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Downscaling Method for Wind Data: Case Study of Agadez in Niger

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Abstract: Surface wind speed estimation important for a variety range of engineering applications such as wind energy generation, pollutant plume dispersion and tall buildings design. Like other climatic variables, wind speed is likely to change in the future and the direction of that change may have large implications for the safety and productivity of several civil engineering structures. Projected wind speed under various climate change scenarios by Global Circulation Models (GCMs) and Regional Climate Models (RCMs) are available from several climate centers. However, surface wind speed is required at much smaller scales than that resolved by GCMs and RCMs. Therefore, it is vital to develop methods to downscale the GCM data to finer scales. In this paper, a linear model and two polynomial models of degrees 2 and 3 were used to link the large scale NCEP reanalysis wind velocity to the station-level wind velocity at the Agadez station in Niger. One model was developed for each of the 365 days of the year. The 1950-1985 period was used for calibration, and the obtained model was verified on the 1986-1988 period. A good agreement was found between the simulated and observed wind velocity at Agadez (R2=0.53, 0.56 and 0.57 for the calibration period and 0.58, 0.58, 0.57 for the validation period). All models were afterward applied using simulated wind values from the KNMI-RACMO2.2 Regional Climate Model. The bias and changes in the standard deviations in the wind values simulated using the RCM data were afterward used to build downscaling relationships for future periods at the Agadez station.

1 Introduction

Climate change is defined as change in statistical distribution of climate variables over periods ranging from several decades to longer time period (Wetterhall, 2005). General Circulation Models (GCMs) are climate models widely applied for weather forecasting, understanding the climate, and climate change projections. Despite notable development, GCMs do not provide perfect simulations of reality and cannot provide the details on very small spatial scales due to the incomplete scientific understanding and limitations of available observations (Jolley and Wheater, 1996). Unfortunately, the computers and programs that run the GCMs are limited to gross representations of the geographic, geologic and atmospheric details that they use to run climate simulations. Thus, many small-scale features cannot be represented, even though they may significantly impact the local, regional, or even global climate (Horvath et al., 2011, Legates, 2002). The issue is often addressed by using Regional Climate Models (RCMs) with are nested climate models with a higher resolution and covering smaller areas. RCMs get their boundary conditions from GCMs and typically simulate climate variables at 25-50km scale. RCMs inherit several limitations of CGMs, including the distortion of climate variables distributions. Statistical models such as neural networks and multiple linear regression are often used to further post-process RCMs output and correct biases at the station level

In most of the practical applications, the climate variables are needed at the much more finer both spatial and temporal resolution than GCMs outputs provided (Carter et al., 1994). For instance, hydrological models as the most widely-used models for simulating flow through the watersheds are concerned with smaller resolution than those resolved in GCMs (Chong-yu, 1999).

Near-surface wind speeds have particular importance for climate change impacts on different aspects such as society, coastal erosion and wind energy resource estimation (Pryor et al.,2005), (Viles and Goudie, 2003). Surface wind speeds exhibit variability at much smaller spatial scales than typify the resolution of coupled atmosphere-ocean general circulation models (Wim et al., 2002).

There are two fundamental approaches for downscaling of coarse-grid GCM's output to a finer resolution. First one is dynamical approach where a higher resolution climate model is embedded within a GCM grid. Second approach is implementing statistical methods to establish empirical relationships between GCM output and local climate variables.

Statistical downscaling, first, develops quantitative relationships between observed small-scale (often station level) variables (predictands) and larger (GCM) scale variables (predictors), using one of the available approaches. Then, future values of the large scale variables obtained from GCM projections of future climate are used to drive the statistical relationships and to estimate the smaller-scale details of future climate (Wilby and Wigley, 1997). Statistical downscaling is based on the view that the regional climate is conditioned by two factors: the large scale climatic state and regional/local physiographic features (e.g. topography, land-sea distribution and land use) (Wilby et al., 2004).

Another important point that should be considered is that for driving a statistical downscaling model with GCM outputs, the climate variable from GCMs should be obtained at the point (Station Level) in which the observation (predictands) are available. Therefore, most of the time, an interpolation approach is needed for obtaining the GCMs output.

There are three major types of statistical downscaling methods: Weather classification, Regression models and Weather generators. These methods will be discussed in the following sections. Regression models are a conceptually simple means of representing linear or nonlinear relationships between predictands and the large scale atmospheric forcing from GCMs output. There is a wide variety of methods in this category starting from simplest on such as linear regression to much more complicated one like nonlinear regression models. Commonly applied methods include multiple regression, canonical correlation analysis (CCA), and artificial neural networks which are akin to nonlinear regression (Vasiliades et al., 2009). Some multi-site regression-based methods are also becoming available in which the unexplained variance is represented by stochastic processes (Wilby et al., 2003). Due to the complexity and issues related to finding a global solution using ANN-based techniques, the Genetic Programming (GP) based techniques have been proposed as potential better alternatives. Compared to ANNs, GP based techniques can provide simpler and more efficient solutions. However, they have been rarely used for downscaling. The results show that GEP-based downscaling models can offer very simple and efficient solutions in the case of precipitation downscaling (Hashmi et al., 2011).

Some methods have been proposed to implement regression models for downscaling the GCMs output in the probabilistic approach. In fact, instead of direct using of GSMs output and local scale values as predictors and predictands, the mean and standard deviation of large and local scales data are used (Pryor et al., 2005). In addition, using this context, some studies carried out to transform the cumulative distribution function (CDF) of large scale outputs for constructing the local scale one. In this approach, first, a CDF-transform function is produced and then implemented for projecting the future local scale CDF (Michelangeli et al., 2009).

In the current study, the station-level daily surface wind speed is selected as the predictand and the daily surface wind speed grid from the NCEP reanalysis (Kalnay et al., 1996) is selected as the predictor. Then, three models based on the regression approach are developed to statistically relate the large scale data to the finer scale. These three models include one linear and two non-linear (Polynomial of 2 and 3 degrees) models. After developing the models, they are used with a RCM (KNMI-RACMO2.2b, described in section 3) output to project the wind data for the future time periods. The bias between NCEP-driven models and RCM-driven models was accounted for when generating future wind-speed data.

2 Study Site and Data

The study area is in AGADEZ, Niger. Agadez, is the largest city in northern Niger, with a population of 88,569 (2005) which lies in the Sahara (Fig 1).

The latitude and longitude of the wind station are 16° 97'N and 7° 98'E, respectively. There are three data set used in this study to downscale and project the wind speed data at Agadez. First, the daily observation of wind speed at the station level which ranges from 1950 to 1988. Next data which is exploited here is the large scale reanalysis NCEP daily wind speed ranging from 1950 to 1988. Finally, for bias correction and projection of the wind at the Agadez station, the KNMI-RACMO2.2 Regional Climate Model large scale daily wind speed is used. The last data set is ranging from 1970 to 1988.

Fig1. Study area, Agadez in Niger

3 RCM model

The RCM model uses in this study is the KNMI-RACMO2.2b model from the AMMA-ENSEMBLE climate experiment. The ENSEMBLES experiment sought to improved regional models at a resolution of 50km for both recent past (1989-2007) and future climate scenarios (1970-2050). 11 RCMs coupled with various RCMs were used to generate data for the African continent. Only one of these models was used in this paper. The driving GCM is the third generation of the ECHAM model developed by the Max Planck Institute for Meteorology (http://www.mpimet.mpg.de), and the RCM is RACMO (Regional Atmospheric Climate MOdel: (Meijgaard et al., 2008) developed by the Dutch meteorological institute)

4 Methodology

In the regression type of statistical downscaling method, the relationship between predictands and predictors is represented by a multiple linear regression model. In this study, one specific model is developed for each day of the year. The general relation of predictands and predictors in this methodology can be written as follow:

[1] $y_i = f_i(x_i)$

Where i indicates the i^{th} day of the year that varies from 1 to 365, y_i and x_i are the predictands and predictors variable belong to the i^{th} day of the year and f can be any desired model which relates the predictor to the predictand.

In fact, in this approach, the model parameters should be evaluated based on the regression of predictands and predictors. In this paper, the observed daily wind speed at Agadez is used as the predictand and the daily NCEP reanalysis wind speed in the cell that covers Agadez is used as the predictor.

Three models include one linear and two nonlinear (Polynomial of degree 2 and 3) were developed. For each of these models, the 1950-1985 was used for calibration and the 1986-1988 period used for validation. Given that there is one model for each day of the year, the model parameters after calibration would be a matrix with 365 columns (one for each day) and two, three or four lines depending of the degree of the polynomial used. The three models which are exploited here will be discussed below.

4.1 Linear model

The linear model, in fact, is the simplest model can be used for downscaling the climate variables. Model formulation is given by:

[2] $$y_i = f_i^1(x_i) = a_i^0 + a_i^1 x_i$$

Where f^1 is the linear model and a_i^0 and a_i^1 are parameters of the linear model for the i^{th} day of the year.

4.2 Polynomial Models

In addition to the linear model, in this study, two polynomial models of degree 2 and 3 are used. Equation (2) and (3) indicate the formulation of these two models:

[3] $$y_i = f_i^2(x_i) = b_i^0 + b_i^1 x_i + b_i^2 (x_i)^2$$

[4] $$y_i = f_i^3(x_i) = c_i^0 + c_i^1 x_i + c_i^2 (x_i)^2 + c_i^3 (x_i)^3$$

Where b_i^0, b_i^1 and b_i^2 are the parameters of second order polynomial model and c_i^0, c_i^1, c_i^2 and c_i^3 are the parameters of third order polynomial model for i^{th} day of the year.

The flowchart in Fig (2) illustrates the procedure of developing of regression models and parameters calibration.

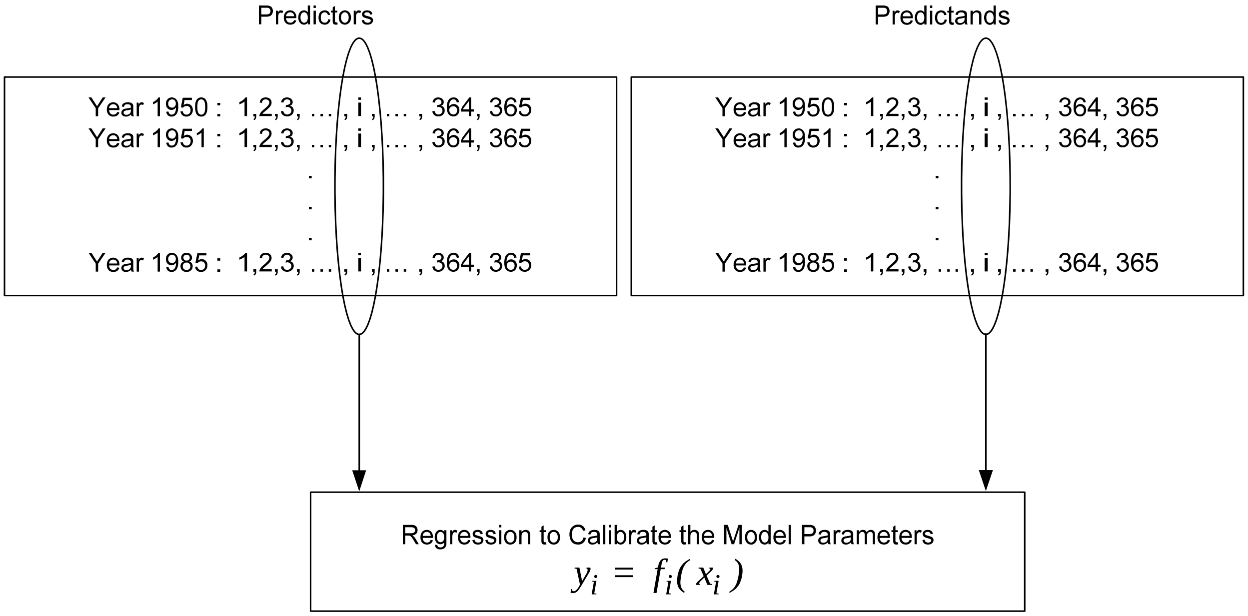


Fig2. Flow diagram of methodology exploited for this study

At the next stage, the calibrated models will be verified using data from 1986 to 1988. The criteria used to assess the model are the coefficient of determination (R^2), the root mean square error (RMSE) and the correlation coefficient (R) defined as follow where Z_i and $\hat{Z}_i$ re the observation and modeled values, respectively:

[5](a) $R^2 = 1 - \frac{\sum_{j=1}^{n}(\hat{Z}_i - Z_i)^2}{\sum_{j=1}^{n}(\hat{Z}_i - Z_{mean})^2}$,(b) $RMSE = \sqrt{\frac{\sum_{j=1}^{n}(\hat{Z}_i - Z_i)^2}{n}}$,(c) $R = \frac{\sum_{j=1}^{n}(\hat{Z}_i - \hat{Z}_{mean})(Z_i - Z_{mean})}{\sqrt{\sum_{j=1}^{n}(\hat{Z}_i - \hat{Z}_{mean})^2}\sqrt{\sum_{j=1}^{n}(Z_i - Z_{mean})^2}}$

5 Results

5.1 Calibration and Validation of Models

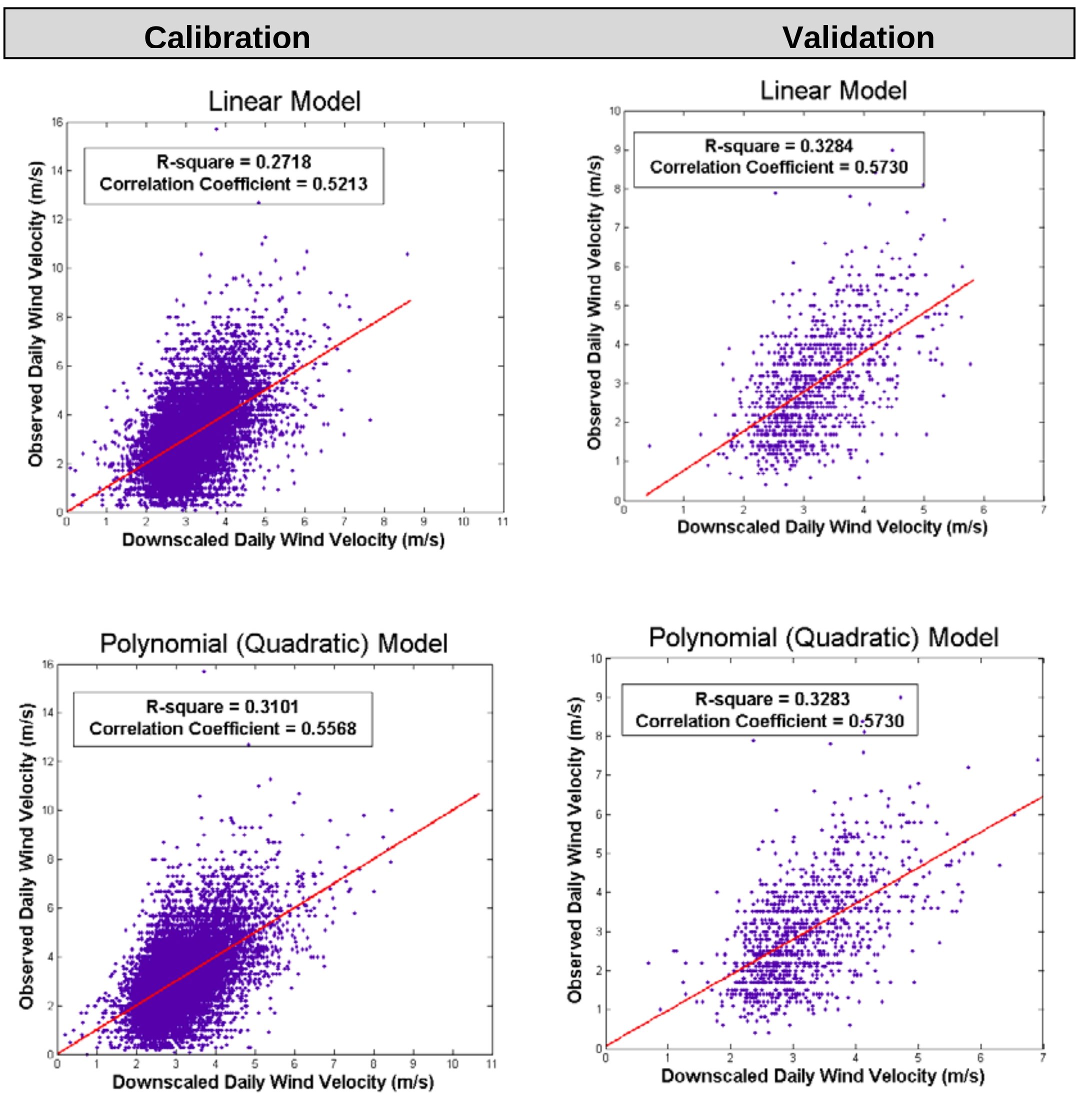
The results of calibration and validation are presented in Table1 and Fig (3). The linear model has the better validation results in comparison to two polynomial models.

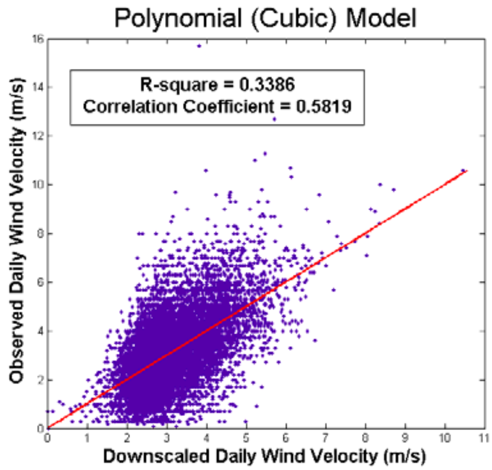
5.2 Bias Modification

The RCMs are the models which can predict the climate variables for the long term future. In fact, reanalysis NCEP models are only able to predict and project the short term future of climate variables. Therefore, for downscaling the long term projection to a finer scale, using the RCMs is inevitable. As a result, it is necessary to have the statistical models which relate the observation to the RCMs climate variable. In the other word, in order to downscale climate variables for long term projection the predictors must be from the RCMs (or GCMs). However, as regression models in this study are calibrated based on the reanalysis NCEP data, it is not possible to use the RCMs daily wind speed as predictors.

Table1. Performance evaluation of models based on different criteria

Criteria	Period	Linear Model	Polynomial (Quadratic)	Polynomial (Cubic)
R^2	Calibration	0.27	0.31	0.34
	Validation	0.33	0.33	0.31
RMSE	Calibration	1.2	1.18	1.16
	Validation	1.07	1.07	1.08
Correlation Coefficient	Calibration	0.52	0.56	0.58
	Validation	0.57	0.57	0.56





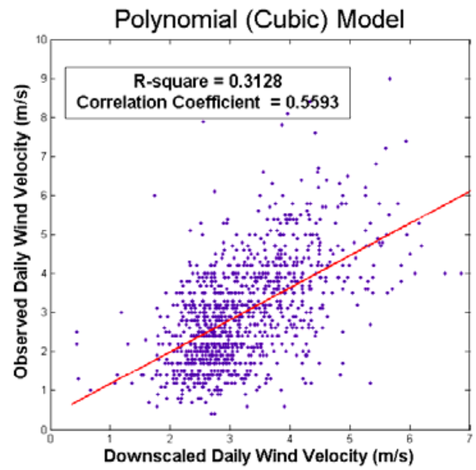


Fig3. Scatter plots of observed and downscaled daily wind velocity. Left and right columns of figures belong to calibration and validation periods respectively.

For instance, the following model describes the linear model with the RCMs data as predictors:

[6] $y_i{*} = f_i^1(x_i) = a_i^0 + a_i^1 x_i^*$

Where $y_i{*}$ is the downscaled wind speed and x_i^* is the RCMs wind speed for ith day of the year.

Therefore, it is vital to modify the calibrated and validated model in the way that can be implemented using the RCMs as predictor. For this purpose, the bias modification should be applied to the calibrated models. At first, assuming the RCMs wind speed as the predictors, the downscaling is done using the calibrated models. Next, each model will be modified based on the observed data set and the results of the just downscaled wind speed. Note that, as the calibrated models are daily (one model for each day of the year), the modification also should be based on a values of each day of the year. The model modification contains two major steps: (i) first the average bias between the observed data set and downscaled wind speed (using RCMs as the predictors) which is calculated for each model:

[7] $Bias_i^1 = \overline{y_i^*} - \overline{Y_i}$

Where $Bias_i^1$ is the bias of the first model (linear) for the ith day of the year and:

[8] (a) $\overline{y_i^*} = \frac{\sum_{j=1}^{N} y_{ij}^*}{N}$ (b) $\overline{Y_i} = \frac{\sum_{j=1}^{N} Y_{ij}}{N}$

In which, N is the number of years available in modification period and Y_{ij} and y_{ij}^* stands for the observed and downscaled wind speed for ith day of the year j.

After calculation of the bias, the intermediate wind velocity is calculated as follow:

[9] $y_i^{**} = y_i^* - Bias_i$

At last, the downscaled wind speed at the station level will be obtained as follows:

[10] $yd_i = [\ y_i^{**} - \frac{1}{365}\sum_{i=1}^{365} y_i^{**}\ ] \times \frac{std_i^{*}}{STD_i} + \frac{1}{365}\sum_{i=1}^{365} y_i^{**}$

Where yd_i is the downscaled wind speed of the i^{th} day of the rear and std_i^{*} and STD_i are the standard deviation of the y_i^{*} and Y_i for the all years in the modification period.

The bias modification is used here for linera model. In fact, after modifying the model, the RCMs daily wind velocity can be used as predictors for this model. Fig 4 shows the verification results of using this model. As can be seen, the results are compared to the observation daily wind velocities.

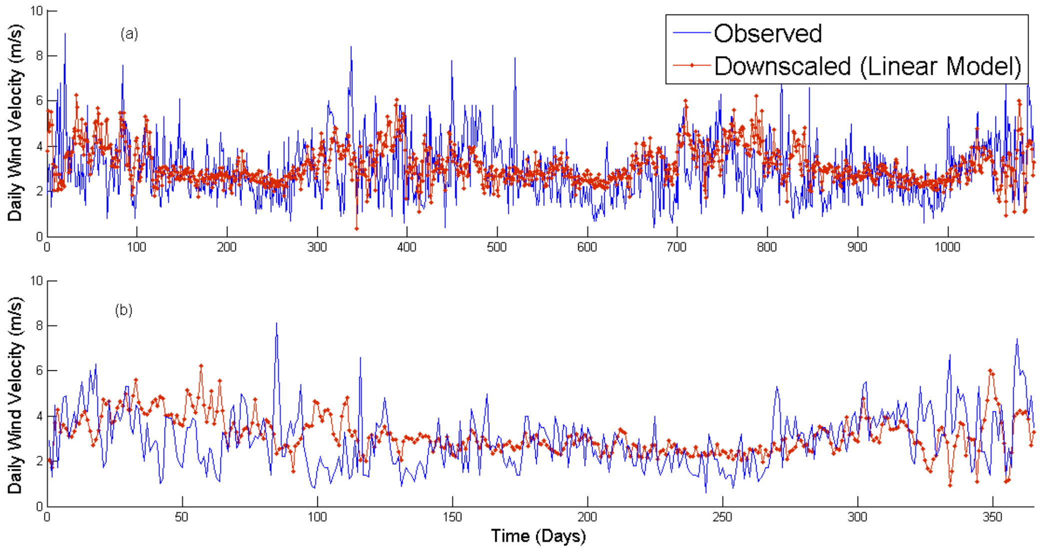


Fig4. Comparison of the downscaled (modified) and observed daily wind velocity (a) From 1986 to 1988 (b) for 1988

Finally, the modified linear model is exploited for wind velocity projection from 2012 t0 2050. The daily wind velocity projection can be seen in Figure 5.

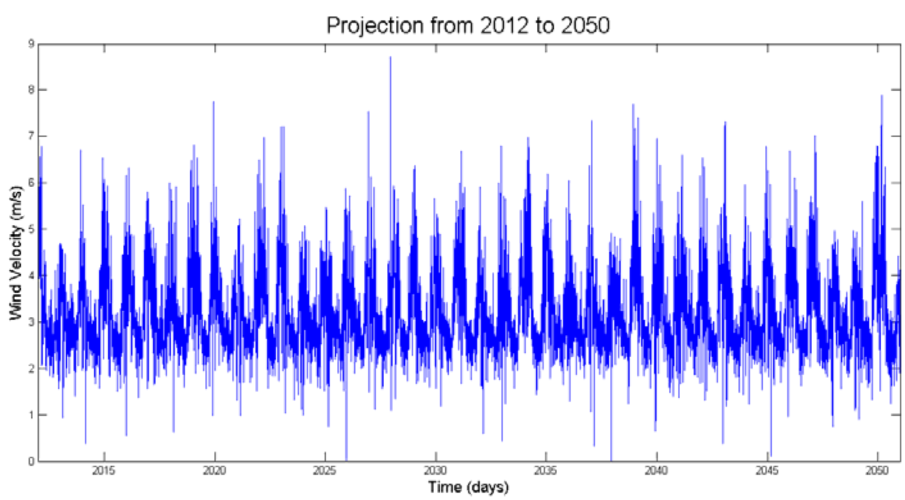


Fig5. Wind velocity projection for 2012 – 2050 period

To investigate the wind velocity variation in the future, the average wind velocity projection are compared with the historical wind velocity observation in Fig6.

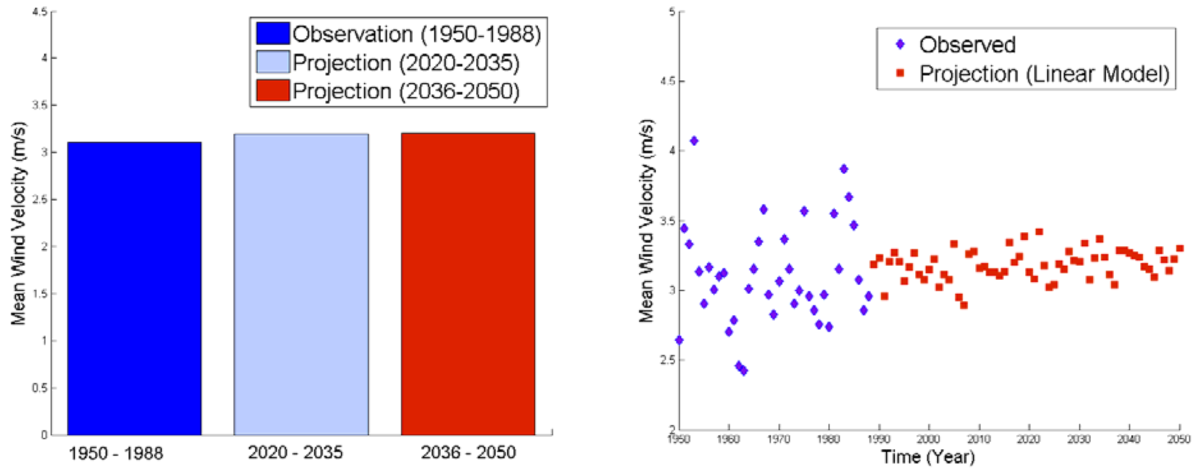


Fig6. Comparison of historical wind velocity and wind velocity projection

As it can be seen the average value of wind velocity is not expected to change significantly. Furthermore, the developed downscaling model significantly underestimate year-to year variability, making it not suitable for the analysis of extreme high and low wind. A potential solution to this drawback would be variance inflation as it is used in SDSM (Wilby et al., 2002). Variance inflation will later be implemented in the model and its ability to reproduce extreme winds distributions assessed

6 Conclusion

One linear model and two polynomial models of degrees 2 and three were used to relate NCEP simulated wind speed to station level wind at Agadez, Niger. Results show that the linear model outperforms the polynomial models in this particular application. The linear model was later used to project the wind speed data in Agadez up to 2050. The results show that wind speed in Agadez will probably not changed significantly in the future under scenario A1B.

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