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Correlation of meteorological parameters to characterize wind sites: A case study of N'guigmi, Niger

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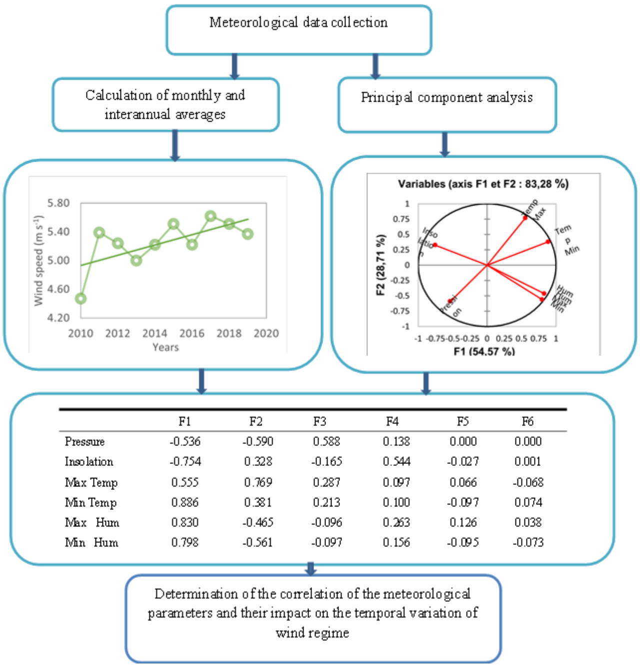
Graphical abstract



Abstract

To assess the impact of climate change on wind regimes, we performed a statistical analysis of some meteorological parameters. Indeed, variables such as temperature, humidity, pressure, and the insolation are rarely or not considered in the estimation of wind regimes and therefore in the characterization of wind sites. In setting wind farm projects, one is limited to assessing the wind potential with data that fluctuate greatly. In this work, we studied the influence of meteorological parameters on the wind regimes in the eastern part of Niger. We have firstly, based on data collected at the station of N'Guigmi, over 10 years, characterized each of the parameters by their monthly and interannual average. In a second step, we studied the interannual variability of these variables. At this level, the curves represented show large fluctuations. We then represented trend curves which showed us that during these ten years, humidity, insolation, and wind have undergone slight increases while temperature and pressure have significantly decreased. Finally, we used principal component analysis with the statistical tool XLSTAT to analyze the correlation of the different meteorological parameters on wind speed. The preponderance of the influence of each variable is evaluated from a factorial design provided by XLSTAT. Thus, after the analysis of the factorial design, we concluded that temperature is a preponderant factor in wind flow. The second variable that conditions the wind flow is humidity. These results meet our expectations. Indeed, the wind being air in circulation, under a high temperature, its density decreases, and its circulation is facilitated. However, with humidity, it becomes heavier, and the wind circulates less quickly.

Keywords: Climate variability, principal component analysis, correlative study, wind patterns, XLSTAT software.

1. Introduction

Niger is a landlocked, semi-desert country in the Sahel with an area of 1.267 million km^2. Wind speed measurements are limited to only a few areas throughout the country. The dimensioning of wind energy projects is a fundamental and indispensable need for its development. It requires to know the wind regime data in a geographical locality of implantation using efficient models to estimate them and, above all, to understand the influence of some meteorological parameters. Wind properties are closely related to seasonal variation, thus to the meteorological environment. The wind is a movement of air masses caused by the differential heating of the earth's surface and its rotation around its axis. As a result of the variability of many parameters that govern it, its instantaneous horizontal velocity has a fluctuating spatio-temporal character that justifies spectral considerations (Omar *et al.*, 2017). A simple approach that is valid for the Saharan climatic zones.

Since the wind speed is always changing, the energy capacity of the wind obviously varies as well. Several factors contribute to determining the variations of the wind: the weather, the topography of the land, and the obstacles. The energy output of wind turbines varies with variations in wind speeds (Saidou Madougou, 2010). The variables that influence the variation of seasonal wind regimes are very diverse, so their study requires the application of multivariate methods. These multivariate statistical techniques have been used by many researchers to facilitate problem solving and understanding. These techniques have been successfully used (Kouassi *et al.*, 2010) to help understand the influence of climate variability on rainfall patterns in West Africa and the hydrochemical study of groundwater in the lake region (Soro *et al.*, 2019).

Many researchers have conducted work in the assessment of wind potential (Kidmo *et al*., 2015, Sohoni *et al*. 2016, Jabbar, 2021), but very few have focused on the parameters that can affect the spatial and temporal variation of these deposits. Belu *et al*. (2012) analyzed the effects of complex wind regimes and meteorological parameters on wind turbine performances. The found a significant effect of ignoring the wind speed shear, turbulence intensity and atmospheric stability on power performance measurement. Koukpemedji *et al.*, 2015 studied the influence of air temperature, pressure, and relative humidity on the wind potential in the coastal zone of Benin in the Gulf of Guinea. They proposed a coefficient that shows the impact of temperature, pressure, and relative humidity on wind power. IZGI *et al*. (2016) researched the variations and relations of meteorological and wind turbine parameters. They showed a high relationship between upwind and downwind wind speed values. El Moustapha *et al*. (2014) and Guerber *et al*. (2008) have also addressed issues related to statistical modeling of wind and the influence of climatic parameters on its transport and distribution.

Our study considers four (4) meteorological parameters namely pressure, temperature, relative humidity, and insolation, spread over ten (10) years with a collection step of three (3) hours. It is based on the use of multivariate statistical analysis techniques, namely Principal Component Analysis (PCA), to understand the influence of these meteorological parameters on the temporal fluctuation of wind in the N'Guigmi area (eastern Niger).

2. Materials and methods

2.1. Presentation of the study site and data used

N'Guigmi is located at 14°15'10'' north and 13°06'39'' east, about 140 km northeast of Diffa and 1493 km east of Niamey, the capital of Niger. The town of N'Guigmi is located on the former shore of Lake Chad and borders Chad and Nigeria. The region has a hot desert climate with a long dry season, very high temperatures, and less than 200 mm of rainfall concentrated over 3 months in summer, typical of the Sahara-Sahel zone between the Sahara and the Sahel. The average daily temperature is between 29°C and 30°C with a maximum average temperature of 38°C and a minimum average temperature of 21°C (classification of Köppen BWhw; Belda *et al*., 2014).

The meteorological parameters studied are wind speed, air temperature, relative air humidity, atmospheric pressure, and insolation collected from the National Directorate of Meteorology (DNM). These data cover a period of ten (10) years, namely from 2010 to 2019, and are measured at 10 meters altitude at a step of 3 hours.

2.2. Study of the variation of meteorological parameters

The average values of temperature, relative humidity, atmospheric pressure, insolation, and wind speed were analyzed to understand their seasonal and interannual variation. It was a question of defining their monthly and annual averages and thus to study their tendency and fluctuation.

The target variable of our work is the wind. To assess the influence of other meteorological parameters on it, the Kaiser criterion was applied. It is translated as a reduced centered variable in the form of equation 1.

$$z^j = \frac{X_i - \bar{X}}{\sigma} \tag{1}$$

With:

X_i: the value of the maximum average wind speed over year i.

$\bar{X}$: the interannual average value of wind speed over the study period.

σ: the interannual value of the standard deviation of the wind speed over the study period.

2.3. Principal component analysis (PCA)

Principal component analysis allows the development of a mathematical model based on the available experimental data, thus allowing the estimation, study, and identification of the relationships between variables and the similarities between individuals.

2.3.1. Characteristics of the correlation coefficient

When |cor(x, y)| = 1, we say that the variables x and y are strongly correlated and there is a linear relationship described by (equation 2) between them.

$$axi + byi = c \tag{2}$$

for all 1 ≤ i ≤ n. In particular, cor(x, x) = 1.

When, on the other hand, cor(x, y) = 0, this is interpreted as saying that the variables x and y are decorrelated. However, this does not mean that they are independent.

According to Jean-Marc Lasgouttes, (2014)**,** The Bravais-Pearson coefficient r or correlation coefficient is given by equation 3:

$$cor(x,y) = r_{xy} = \frac{\sigma_{xy}}{\sigma_x \sigma_y} = \frac{\sum_{i=1}^{n} p_i (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} p_i (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^{n} p_i (y_i - \bar{y})^2}} \tag{3}$$

This statistical index expresses the intensity and direction of the linear relationship between two quantitative variables. It assumes values between -1 and 1. We always have (Cauchy-Schwarz inequality (4))

$$-1 \leq \boldsymbol{cor}(\boldsymbol{x}, \boldsymbol{y}) \leq 1 \quad (4)$$

2.3.2. Number of axes to retain

Since PCA aims to reduce the size of the space of individuals and to retain only the most significant, we want to keep as few axes as possible. To do this, the original variables must be reasonably correlated with each other. The only criteria that can be used are empirical. We try to retain only those axes for which some form of interpretation is possible (either directly or in terms of the variables with which they are highly correlated).

2.3.3. Correlation between components and initial variables

Considering centered-reduced variables, this correlation is written by equations 5 and 6:

$$cor\left(z^j, c_k\right) = \frac{1}{\sqrt{var\left(c_k\right)}} cov\left(z^j, c_k\right) = \frac{1}{\sqrt{\lambda_k}} cov\left(\sum_{l=1}^{p} a_{lj,} c_k\right) \quad (5)$$

$$= \frac{1}{\sqrt{\lambda_k}} \sum_{l=1}^{p} a_{lj} cov(c_l, c_k) = \frac{1}{\sqrt{\lambda_k}} \lambda_k a_{kj} = \sqrt{\lambda_k} u_{kj} \quad (6)$$

Position in a scheme: We know that var(zj) = 1, but we can also write:

$$var\left(z^j\right) = cov\left(z^j, z^j\right) = cov\left(\sum_{l=1}^{p} a_{kj} c_k, \sum_{l=1}^{p} a_{lj} c_k\right)$$
$$= \sum_{k=1}^{p} \sum_{l=1}^{p} a_{kj} a_{lj} \, cov(c_k, c_l) = \sum_{k=1}^{p} \lambda_k a_{kj}^2 = \sum_{k=1}^{p} [cor(z^j, c_k)]^2. \quad (7)$$

Therefore, the first 2 coordinates are in a disk of radius 1, since:

$$\left[cor\left(z^j, c_1\right)\right]^2 + \left[cor\left(z^j, c_2\right)\right]^2 \leq 1 \quad (8)$$

In the case of our study, we used Excel from the Office to analyze our parameters. The statistical study tool XLSTAT, which goes with Excel, allowed us to conduct the principal component analysis. This data mining tool allows us to explore a multidimensional data set of quantitative variables to study and visualize the correlations between the variables, to eventually limit the number of variables to be measured later on. Our quantitative input variables are pressure, temperature, sunshine, and relative humidity, while the observation label is wind speed. The type of PCA performed is Pearson correlation and all variables are the monthly averages of the three-hourly data collected from 2010 to 2019.

3. Results and discussions

The analysis of meteorological parameters leads us to determine the monthly and interannual averages of temperature, humidity, pressure, insolation, and wind speed. The table below gives us the monthly averages of these parameters.

Table 1. Monthly averages of metrological parameters used in the study

Parameter/ Period	Jan	Feb	Mar	April	May	June	Jul	Aug	Sept	Oct	Nov	Dec
Temperature	21.69	25.64	29.66	33.09	34.60	34.39	32.07	29.94	31.46	31.12	27.19	22.23
Humidity	24.41	19.84	18.37	19.89	30.31	42.96	55.84	66.76	56.02	34.69	25.69	27.99
Pressure	980.96	978.22	976.88	975.50	971.13	973.20	973.81	977.17	977.04	975.98	977.57	980.47
Insolation	9.49	9.62	8.78	8.78	9.09	8.54	8.07	7.55	8.43	9.53	10.17	9.48
Wind	6.06	5.83	5.82	5.16	4.95	4.58	4.80	4.50	4.32	5.13	5.56	6.35

The interannual variations are represented in Figures 1–5. These variations are accompanied by their trend line to visualize their progression or regression.

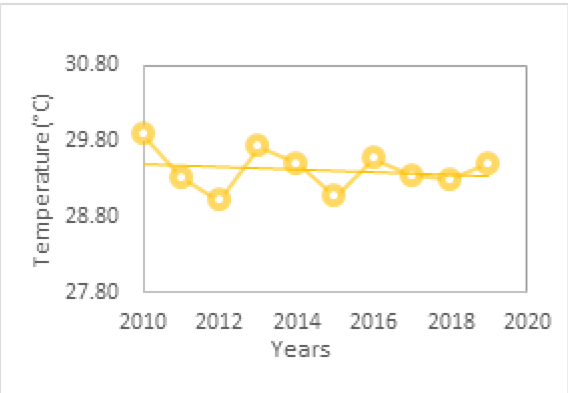


Figure 1. Interannual variation in temperature.

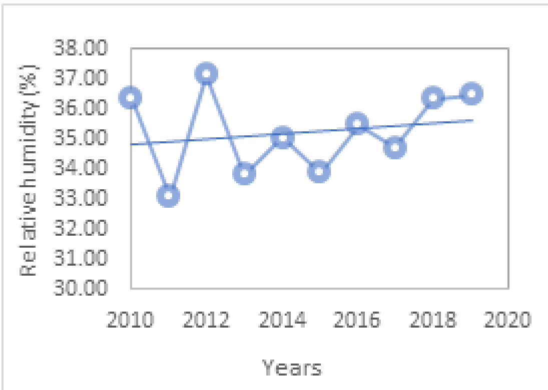


Figure 2. Interannual variation in relative humidity.

The analysis of the data collected highlights the general trend in the variation of wind speed and other meteorological parameters studied in the N'Guigmi area from 2010 to 2019.

The study of Table 1 shows us a noticeable increase in temperature during April, May and June and a decrease during December and January. These average monthly temperatures vary between 21.69 °C (Jan) and 34.60 °C (May). Figure 1 shows the temperature variation over the ten years. Over the study period, the years with the highest temperatures remain the years 2010 and 2013.

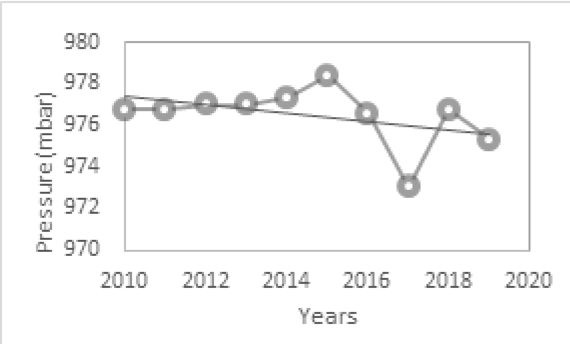


Figure 3. Interannual variation in pressure.

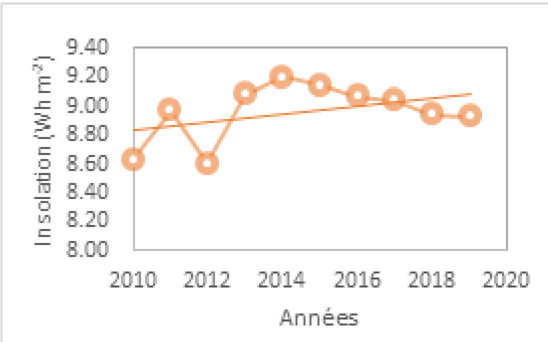


Figure 4. Interannual variation in insolation.

The analysis of the relative humidity curve informs us of the low level of this parameter in this area. These values perfectly reflect the peculiarity of the region. The low values of relative humidity are justified by the fact that the area of N'Guigmi is a desert area, therefore with much sun and wind.

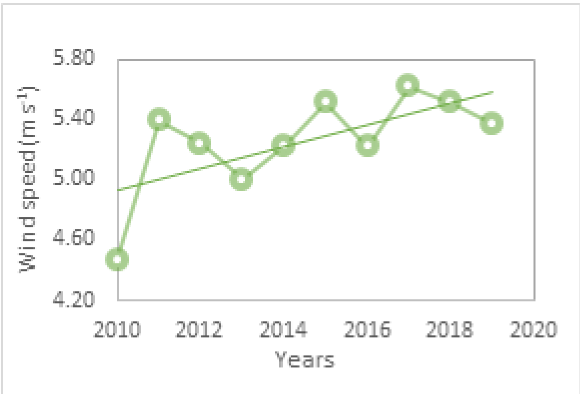


Figure 5. Interannual variation of wind speed.

The curves of interannual variations of atmospheric pressure and insolation show their maximum value over the year 2015 for atmospheric pressure and 2014 for the insolation. The minimum average values of insolation are observed in 2012, the year with the lowest recorded average temperatures and the highest relative air humidity, which is perfectly consistent. The maximum average velocities are recorded in 2017, which corresponds to the year with the lowest pressures, fairly high insolation, and temperature values, and relative humidity close to the average. In this case, too, we notice a concordance of results, since the wind is air in motion, the more sunlight there is and the less dense and therefore lighter the air is, which facilitates its movement.

4. Application of principal component analysis (PCA)

Principal Component Analysis (PCA) is a very efficient method for the analysis of quantitative data (continuous or discrete) in the form of tables with M observations and N variables. It is a descriptive method that allows a simplified representation of a series of intercorrelated variables. Its application to the 6 variables which are the maximum and minimum temperature, the maximum, and minimum relative humidity, the atmospheric pressure, and the insolation gave the results constituting our basis of interpretation.The first interesting result to be identified as a result of a principal component analysis is the correlation matrix that allows us to analyze the relationships between the different variables selected (Figure 6). This matrix is shown in Table 2.

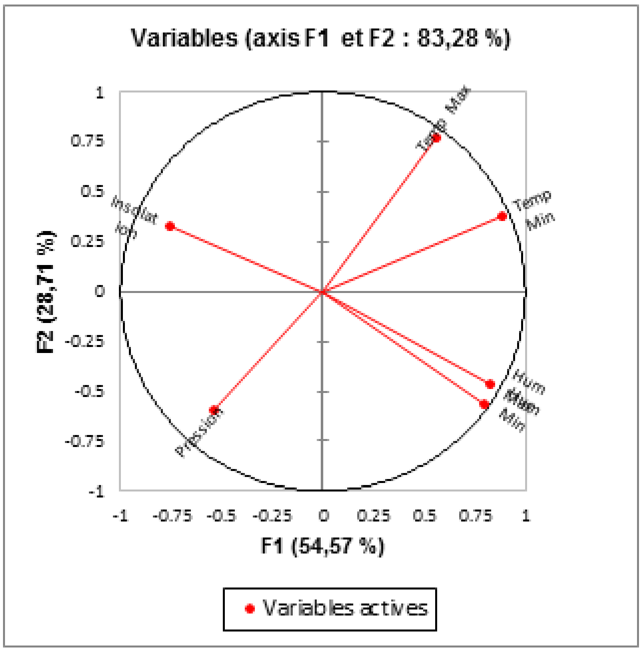


Figure 6. Space of the variables of the factorial designs F1-F2.

Table 2 presents the correlation matrix expressing the different correlations between the analyzed variables. The objective of this analysis is to verify the redundancy of these variables. It can be seen by interpreting the matrix that the set of correlation values is relatively low. Indeed, most of the correlation coefficients are lower than 0.70. It follows that the variables analyzed are not strongly correlated with each other. This significantly reduces the redundancy of the information and demonstrates the relevance of the choice of these variables for the study.

Diagonalization of the correlation matrix yields the eigenvalues shown in Table 3. Each factor is characterized by an eigenvalue, a share of the total variance (% variability), and a share of the cumulative variance (% cumulative).

Through Table 3, we notice that the first axis (F1) allows explaining (54,575%) of the total variance of the scatter plot, that the second axis (F2) allows explaining (28,709%) of the total variance. By projecting each individual on an (F1, F2) we keep 83.284% of the total variance. Now, 75% is the accepted reference value for a PCA study. The first two factors, therefore, contain most of the information about the data matrices.

Table 2. Correlation matrix (Pearson) between the analyzed variables

Variables	Pressure	Insolation	Max Temp	Min Temp	Max Hum	Min Hum
Pressure	**1**					
Insolation	0.189	**1**				
Max Temp	-0.569	-0.163	**1**			
Min Temp	-0.561	-0.521	**0.844**	**1**		
Max Hum	-0.190	-0.623	0.107	0.555	**1**	
Min Hum	-0.132	-0.683	-0.002	0.492	**0.959**	**1**

Table 3. Eigenvalues of the main axes

	F1	F2	F3	F4	F5	F6
Eigenvalues	3.274	1.723	0.519	0.427	0.039	0.017
Variability (%)	54.575	28.709	8.653	7.124	0.658	0.282
Cumulated (%)	54.575	83.284	91.936	99.060	99.718	100.000

Table 4. Correlations between variables and factors

	F1	F2	F3	F4	F5	F6
Pressure	-0.536	-0.590	0.588	0.138	0.000	0.000
Insolation	-0.754	0.328	-0.165	0.544	-0.027	0.001
Max Temp	0.555	0.769	0.287	0.097	0.066	-0.068
Min Temp	0.886	0.381	0.213	0.100	-0.097	0.074
Max Hum	0.830	-0.465	-0.096	0.263	0.126	0.038
Min Hum	0.798	-0.561	-0.097	0.156	-0.095	-0.073

The factorial correspondence analysis allowed a description of the relationships between the wind regime and the other meteorological parameters. Analyses of variance were used to assess the significance of the relationships identified by the factor analysis.

The analysis in the space of the variables was performed in the factorial planes F1-F2. Table 4 shows us very high positive correlation values of maximum and minimum temperature with the F1 and F2 principal components. The humidity variable is highly correlated with the F1 axis and negatively correlated with the F2 axis. Pressure is negatively correlated with both principal axes and insolation is negatively correlated with F1 and positively with F2. The results obtained reveal that temperature and relative humidity are the factors that most influence the variation of wind speed. Indeed, the temperature remains the most influential meteorological parameter in the variation of the wind speed because of its very strong correlation with the factors F1 and F2. Next comes relative air humidity, insolation, and finally pressure (Table 4).

We can observe that it is the combined effect of air temperature and relative humidity that acts on the wind speed. The temperature, because of its positive correlation with the two main components remains the most influential parameter, while the humidity, with a very positive correlation with the main component F1 and negative with the component F2, also influences.

A look at the values recorded in Table 4 allows us to establish a ranking in terms of the influence of each of the four parameters studied on the variation of wind speed. Thus, we can see that the most influential parameter is temperature, followed by relative humidity, insolation, and finally atmospheric pressure. These results lead us to assert that to effectively characterize a wind site, it would be preferable to know the meteorological parameters that govern the area. The topographic and obstacle parameters alone do not allow to really define a wind site.

With these results, knowing the variation of temperature, humidity, and sunshine in an area will allow to determine the trend of the variation of the wind speed and thus to decide the viability or not of a wind farm site.

The results obtained can be related to the work of other researchers. According to the results of the work of Koukpemedji *et al*., 2015, Omar *et al*., the variability of meteorological parameters, including temperature, humidity, and pressure greatly influence the seasonal wind regimes. Kouassi *et al*., 2010 have shown that the fluctuation of climatic parameters such as temperature or relative humidity is felt on other meteorological parameters including rainfall.

5. Conclusion and perspectives

From the outset, an analysis of the distribution of relative humidity, temperature, pressure, and insolation is carried out to visualize their temporal evolution.

The average monthly temperatures studied vary between 21.69 °C (Jan) and 34.60 °C (May). The maximum monthly averages are observed during April and May, which are generally the warmest months in the country. Temperatures are high overall and vary greatly during the year. Above-average values have been recorded with a significant drop in 2012 and 2015 compared to the average temperature of 29.42°C.

Regarding relative humidity, the general observation is that it has fairly low values because the study area is located at the gateway to the desert. Nevertheless, the values observed are of the order of 18.37% in minimum (March) and 66.76% in maximum (August, which remains the wettest month in Niger).

Insolation and atmospheric pressure are also manifested by their maximum and minimum values of 10.17 wh m^{-2} and 7.55 wh m^{-2}; and 980.96 mbar and 971.13 mbar respectively. It is noted that December and January have the highest-pressure values, while the minimum values of insolation are observed during the rainy season (June, July, August, Sept).

Then, principal component analysis is used to study the correlation of relative humidity, temperature, pressure, and insolation with wind speed. Thus, after analysis of the factorial design, we concluded that temperature is a major factor in wind circulation. The second variable that conditions the production of wind is humidity. These results are very satisfactory, since the wind is air in circulation, under a high temperature, its density decreases, and its circulation is facilitated. However, with humidity, it becomes heavier, and the wind circulates less quickly. We can undoubtedly affirm, based on the observation of temperature variations cumulated with those of humidity, that it is possible to predict the wind regime by knowing these parameters.

Finally, the conclusions of this study show that the analysis of meteorological parameters such as temperature and relative humidity allows us to know the variation of the wind or to predict its behavior in time and consequently, to determine a site that can shelter a wind farm.

Future work will lead us to determine the quantitative influence of each of the studied parameters and thus give their exact level of participation in the characterization of wind sites.

Nomenclature

DNM	National Meteorological Directorate
PCA	principal component analysis
X, Y, Z	raw/centered/reduced data
xj, yj, zj	raw/centered/reduced center variable
p	weights p1,..., pn of the individuals (of sum equal to 1).
Λk	eigenvalues of the matrix
σjl, rjl	real covariance/correlation of xj and xl
ck	principal component (new variable)
ak	main axis weights of ck in each variable zj
uk	main factor: weight of each variable in ck
var (x)	variance
σ	standard deviation
cor (x, y)	correlation coefficient
°C	degree celsius
mbar	millibar
m s-1	meter per second
wh m-2	watt-hour per square meter
F1 to F6	main axes of PCA

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Author contributions

MOUMOUNI GUERO Mohamed conceived and performed the synthesis, arrangements, and data calculations; MOUMOUNI GUERO Mohamed and PRODJINONTO Vincent analyzed the data; FANNOU Jean-Louis and PRODJINONTO Vincent contributed analysis tools; MOUMOUNI GUERO Mohamed wrote the paper.

Conflicts of interest

The authors declare no conflicts of interest. The sponsors had no role in the design of the study; analyses or interpretation of data; in the writing of the manuscript, and in the decision to publish the results.

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