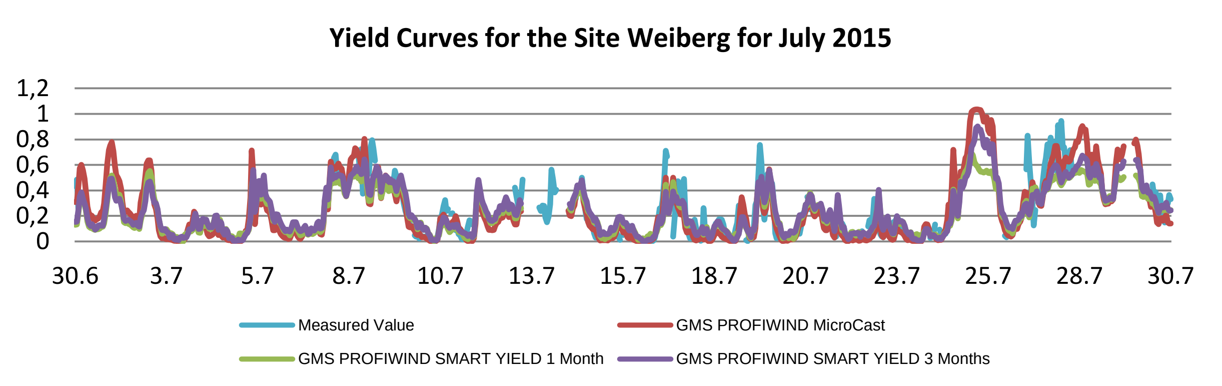

Uhrsleben
y = 0,9097x + 0,0407
R² = 0,7494
Measured Value
GMS PROFIWIND MicroCast

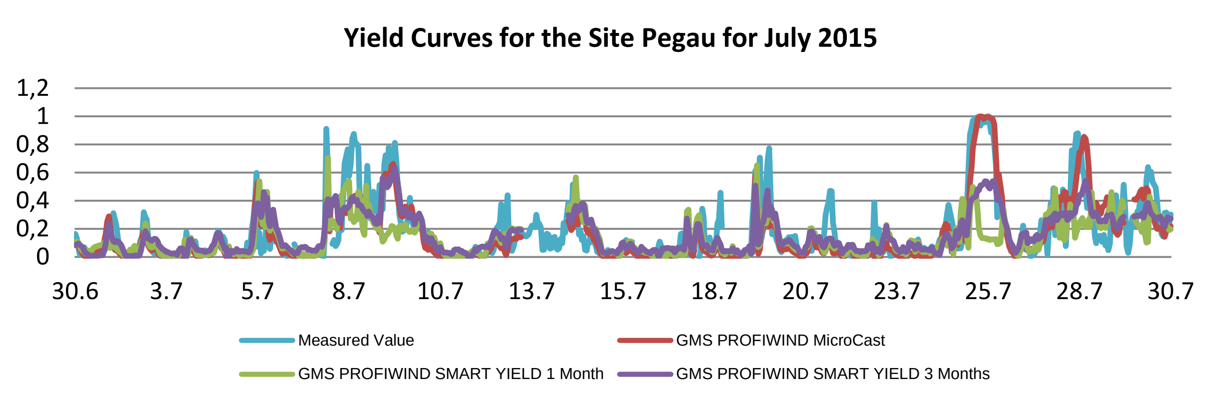

Alpen-Veen
y = 0.8982x + 0.0456
R² = 0.6888
Measured Value
GMS PROFIWIND MicroCast

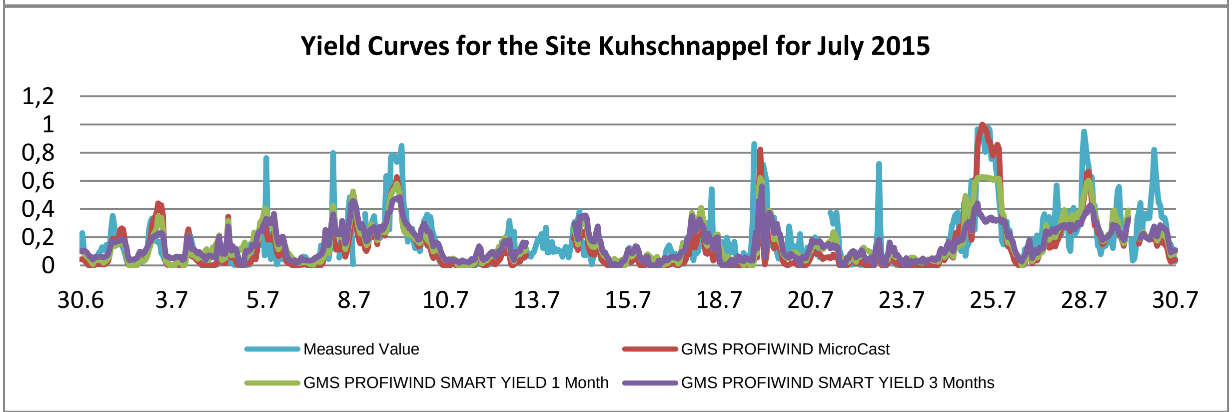

Werl
y = 0,9123x + 0,0296
R² = 0,6946
Measured Value
GMS PROFIWIND MicroCast

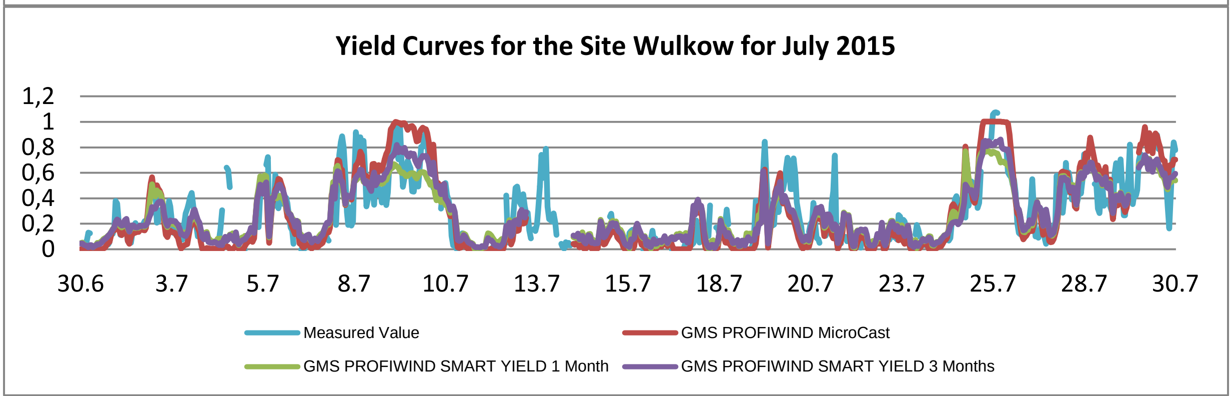

Wewelsburg
y = 0.8653x + 0.0796
R² = 0.6754
Measured Value
GMS PROFIWIND MicroCast

Appendix II – Yield Curves for the Month of July for all Wind Farms

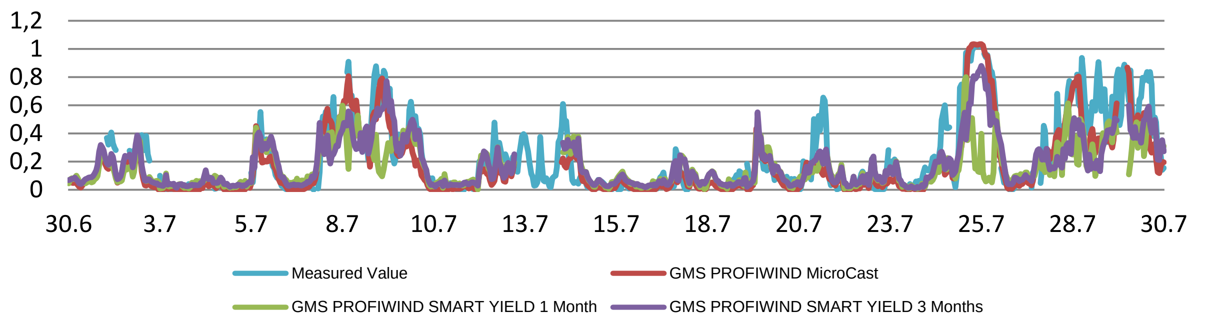




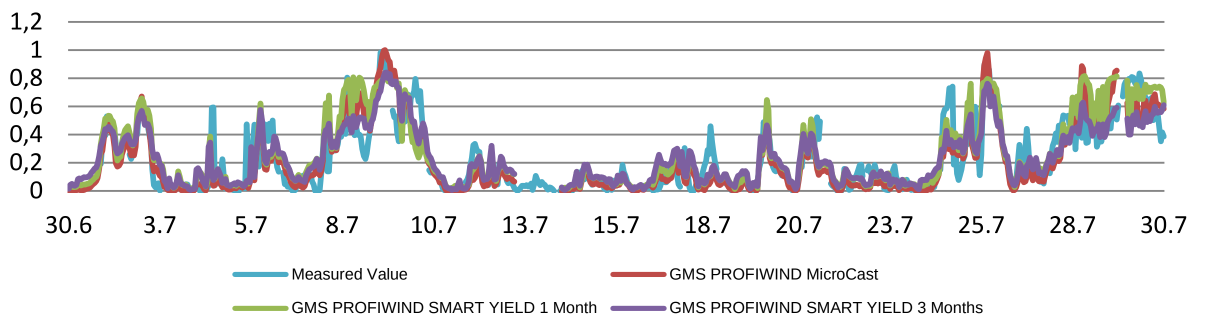




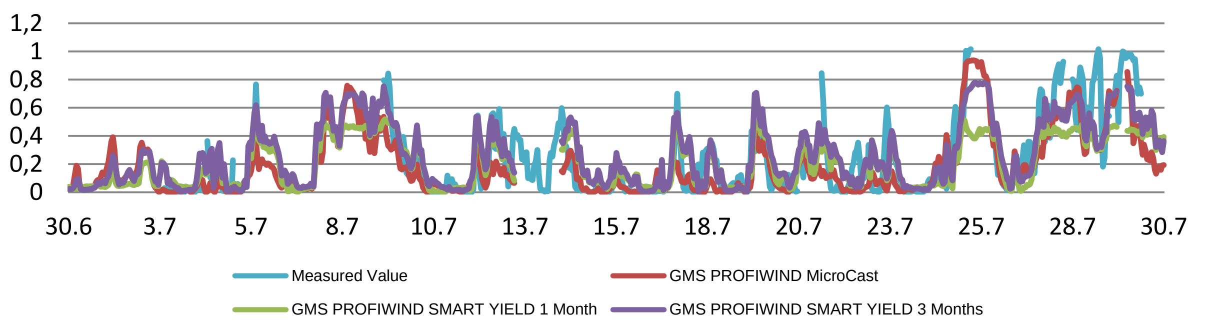
Yield Curves for the Site Gevensleben for July 2015



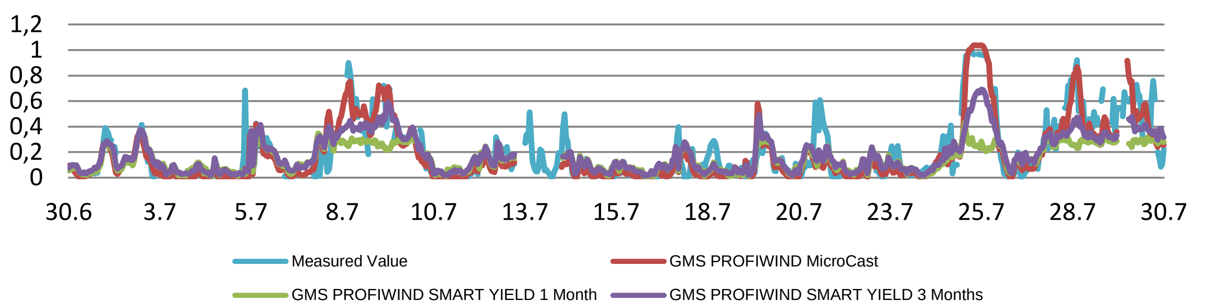
Yield Curves for the Site Harmshagen for July 2015



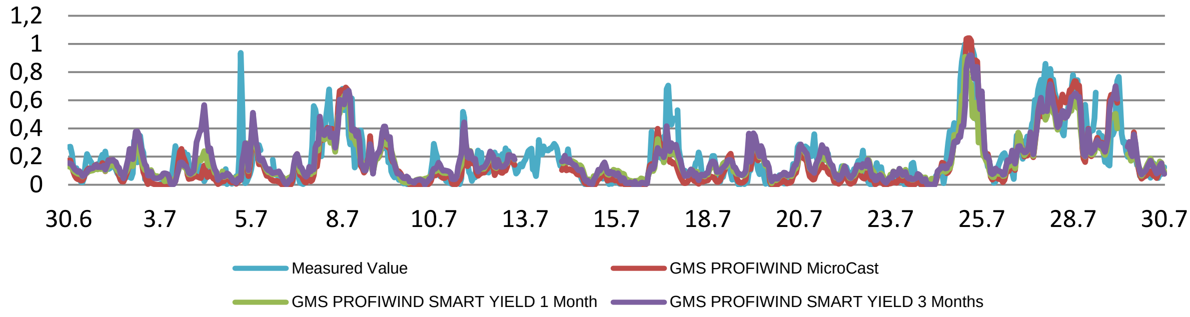
Yield Curves for the Site Salzhemmendorf for July 2015



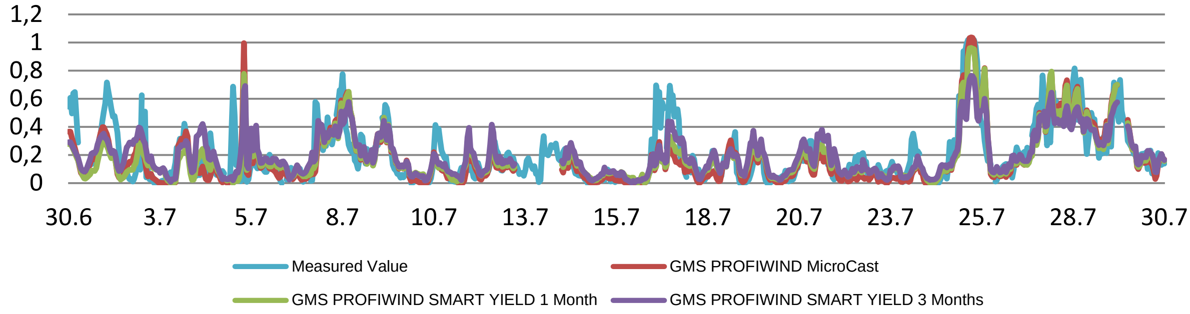
Yield Curves for teh Site Uhrsleben for July 2015



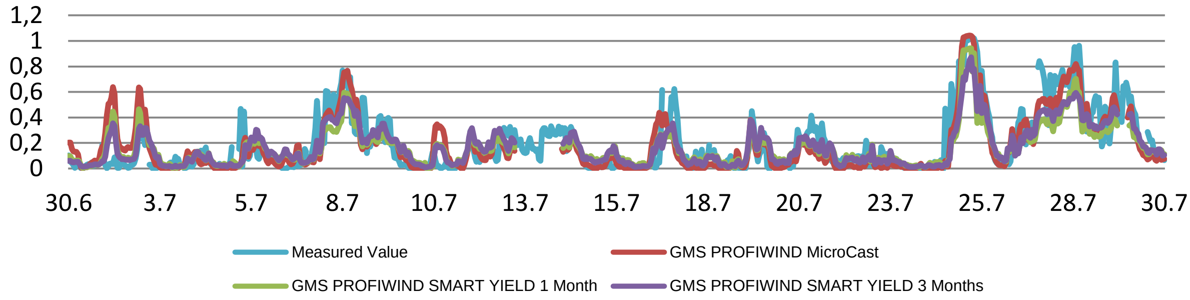
Yield Curves for the Site Alpen-Veen for July 2015



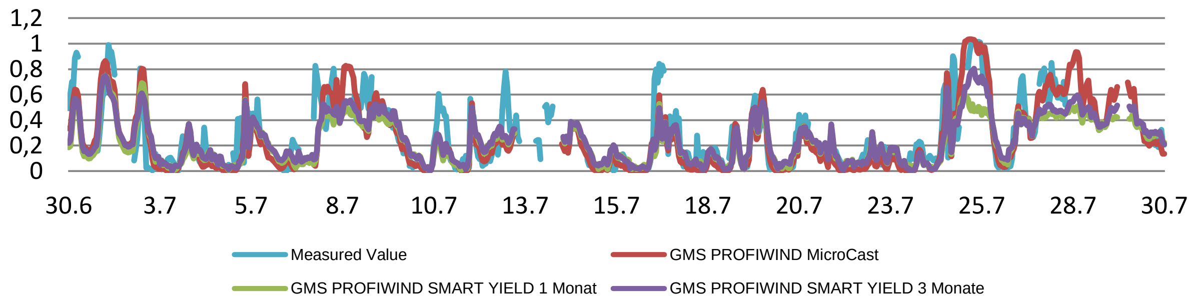
Yield Curves for the Site Coesfeld for July 2015



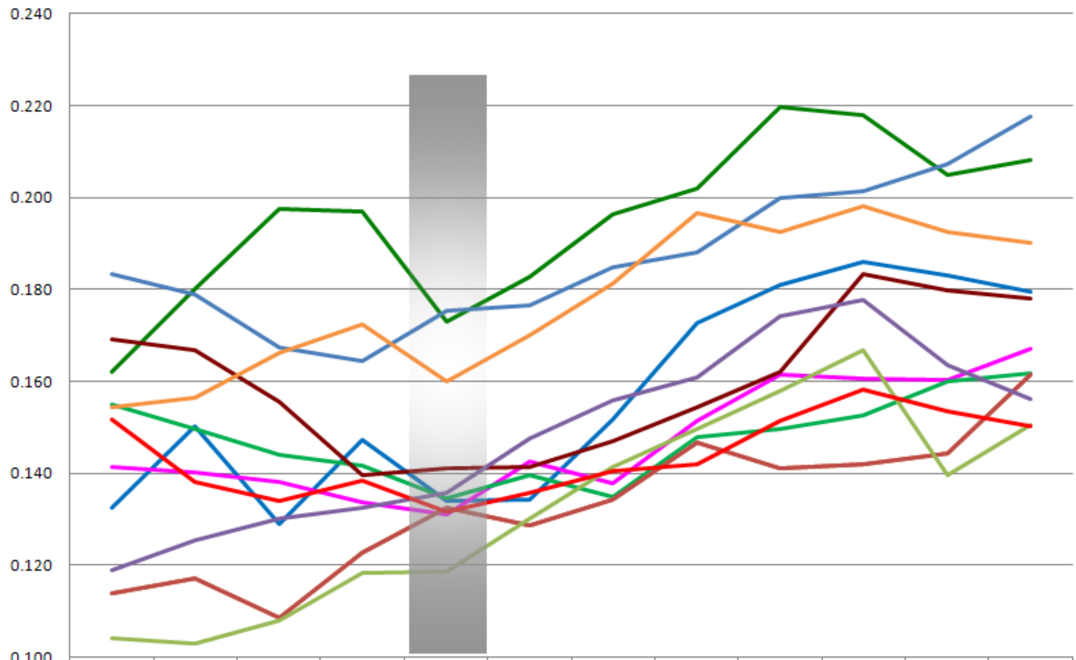
Yield Curves for the Site Werl for July 2015



Yield Curve for the Site Wewelsburg for July 2015

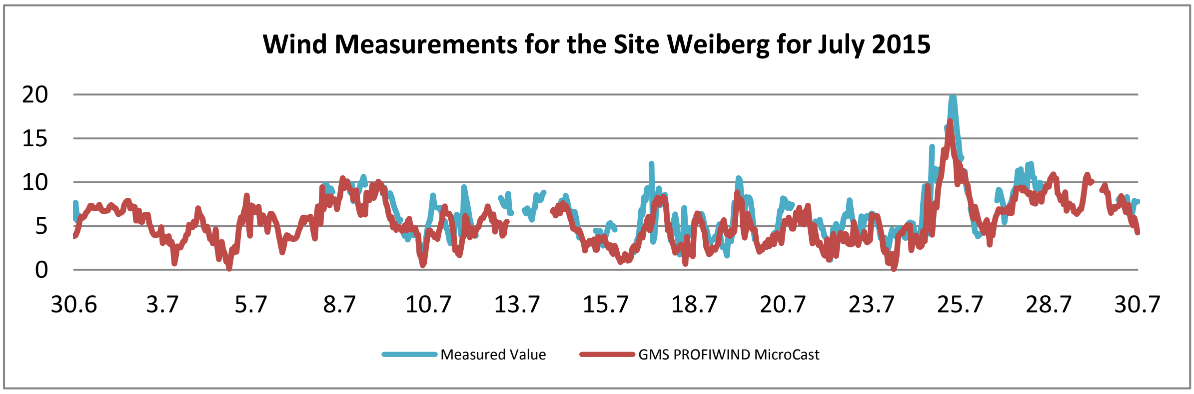


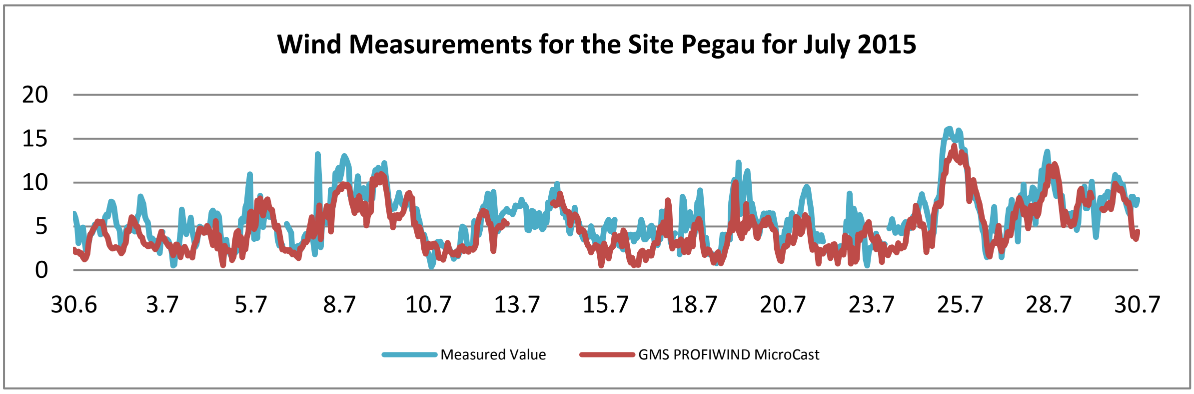
Appendix III – RMSE for all Horizons for all Wind Farms

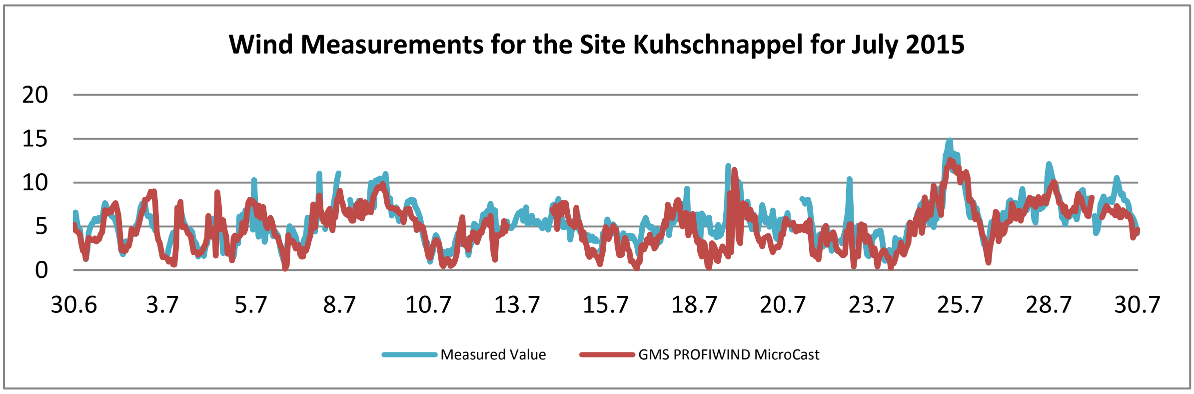


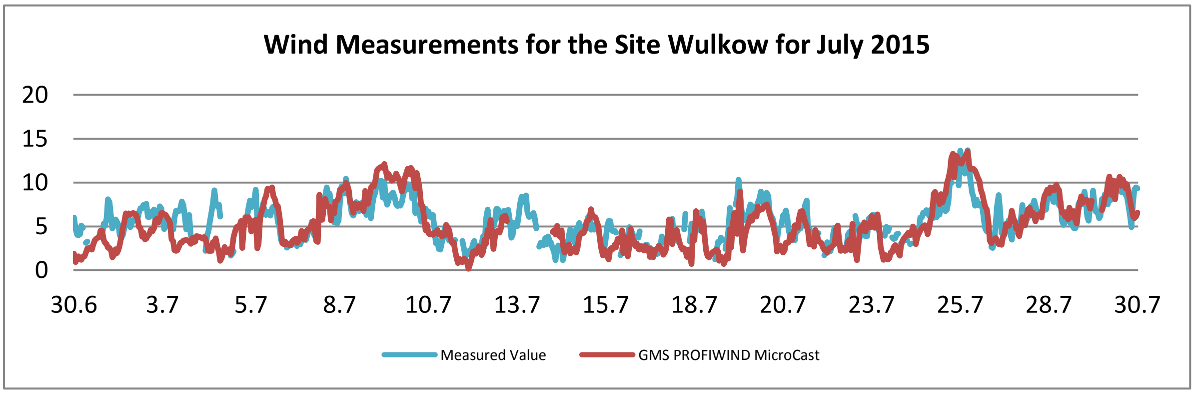
	1	2	3	4	5	6	7	8	9	10	11	12
Weiberg	0.133	0.150	0.129	0.147	0.134	0.134	0.152	0.173	0.181	0.186	0.183	0.180
Pegau	0.141	0.140	0.138	0.134	0.131	0.143	0.138	0.152	0.161	0.161	0.160	0.167
Kuhschnappel	0.155	0.150	0.144	0.142	0.134	0.140	0.135	0.148	0.150	0.153	0.160	0.162
Wulkow	0.162	0.180	0.198	0.197	0.173	0.183	0.196	0.202	0.220	0.218	0.205	0.208
Gevensleben	0.169	0.167	0.156	0.140	0.141	0.142	0.147	0.155	0.162	0.183	0.180	0.178
Harmshagen	0.114	0.117	0.109	0.123	0.132	0.129	0.134	0.147	0.141	0.142	0.144	0.162
Salzhemmendorf	0.183	0.179	0.167	0.165	0.175	0.176	0.185	0.188	0.200	0.201	0.207	0.218
Uhrsleben	0.114	0.117	0.109	0.123	0.132	0.129	0.134	0.147	0.141	0.142	0.144	0.162
Alpen-Veen	0.104	0.103	0.108	0.118	0.119	0.130	0.141	0.150	0.158	0.167	0.140	0.150
Coesfeld	0.119	0.125	0.130	0.133	0.136	0.148	0.156	0.161	0.174	0.178	0.164	0.156
Werl	0.152	0.138	0.134	0.138	0.132	0.136	0.141	0.142	0.151	0.158	0.154	0.150
Wewelsburg	0.154	0.157	0.166	0.172	0.160	0.170	0.181	0.197	0.192	0.198	0.193	0.190

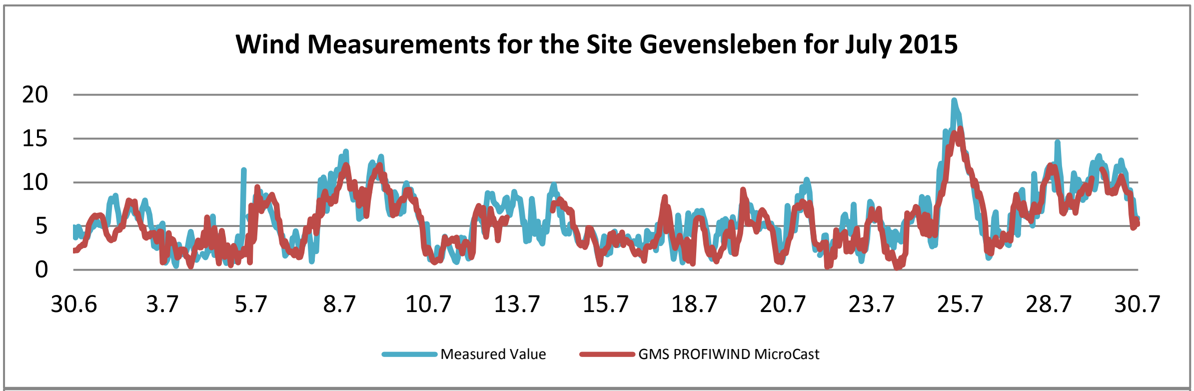
Appendix IV – Measured and Calculated Wind Profiles for all of the Wind Farms for July 2015.

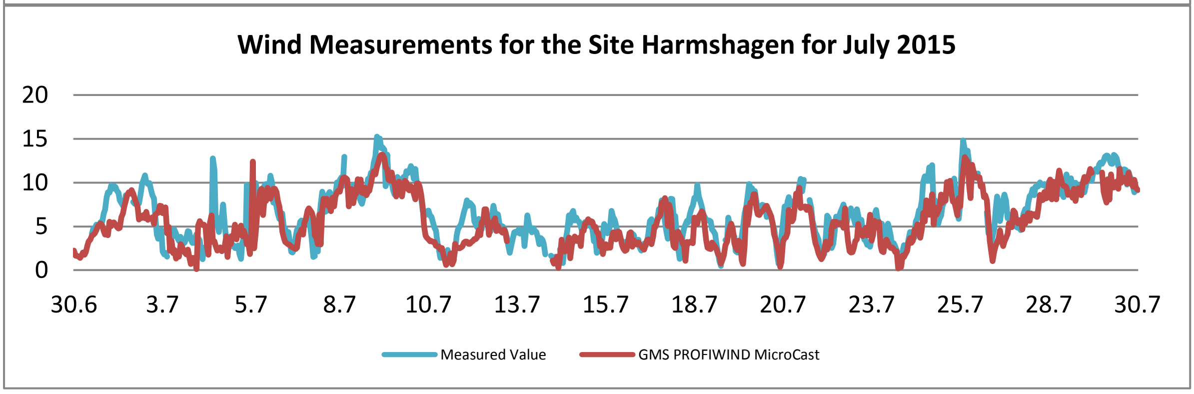


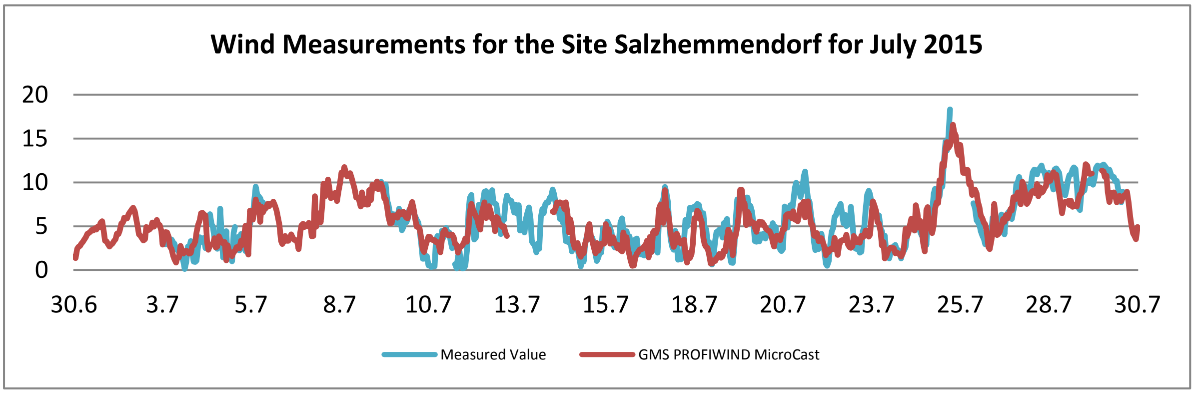


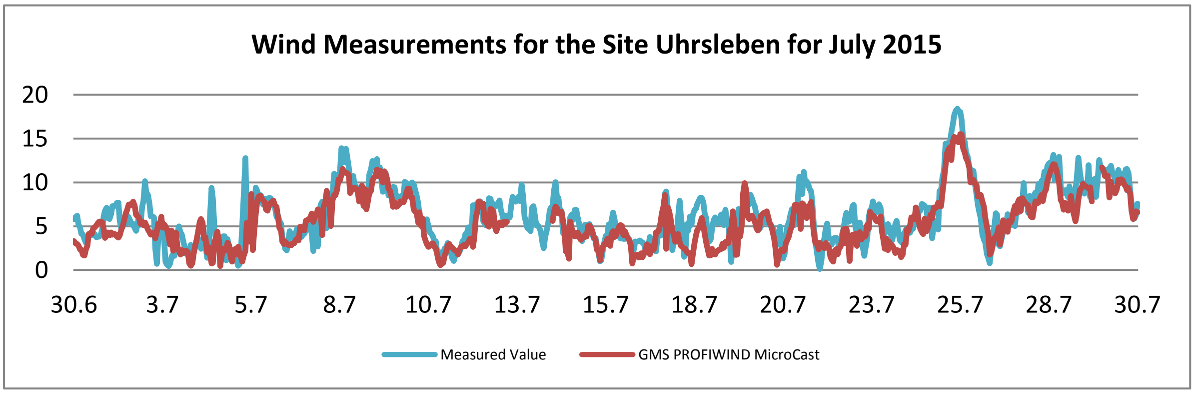





Wind Measurements for the Site Gevensleben for July 2015
20
15
10
5
0
30.6
3.7
5.7
8.7
10.7
13.7
15.7
18.7
20.7
23.7
25.7
28.7
30.7
Measured Value
GMS PROFIWIND MicroCast


Wind Measurements for the Site Harmshagen for July 2015
20
15
10
5
0
30.6
3.7
5.7
8.7
10.7
13.7
15.7
18.7
20.7
23.7
25.7
28.7
30.7
Measured Value
GMS PROFIWIND MicroCast


Wind Measurements for the Site Salzhemmendorf for July 2015
20
15
10
5
0
30.6
3.7
5.7
8.7
10.7
13.7
15.7
18.7
20.7
23.7
25.7
28.7
30.7
Measured Value
GMS PROFIWIND MicroCast


Wind Measurements for the Site Uhrsleben for July 2015
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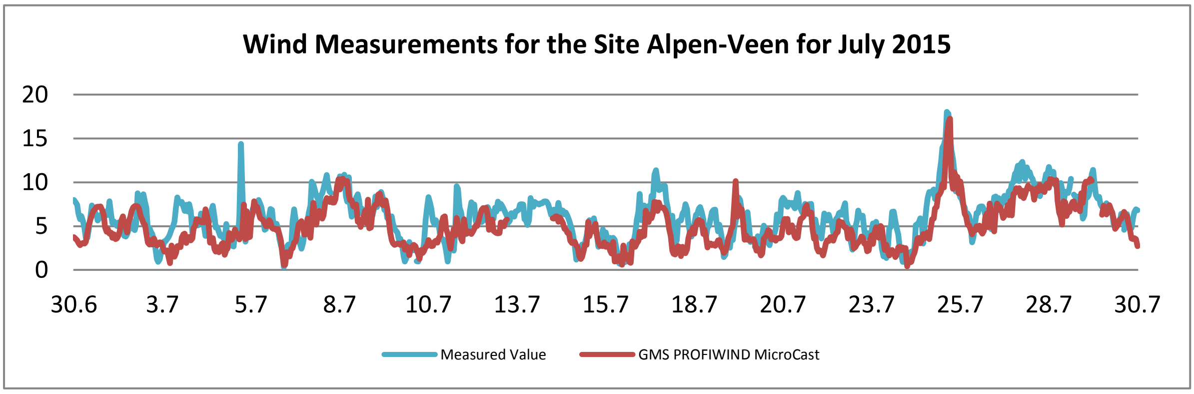
15
10
5
0
30.6
3.7
5.7
8.7
10.7
13.7
15.7
18.7
20.7
23.7
25.7
28.7
30.7
Measured Value
GMS PROFIWIND MicroCast


Wind Measurements for the Site Alpen-Veen for July 2015
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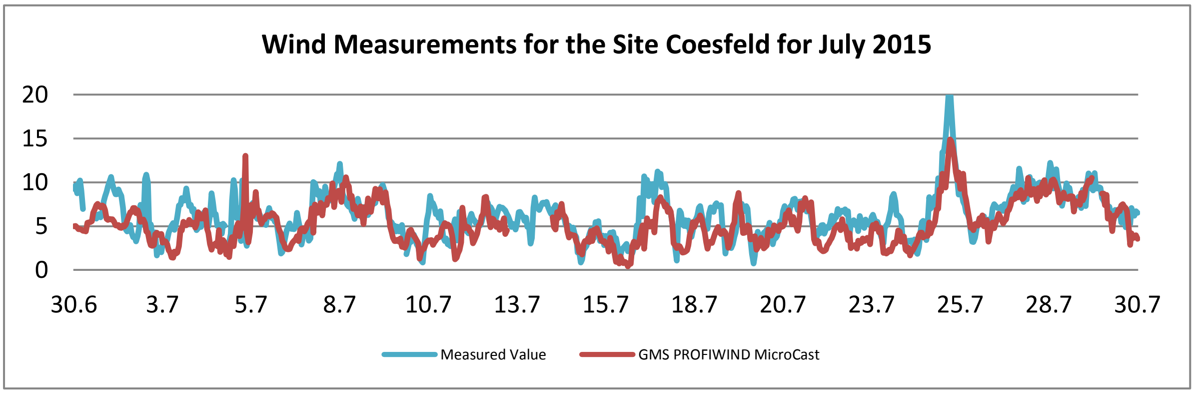
15
10
5
0
30.6
3.7
5.7
8.7
10.7
13.7
15.7
18.7
20.7
23.7
25.7
28.7
30.7
Measured Value
GMS PROFIWIND MicroCast


Wind Measurements for the Site Coesfeld for July 2015
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5.7
8.7
10.7
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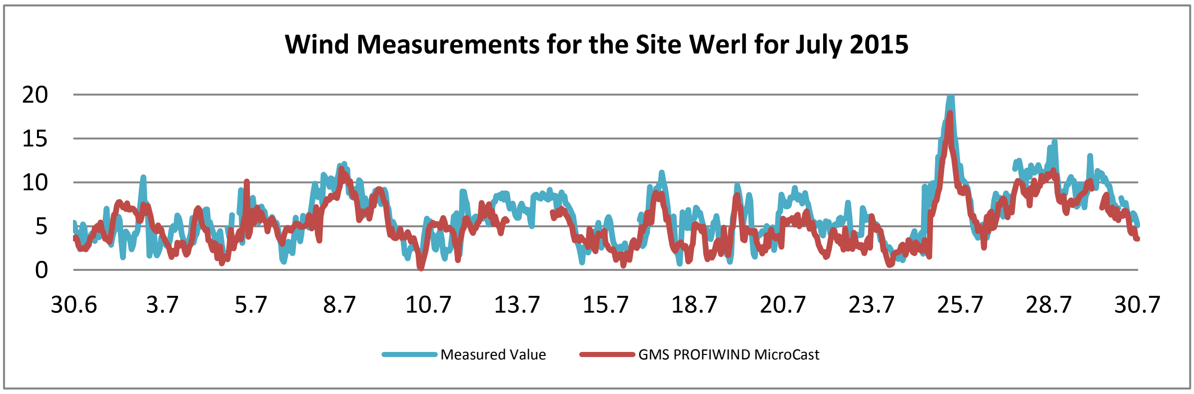
15.7
18.7
20.7
23.7
25.7
28.7
30.7
Measured Value
GMS PROFIWIND MicroCast


Wind Measurements for the Site Werl for July 2015
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3.7
5.7
8.7
10.7
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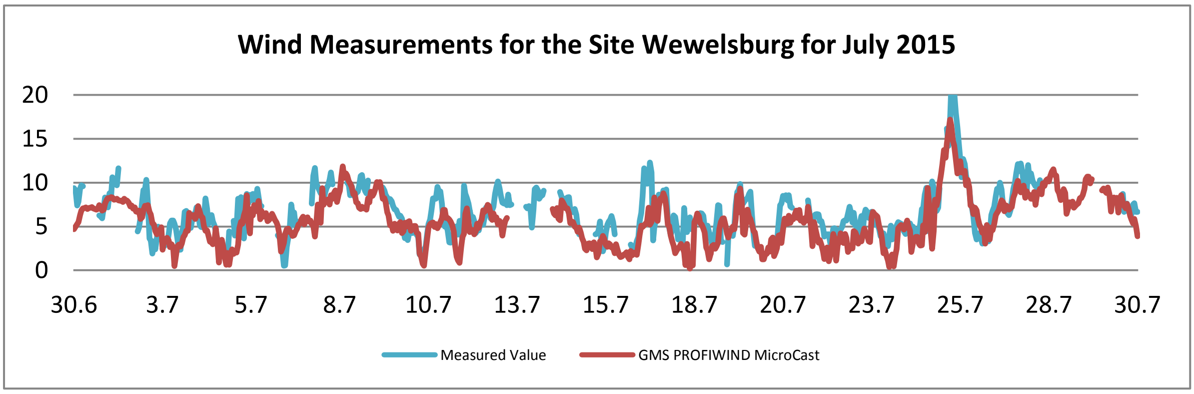
15.7
18.7
20.7
23.7
25.7
28.7
30.7
Measured Value
GMS PROFIWIND MicroCast


Wind Measurements for the Site Wewelsburg for July 2015
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30.6
3.7
5.7
8.7
10.7
13.7
15.7
18.7
20.7
23.7
25.7
28.7
30.7
Measured Value
GMS PROFIWIND MicroCast