Spatiotemporal Kriging modeling on Alberta wind farms using R

Mehdi Salamati

June 2019

1 Introduction and importance

After hydropower, Wind energy presents the second most economically viable renewable solution (DeCarolis & Keith, 2005). Driven by the goal to achieve a sustainable and clean energy source, Canada increased its wind energy capacity by an average of 20 percent per year from 2008 to 2018 (Canwea, 2018). The Canadian Wind Energy Association (CanWEA) has a target of generating 20% of Canada's electricity by 2025 from wind energy (GE Energy Consulting, 2016).

Alberta has a leading role in using wind energy in Canada. Cowley Ridge wind farm, built in 1993, is one of the first commercial wind farms in Canada. Wind energy is the most inexpensive resource of new electricity in Alberta (CanWEA, 2018).

Wind energy can be utilized efficiently if a reasonable prediction of wind characteristics for different time scales is made. However, Intermittency, nonlinear dynamics and dissipation of wind characteristics is a huge challenge for scientists (Y.luo, 2018).

For finding optimal siting and sizing of wind farms, not only is the annual prediction of aggregated wind power at any individual windfarm important, but also variability of the wind power among different wind farms during different time periods needs to be taken into account. Different wind farms need to be able to balance their power generating fluctuations during different time periods to be capable of providing a reliable and sustainable source of energy (HaleCetinary, 2017).

Wind power output generated by each wind turbine depends on the wind speed and the power curve of the turbine. Modeling of variation of wind speed is important to both investors of wind farms and power system operators. Investors generally look for locations with the maximum capacity of wind power generation while the power system operators also worry about the reliability and stability of the system (HaleCetinary, 2017).

Monitoring of environmental processes and data gathering both in space and time is usually time and money consuming. Using Statistical models (based on limited observations) in continuous space and time helps us to be able to avoid dense monitoring costs (Tilmann Gneiting, 2006).

2 Objectives

This report has two main objectives. The first one is to investigate the wind speed behaviour in Alberta wind farms. This aim will be reached by performing some timeseries analyses and looking at the most important statistics of characteristics such as mean and variability of wind speed. The correlation of wind speed at different sites during different time lags will be discussed as well.

The second objective is to provide a spatio-temporal Kriging analysis for predicting the wind speed in the study Area (Figure 3a). To fulfill this goal, an empirical spatio-temporal variogram was calculated using hourly wind power data during 2008 then some valid models were fitted to the empirical model. After selection of the best fitted model, Kriging prediction was made.

3 literature review

To predict wind characteristics in unknown locations, multiple models have been developed during the last decades. Physical models, statistical models, and hybrid models are the major categories described below.

3.1 Different forecasting models

- **Physical models**

The physical methods models (also known as numerical wind flow models) are based on solving physical equations. These Models focus on equations which control motion of air in the atmosphere such as the mass and momentum-conservation laws.

- **Statistical Models**

Generally, statistical models estimate wind resources by calculating spatial correlation among observed data and environmental indicators such as topography and land use (F. Veronesi, S. Grassi, M.Raubal , 2016). Using time-series models and data mining techniques is very common in statistical methods (Hu Qian, 2014).

W. Luo, M. C. Taylor and S. R. Parker compared seven spatial interpolation techniques such as Trend Surface Analysis (TSA), Inverse Distance Weighting (IDW), Local Polynomial (LP), Thin Plate Spline (TPS), Ordinary Kriging, Universal Kriging and ordinary Co-kriging to determine their suitability for estimating daily mean wind speed surfaces in England and Wales. They found that the accuracy of results for these different interpolation methods have significant differences. And the geostatistical methods were more accurate than the deterministic methods (W. Luo, M. C. Taylor and S. R. Parker, 2008).

Although, it is very difficult to compare different types of models because of variations in terrain topography and land cover of the study areas as well as using various validation methods, Veronesi et al. reviewed the literature of multiple researchers for comparison of different numerical wind flow models and statistical models. They generally concluded that from an accuracy point of view, numerical wind flow models were superior to statistical ones (F.Veronesi, S.Grassi, M. Raubal, 2016).

- **Hybrid models**

An effective alternative to conventional single forecasting models such as autoregressive integrated moving average (ARIMA) and artificial neural network (ANN) is Hybrid forecasting of time series data. Hybrid forecasting model usually has two parts: a classic prediction model for the linear component of a time series and a nonlinear prediction model for the nonlinear component (G. W. Chang, H. J. Lu, L. Y. Hsu and Y. Y. Chen, 2016).

3.2 Spatio-temporal kriging modelling

Statistical analysis based on random fields is heavily used nowadays to get a better understanding of real processes in many fields such as engineering and environmental sciences (Simone A Padoan,Moreno Bevilacqua, 2015). From a statistical perspective, some environmental processes such as wind speed and atmospheric pollution density have both temporal and spatial variability (Y.luo, 2018).

Tobler's first law of geography says, "everything is related to everything else, but near things are more related than distant things". This concept could be extended from the spatial S into the spatio-temporal space S×T. Thus, it could be assumed that two close windfarms' outputs are more correlated to each other than two distant wind farms. In addition, today's wind speed is more strongly related to tomorrow's wind speed than to the wind speed of the next week (Graler, 2013). In other words, Tobler's law means that the autocorrelation between two close points is higher than two far points. This law is the basis for the Kriging modeling and will be examined in this research.

Kriging is a method that predicts a spatial process based on a weighted average of observations. Kriging method also is used for spatio-temporal processes. Some good examples of using kriging methods for weather predictions and air quality monitoring are available in (Atkinson and Lloyd,1998), (Ignaccolo ,2014) and (Guillot1, 2017).

Spatio-temporal kriging method generally includes the following steps (José-Mar´ıa Montero, Gema Fernández-Avilés, 2015):

1- Constructing the empirical semi-variogram from data
2- Fitting one of the theoretical models to the empirical semivariogram
3- Selecting the best fitted theoretical model
4- Spatio-temporal prediction

3.2.1 Constructing the empirical semi-variogram

The first step in spatio-temporal kriging process is semi-variogram analysis. This is a key step in the subsequent process of spatio-temporal kriging prediction since it defines the structure of the spatio-temporal dependencies or correlation among the observed data. The success of the spatio-temporal kriging methods relies on the semi-variogram function which yields information about the spatio-temporal dependencies. (José-Mar´ıa Montero, Gema Fernández-Avilés, 2015)

The relationship between two observations Z(si,ti) and Z(sj,tj) is determined by the distance between them (si −sj,ti −tj). Here, s and t are relate to their spatial and temporal locations. As expected from the Tobler's first law, for spatio-temporal domain it is normal that two close points Z(s1,t1) and Z(s2,t2) have a stronger relationship than two distant points Z(s1,t1) and Z(s3,t3). This is shown in Figure 1 (José-Mar´ıa Montero, Gema Fernández-Avilés, 2015).

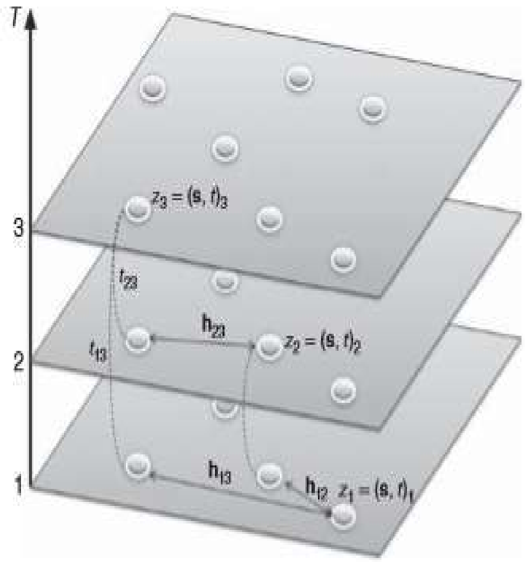


Figure1: A spatio-temporal dataset on D(distance) ×T(Time) for7 spatial locations observed at 3 moments in time

Semi-variance of the process (ɣ, gamma) is determined by the equation below (Graler, 2013). Based on this equation the empirical Semi-variogram of experimental data should be calculated and drawn for every pair of spatio-temporal datapoints. The value of the empirical semi-variogram model for two close points is low due to their strong autocorrelation. As the distance between the two points increases, their ɣ value raises as well. Depending on our data variability, after a certain distance, called Range, ɣ becomes constant and semi-variogram plateaus.

$$\hat{\gamma}(h,u) = \frac{1}{2\,N(h,u)} \sum_{N(h,u)} \{[Z(s_i,t_i) - Z(s_j,t_j)]\}^2 \qquad \text{Equation 1}$$

$$\textit{where } N(\mathbf{h},u) = \{(\mathbf{s}_i,t_i)(\mathbf{s}_j,t_j)\colon \mathbf{s}_i - \mathbf{s}_j = \mathbf{h} \;\; \textit{and } t_i - t_j = u\}.$$

3.2.2 Assumptions of Kriging modeling and their justification in this study:

There are several Kriging models with different assumptions. For example, in Simple kriging and Ordinary kriging, Wide Sense Stationarity (WSS) is a fundamental assumption. Under this assumption Z(s,t) has a constant mean and the covariance function C is just a function of spatio-temporal distance.

$\forall s \in S,\ t \in T,\ C(s1,s2,t1,t2) = C(s2 - s1, t2 - t1) = C(h,u)$

Where, h=si −sj and u= ti −tj are any two given vectors in space and time, respectively. As it is shown in this research (Figure 6), there are seasonal patterns in wind speed. Therefore, the mean wind speed is not constant at a location over time. Stationarity in spatial domain is harder to be examined because our locations are limited to only 20. Considering the restrictions of WSS assumption, Simple and ordinary kriging models are not realistic most of the times.

There is another Kriging model, named Universal kriging, which can solve the problem of the unrealistic stationarity assumption. In Universal kriging the trend in dataset is eliminated firstly by another model such as a Trend Surface Polynomial (TSP). The errors of this detrending model are residuals which are assumed to have stationarity (Figure 2). In Universal kriging the residuals are modeled by a Kriging model and they will be added to the preliminary detrending model to

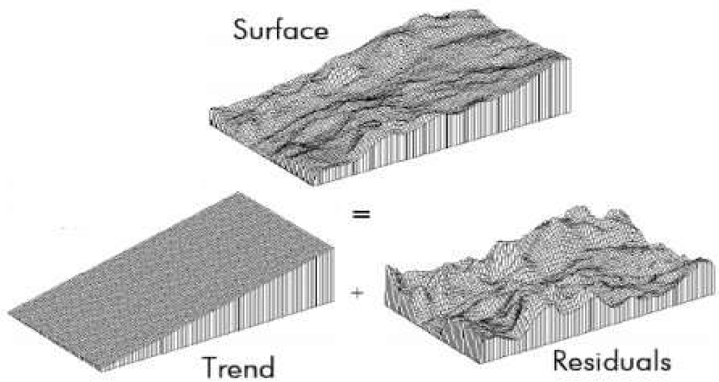


Figure 2: Detrending process in Universal kriging

Source: http://www.kgs.ku.edu/Tis/surf3/s3trend2.html

estimate the final result (Geldsetzer, ,2019). Since the Universal model can relax WSS constraints, it is widely used in literature, especially for wind speed modeling (Y.luo, 2018). In this study, to avoid WSS assumption, we used Universal kriging method.

3.2.3 Fitting and validation of the theoretical models to the empirical semi-variogram

A set of valid semivariogram models (a covariance function is valid if it satisfies positive definite characteristics) and appropriate methods of fitting are required to be fitted into the empirical semi-variogram. According to the characteristics of the empirical semivariogram, some hypotheses for the space-time should be chosen. Examples include: time and space lags and the covariance structure between temporal and spatial domain. These models are well introduced in (Sherman, 2011).

Two main types of approaches consider separability and non-separability. Separable models assume separability of the spatial and the temporal component. On the contrary, non-separable models assume that the spatial and temporal processes are correlated, and there are purely spatial, purely temporal, and/or joint spatio-temporal semi-variogram models (X. L. Liu . X. Q. Fu, 2016). Five different types of models which are fitted in this study are: Separable model, Product-sum model, Metric model, Simple Sum Metric model and Sum-metric model.

A validation process for comparison of the fitted models is needed as well. The most important factor to consider for choosing the best model is Mean Squared Error (MSE) (Veronesi, 2015). The mathematical equations related to kriging prediction can be found in (José-Mar´ıa Montero, Gema Fernández-Avilés, 2015) and (Sherman, 2011).

4 Dataset and software

The hourly data (timeseries) of wind speed in the Alberta existing wind farms (20 windfarms), is used in this study. It is a full space-time grid observational data (for every wind farm observation is stored for every hour). The data was provided during The Pan-Canadian Wind Integration Study (PCWIS). This study explores the implications of integrating large amounts of wind energy in the Canadian electricity network (CanWEA, 2018). Different scenarios were studied in PCWIS. The 5% Business As Usual (BAU) scenario data is used in our report. The data is public and available in The Canadian Wind Energy Association (CanWEA) website (CanWEA, 2018).

The wind farm locations (latitudes and longitudes) are driven from the metadata of PCWIS. For time series analysis and explanatory purposes, datasets from 2008 to 2010 are used while for spatio-temporal kriging only the data of year 2008 is used to reduce the computational time.

The data preparation and data cleaning were a very time-consuming process of this study. Several packages from R language and Arcmap are used in this study. The R packages mostly used are as below:

- sp: for handling spatial objects.
- spacetime: to build spatio-temporal objects.
- gstat: to access functions needed for spatio-temporal kriging.

4.1 Results and Discussion

All analyses, tables, maps, graphs, and figures presented from this section onward were created during this project and they are entirely original.

4.1.1 Timeseries analysis results

In the first step, to explore the effect of spatial distance on variability of wind speed, the autocorrelations of wind speed between three pairs of windfarms were calculated. As it is shown in Figure 3, three windfarms differently distanced from windfarm 2087 were selected. Windfarm 2088 is the nearest one with an only 7 Km distance, Windfarm 2579 is relatively further away (95 Km) and Windfarm 3417 is the furthest away (335 Km). Looking at the Table 2 it is obvious that windfarms that are further distanced, are less autocorrelated. These autocorrelations are shown in Figure 4. Due to the effect of 24-hour cycle, a local maximum can be seen around the hour 24.

A visualization of hourly wind speed for the year 2008 for Alberta windfarms is shown in Figure 7. To see how the mean of wind speed changes by time (seasonal pattern), the hourly mean for 36 months (2008 to 2010) is shown in Figure 6. As we can see, since the mean is not constant, the assumption of wide sense stationarity in time domain is violated. However, as it was explained in section 3.2.2., this issue can be resolved using the Universal Kriging which removes the seasonal trend. Other studies have used the same method for relaxing the WSS constraint as well (Y.luo, 2018).

To investigate the same concept in temporal domain, the autocorrelation between wind speeds for different time lags at windfarm 2087 is calculated and shown in Figure 5. The maximum autocorrelation is about 0.96 which is for time lag 1. As it is shown, closer time lags have stronger autocorrelations (Tobler's first law for temporal domain).

4.1.2 Spatio-Temporal Kriging analysis

4.1.2.1 Empirical spatio-temporal semi-variogram

The Empirical (experimental) spatio-temporal semi-variogram is calculated based on our available data. Both Time series hourly wind speed data and data related to the latitudes and longitudes of the windfarms are used in this section. As it is shown in the top left of Figure 8, the value of semi-variance Gamma (Equation 1) increases by increasing the spatial or temporal distances (lags).

4.1.2.2 Fitting different valid theoretical models, validation and finding the best fitted one

The theory behind this part was explained in section 3.2.3. Five different theoretical models are fitted, and they are shown in Figure 8 besides the empirical variogram. Visually it seems that the metric and sum-metric models are more similar than other ones to the experimental model. A method to aid in selecting the best theoretical Kriging model is Cross validation. This method removes one windfarm at a time from the kriging process and tests the predicted results against it. The Theoretical model with the lowest Mean Squared Error (MSE) is chosen as the best fitted one (Veronesi, 2015). For each model type, parameters are assigned by both manual and automatic approaches. The MSEs are shown in table 1. The minimum MSE is for metric model which confirms our visual judgment.

Model type	MSE	
	Manual fitting	Automatic fitting
Metric	2.58	1.32
SimplesumMetric	10.62	25.9
sumMetric	7.84	2.92
ProductSum	6.27	2.59
Saparable	10.34	77

Table 1: MSEs for different fitted model

4.1.2.3 Prediction and discussion

To make a prediction, we need a spatio-temporal grid. One thousand evenly distributed spatial points are defined in the study area and for each point, six times were assigned. The predictions for 6000 spatio-temporal locations (1000*6=6000) are shown in Figure 9. Although the goodness of fit was evaluated by cross validation, the scatter plot of observations versus predictions for 120 spatio-temporal points (20 wind farm in 6 times) is provided in Figure 10.

Although in theory kriging is the best unbiased interpolation technique, there are some parameters which can affect its accuracy. These include distribution of data points, appropriate trend removal model as well as correct selection of model parameters (type, lags and ranges…) (Geldsetzer, ,2019). As theoretically discussed in 3.2.2, by using Universal kriging the stationarity assumption was relaxed. Our fitted theoretical models and selection process are based on previous works in the literature. It seems that the weakest point of our model is the spatial distribution of the observations. There are only 20 locations (windfarms) and as it is shown in Figure 3, most of them are clustered in southern part of the study area. Therefore, for prediction in other regions such as the northwestern part, there are not enough observations at neighbouring points to make a reliable prediction. Figure 9 demonstrates this effect, where in points far from our windfarm locations, the predicted values are considerably low. I think it would have been better if I had limited the study area to just the southern region.

Windfarm Id	distance with Windfarm 2087 (Km)	The maximum Autocorrelation with Wind farm 2087	Time lag(hour) at the maximum autocorrelation
2088	7	0.96	0
2579	95	0.48	-1
3417	335	0.27	-1

Table 2: The maximum of autocorrelations of three selected windfarms with windfarm 2087

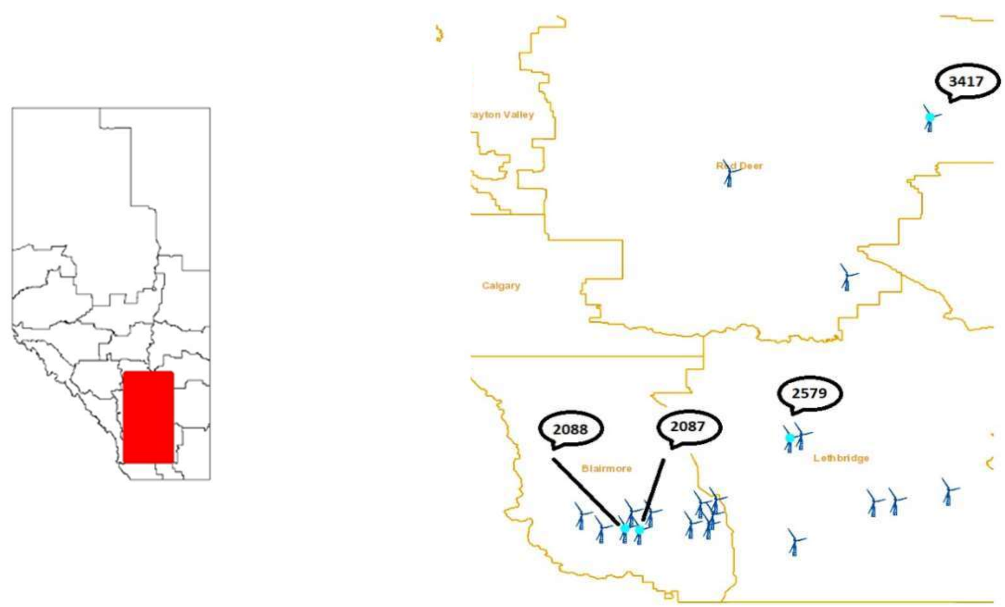
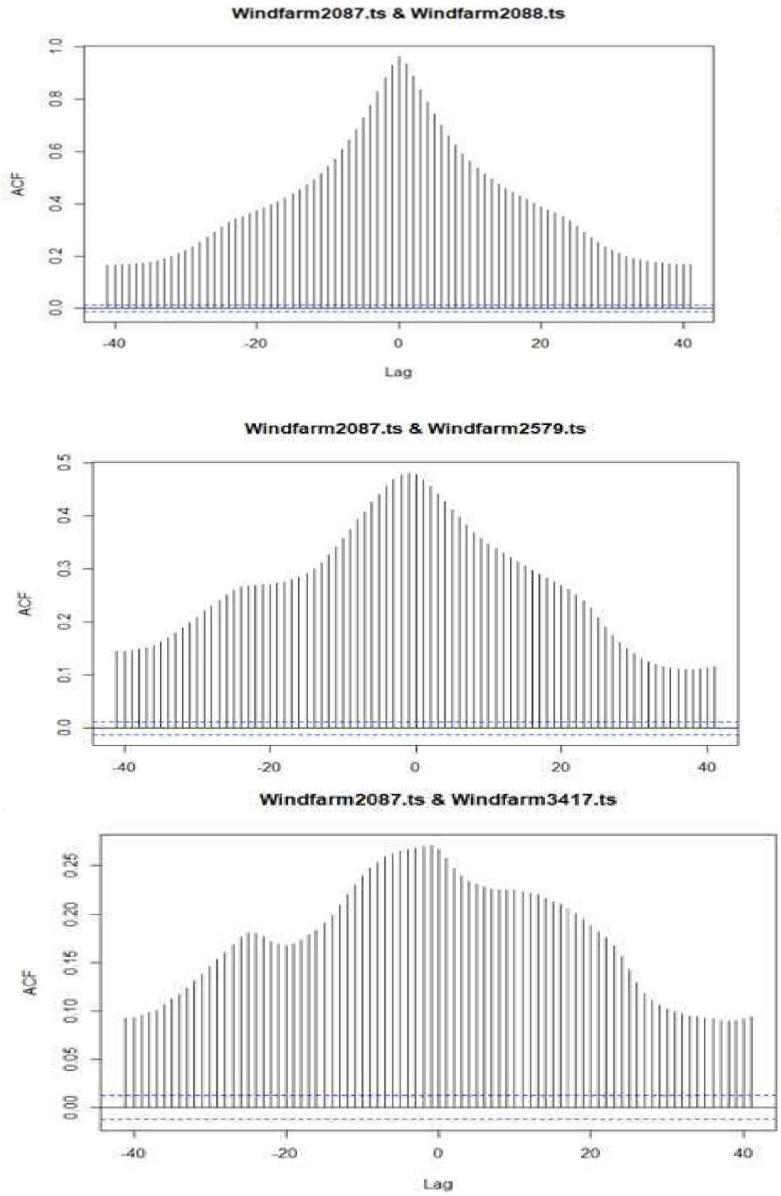


Figure 3: a) On the left our study area b)On the right locations of windfarms and 4 selected ones .



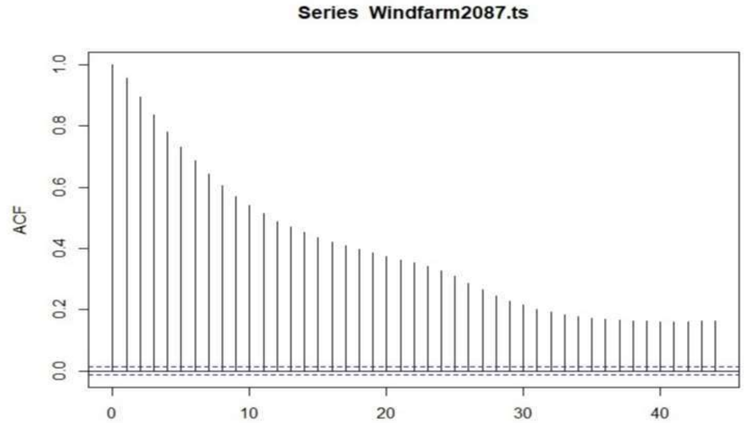


Figure 5: Autocorrelation of windfarm2087 for different time lags

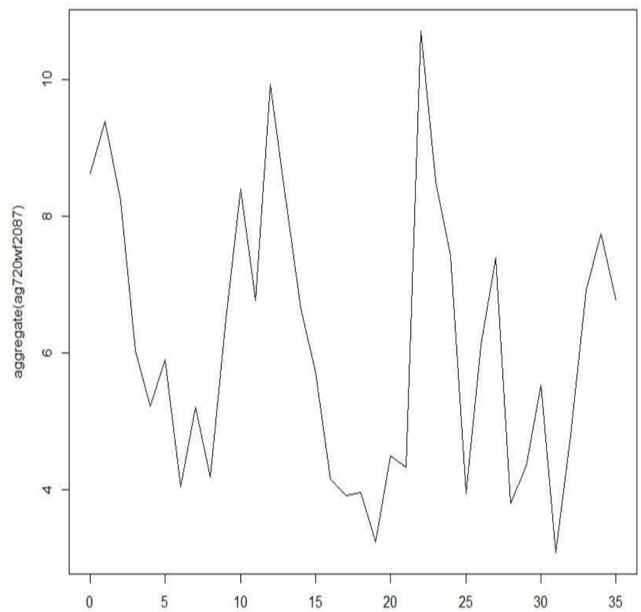


Figure 6: Hourly mean for every36 months for wind farm 2087

Figure 4: Autocorrelations between selected windfarms in Figure3

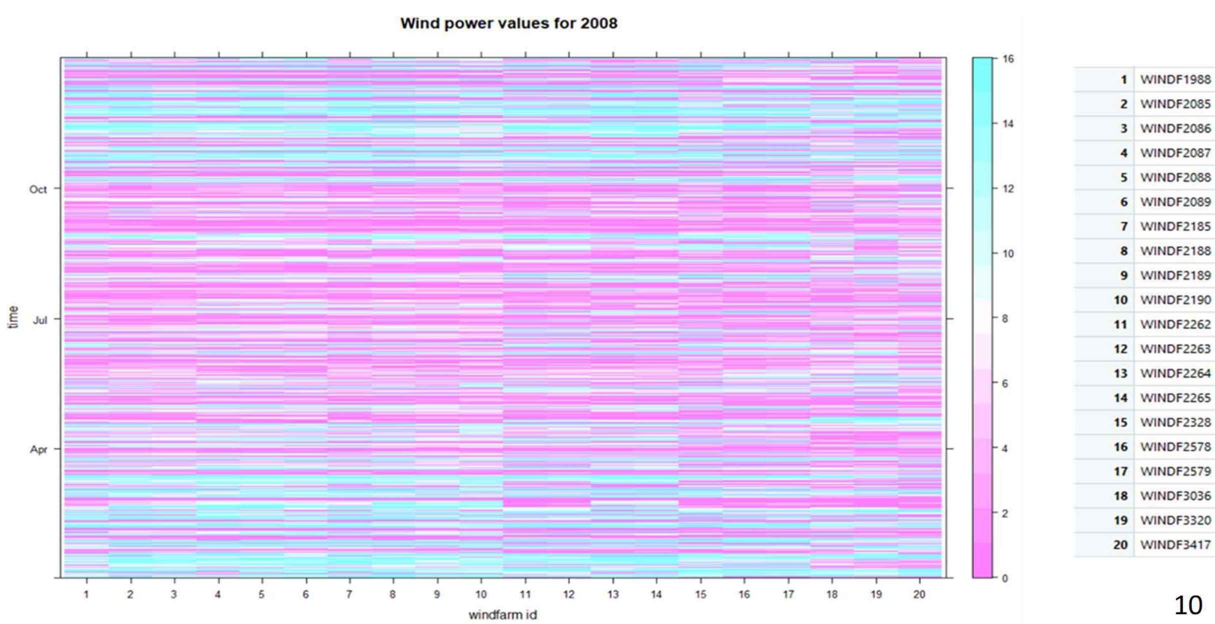


Figure 7: observed wind speed for20 windfarms of Alberta during the year 2008.

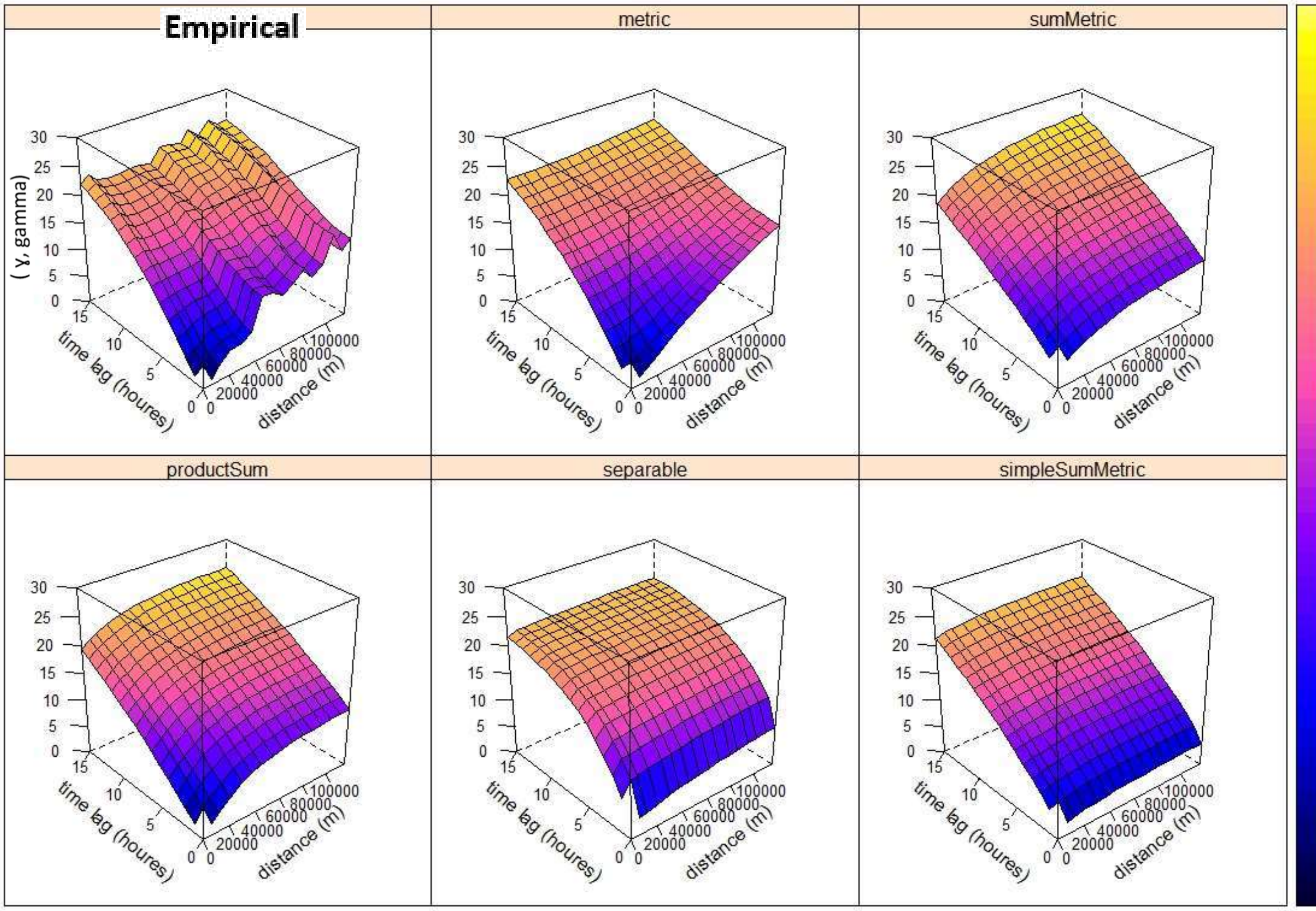


Figure 8) Empirical semi-variogram versus 5 theoretical fitted models.

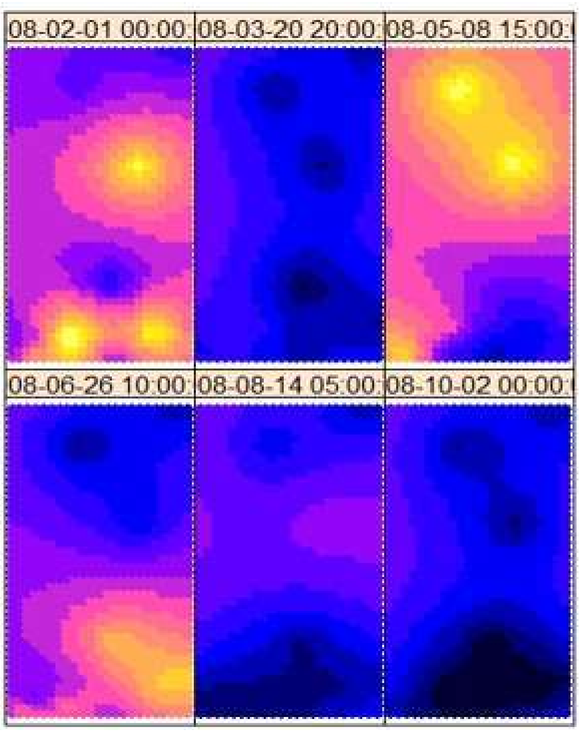


Figure 9) Predicted Wind speed map for 6000 spatio-temporal point

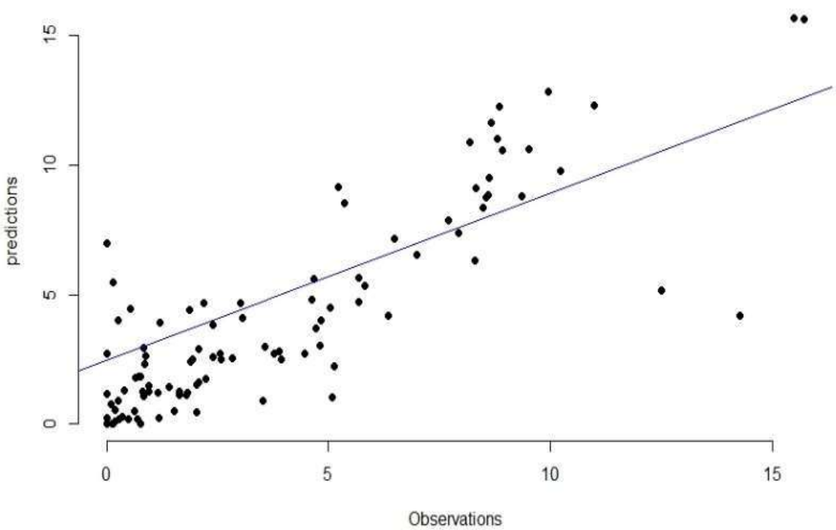


Figure 10) Scatter plot for the observed data and the predicted wind speed for the 120 spatio-temporal points (20 Alberta wind farms for 6 times)

References

Benedikt Gr¨aler, E. P. (2016). *Spatio-Temporal Interpolation using gstat.* Retrieved from https://cran.r-project.org: https://cran.r-project.org/web/packages/gstat/vignettes/spatio-temporal-kriging.pdf

José-Mar´ıa Montero, Gema Fernández-Avilés. (2015). *Spatial and Spatio-Temporal Geostatistical Modeling and Kriging.* Wiley.

Simone A Padoan,Moreno Bevilacqua. (2015). Analysis of Random Fields Using CompRandFld. *JournalofStatisticalSoftware*.

Veronesi, F. (2015). *Spatio-Temporal Kriging in R.* Retrieved from R-bloggers: https://www.r-bloggers.com/spatio-temporal-kriging-in-r/

X. L. Liu . X

Burch, S. ,. (1992). *Computer modeling of the UK wind energy resoursec over view report.* UK department of Business enterprise and regulatory reform.

Canwea. (2018). Retrieved from Canadian wind energy assosiation: https://canwea.ca/wind-facts/why-wind-works/

DavidBarbosadeAlencar, C. 1. (2017). Different Models for Forecasting Wind Power Generation: Case Stud. *Energies*, 1-27.

Esri. (n.d.). *ArcGIS Desktop help.* Retrieved from http://desktop.arcgis.com/en/arcmap/latest/extensions/geostatistical-analyst/choosing-a-lagsize.htm.

Soumis.au. (2016). Analyzing spatio-temporal data with R: Everything you always wanted to know – but were afraid to ask. *Journal de la Société Française de Statistique*.

Tilmann Gneiting, M. G. (2006). *Geostatistical Space-Time Models, Stationarity, Separability and Full Symmetry.* Washington: Department of Statistics University of Washington.

Y.luo. (2018). *A master thesis about Forecasting of Wind Energy Generation in Alberta.*

Hu Qian, C. H. (2014). Wind Speed Spatio-temporal Forecasting of Wind Farms Based on Universal Kriging and Bayesian Dynamic Model. *International Conference on Power System Technology*, (pp. 2897-2902). Chengdu-china.

Johan Lindstrom, A. S. (2019, February 9). *Package'SpatioTemporal' manual.* Retrieved from https://cran.r-project.org: https://cran.r-project.org/web/packages/SpatioTemporal/SpatioTemporal.pdf

Lorenc, A. C. (1980). *A Global Three-Dimensional Multivariate Statistical Interpolation Scheme.* Berkshire, England: European Centre for Medium Range Weather Forecasts, Reading, Berkshire, England.

Mewati.S. (2016). Retrieved from Quora: https://www.quora.com/Whats-the-difference-between-ARMA-ARIMA-and-ARIMAX-in-laymans-terms-What-exactly-do-P-D-Q-mean-and-how-do-you-know-what-to-put-in-for-them-in-say-R-1-0-2-or-2-1-1

Philips, G. (1978). *Preliminary user's guid for the NOBAL.* California.

G. W. Chang, H. J. Lu, L. Y. Hsu and Y. Y. Chen. (2016). A hybrid model for forecasting wind speed and wind power generation. *IEEE*, 1-5.

GE Energy Consulting. (2016). *Pan-Canadian Wind Integration Study (PCWIS).*

Gr¨aler, B. (2013, 12). *Seminar Analysis of Spatio-Temporal Data,* . Retrieved from file:///D:/wind%20farm/final%20resources/Spatio-Temporal%20Kriging.pdf

Graler, B. (2013). *Different concepts of spatio-temporal kriging.* Retrieved from University of Muenster: http://ifgi.de/graeler Institute for Geoinformatics

Guillot1, A. L. (2017). Spatial models for probabilistic prediction of wind power with application to annual-average and high temporal resolution dat. *Stoch Environ Res Risk Assess* , 1615-1631.

HaleCetinary,Fernardo A,Kuipers,A.Nazih Guveh. (2017). Optimal siting and sizing of wind farms. *Renewable Energy*, 51-58.

W. Luo, M. C. Taylor* and S. R. Parker. (2008). A comparison of spatial interpolation methods to estimatecontinuous wind speed surfaces using irregularly distributeddata from England and Wales. *INTERNATIONAL JOURNAL OF CLIMATOLOGY*, 947-959.