# Potential Impact of Global Warming on Electricity Demand in Niger

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**Research Article**

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## Abstract

The present study examines the potential impact of climate change on daily electricity demand (DED) and climate variables in Niger at specific Global Warming Levels (GWL1.5, GWL2.0, GWL2.5, and GWL3.0). The principal component analysis (PCA) and the Multiple Linear Regression (MLR) model was utilized to build the electricity demand model. Furthermore, fourteen (14) regional climate models from the Coordinated Regional Climate Downscaling Experiment (CORDEX) were used for the study. The ability of the model ensemble-mean in reproducing the annual cycle of the climate variables was evaluated. The impact of climate change at specific GWLs on electricity demand and each climate variable is quantified. The MLR predicted the demand with a coefficient of determination $R^2$ equals to 0.808 and a root mean square error (RMSE) equals to 149.87. The residuals analysis indicated that the model complies with the regressions assumptions. The models projected an increase of electricity demand at all the GWLs. More than 75% of the models agree on the noticeable change in electricity demand. The results of the study showed how climate services could be used to quantify the impacts of climate change on electricity demand. This has application on providing useful information for policymakers regarding the potential impacts of climate change in the energy sector

Keywords: regional climate models; model ensemble mean; climate variables; global warming levels; daily electricity demand

## 1. Introduction

In most African countries, the energy sector faces a number of challenges including insecure energy supply, continuous growth of electricity demand and recurrent blackouts. For example, in Niger, the electricity consumption has increased by more than 150% since 2001 with the largest increase in the residential and commercial sectors.  As the cities are becoming more populated and the extreme hot days more frequent, the demand will continue to rise. Yet, the electricity supply system has not been able to adequately keep up with the peaks demand during the hot periods when the demand exceeds the available generating capacity, resulting to blackouts in several localities. For example, during the hot periods in 2016, the power company in Niger

(NIGELEC) was not able to meet half of the demand resulting to blackout in many areas. This problem will be compounded the incoming years since the government of Niger has taken a number of measures to achieve 100% of electricity access in the urban by 2030. In addition to the rise in electricity demand, significant increase in mean and extreme temperatures is also projected to result from climate change. Indeed, an increase in mean and extreme temperatures is projected to result from climate change over West Africa (IPCC, 2013; Klutse et al. 2018, Nikulin et al., 2018). Previous studies have shown the relation between electricity demand and climate variables and demonstrated that demand might get altered with changing climate (Aldl & Waris, 2014; Kaufmann *et al., 2013;* Jovanović et al., 2015; Valor et al., 2001; Guan et al., 2017; Pardo et al., 2002). Hence, for a better management of future electricity supply, there is a need to quantify the potential impacts of climate change on electricity demand. The present study intends to provide more information in this area.

Many studies have addressed the impacts of climate change on electricity demand in several countries across the world, and show that the impacts differ from one climate zone to another, and from one city to the other. For instance, in cold climate, it is projected that climate change would decrease the energy demand since less energy will be required for heating the buildings during winter. In Finland, Jylhä et al. (2015) reported a decrease of 20-35% in total energy consumption by 2100 depending on the magnitude of climate change. Wan et al. (2012) shows that the reduction of heating demand may be up to 22.3% in Harbin, 23.6% Hong Kong, 26.6% in Beijing, and 55.7% in Shanghai (55.7%). On the other hand, the energy demand is projected to increase in tropical countries where more electricity will be required for cooling the buildings. Shourav et al., (2018) revealed that climate change would increase the daily electricity and peak demand in Dhaka City by up to 5.9-15.6% and 5.1-16.7% respectively toward the end of this century under different climate change scenarios. Ahmed et al (2012) reported that an increase in temperature alone may lead to 1.36, 2.72 and 6.34 % rise in per capita demand during summer season and 2.09, 4.5, and 11.3% rise in per capita demand during the spring of 2030, 2050, and 2100 respectively. In Brazil, Invidiata et al., (2015) reported that climate change would induce an increase in the annual energy demand from 19-65% in 2020, 56-112% in 2050, and 112%-185% in 2080. While, it could be speculated that the electricity demand in Niger would also increase because of climate change, no such study has quantified the percentage of increase in this West African country. Since the impacts of climate change may differ from one geographic location to another, it is worth to investigate the potential impact of climate change at specific location. Indeed, according to IPCC, the effects of climate change should be carried out at a location where the impacts are felt and the responses are implemented. Hence, given the heterogeneity of climate change, carrying out such study will provide reliable information to the policymakers and electricity planners to take anticipated measures as far as the energy sector is concerned.

To project the impacts of future global warming, information on how future climate projection under different emissions scenarios is needed. This information is provided by means of the Global Climate models (GCMs) also known as General Circulation Models. However, the spatial resolutions of these GCMs are too coarse for impact assessments (100-300 km). Therefore, there is a need to downscale the outputs of these GCMs by using either the statistical or dynamical downscaling techniques. The statistically downscaling techniques by means of morphing approach have been widely used to assess the impacts of climate change on electricity consumptions in previous works *(Wang, Chen and Ren, 2010; Shen, 2017; Wang, Liu and Brown, 2017; Cellura et al., 2018)*. While the morphing technique only reflects changes in the average weather conditions and not possible to see changes in extreme climate conditions for the morphed data, the extreme climate conditions are projected to increase as a result of climate change (IPCC, 2013). Hence, the morphing technique might underestimate the impact of climate change on energy consumption. This shortcoming makes the morphing technique less relevant for assessing the impact of climate change on electricity consumption. In contrast, the dynamical downscaling technique by means of Regional Climate Models has the ability to generate physically consistent datasets across different variables. The RCMs have the advantage to provide the state of the atmosphere at each time step as well as in long integrations over a century. This provides a better representation of future climate compared to morphed data. However, given a variety of RCMs, selecting a single RCM model with specific boundary conditions is not a trivial task.  The IPCC suggests that given the strengths and weaknesses of various models, no single models can be considered as the best. To assist developing countries that lack computer infrastructure have access from multi-RCM projections, The Coordinated Regional Climate Downscaling Experiment (CORDEX) has made their datasets available publicly, and several studies have already used the

CORDEX data to assess the impacts of global warming on various sectors over the continent (Abiodun et al., 2017; Kumi & Abiodun, 2018; Klutse et al., 2018, Nikulin et al., 2018; Maúre et al. 2018; Abiodun et al., 2018). Nevertheless, none of these studies have investigated the impact of climate change on energy demand over West Africa. The present study intends to fill in this gap.

Hence, the present paper aims at investigating the potential impact of climate change on electricity demand in Niger at specific Global Warming Level (GWL1.5, GWL2.0, GWL2.5 and GWL3.0) using the multi-RCMs. In the study, we develop a multiple linear regression model (MLR) based on the historical relationship between the electricity demand and climate variables, analyze the multi-simulations datasets CORDEX RCMs; and project the impacts of climate change on electricity demand based on MLR model. Section 2 of the paper describes the data and methods used in the study, section 3 presents and discusses the results and section 4 concludes the paper.

# 2. Data and methods

## 2.1 Data

### 2.1.1 Study area

Geographically, Niger is located in West Africa, between 12 and 24°N latitude and 0 to 16°E longitude with a total land area of 1,267,00km$^2$ (Figure 1). Climatically, four distinct climate zones can be identified: the Soudano-Sahelian zone (about 1% of the total) with an annual rainfall ranging from 600 to 800mm, the Sahelian zone (about 10% of the total land area) with an annual precipitation ranging from 350mm to 600mm; the Sahelo-Saharan zone (12% of the total land area) with an annual rainfall ranging from 150mm to 350mm; and finally the Saharan zone, which occupies about 77% of the total land area with an annual precipitation less that 150mm. The study focuses on Niamey, which is the capital and the largest city of Niger with a total land area of 256km$^2$ and a population of about 1.5 million inhabitants. Niamey belongs to the Sahelian zone with average temperature ranging in summer (March-June) from 30 to 35 and 20 to 27 in winter (December-February). It is most important city in Niger in terms of infrastructure, institutions, and industries, making this city more attractive to rural dwellers. Indeed, in 2015, the electricity consumption of Niamey is about 63% of the total electricity consumed by whole country. Figure 1 presents the map of Africa showing the study are and the main cities.


Figure 1: Map of the Study area with main cities (Wikipedia).

### *2.1.2. Energy Sources and Status of Electricity Used in Niger*

The current energy situation in Niger is characterized by a dual energy system containing co-existing traditional and modernized energy systems and practices (IRENA,2013). As a matter of fact, 79% of the Total Primary Energy System (TPES) is from biomass, which meets 83% of the total household energy needs. The household sector is the main end user of energy consumption in Niger and represents 90% of the total energy consumption, followed by transport with 8% and industry which accounts for 2%. Moreover, the electricity access rate is one of the lowest in the world, with high disparities between urban and rural areas. Indeed, in 2018, the percentage of population having access to electricity was estimated to 20% with 67% in urban area and 10% in rural areas. As stated earlier, more than 63% of the total electricity is consumed by Niamey. Figure 2 shows the share of electricity consumption for the main cities in Niger.

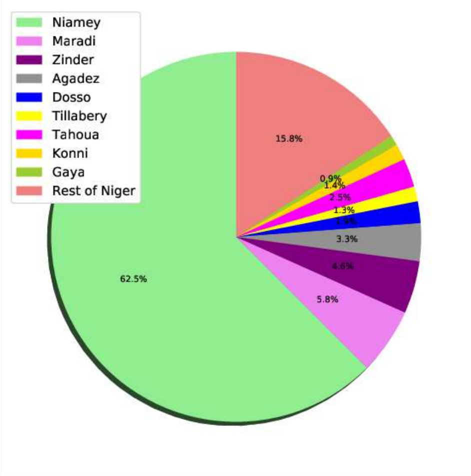


Figure 2: Electricity Consumption Share of the Main cities Niger

The electricity produced is mainly from fossil fuel sources mainly coal, oil and diesel which accounted for 99.4% of the total electricity production in 2015 while the electricity produced from renewable energy sources accounted for 0.75% which is mainly solar photovoltaic. For instance, in 2018 the total installed solar PV was 20 MW despite the high solar potential estimated to 5-7 kWh/m2/day with sunshine duration of about 7 to 10 hours.

In addition to high solar energy potential, the country has also high hydropower potential estimated to 130MW on Kandadji site, 122.5MW at Gambou, and 26MW at Dyondonga. Currently, there is no hydropower plant in Niger.

The coal reserves are estimated to 15 million tons with energy content equals to 3650kcal/kg in Agadez Region and 70 million of tons with an energy content of 6000kcal/kg at Salkadamna in Tahoua region. The annual production of uranium is estimated to 3400 tons while the oil and gas reserves are also estimated respectively to 700 million barrels and 14 billion $m^3$

### 2.1.3 Observed data

The observed daily electricity demand, weather variables data for Niamey spanning from January 2005 to December 2017 are used in this study. The electricity data were obtained from the National Company of electricity of Niger (NIGELEC), which is indeed, the only company responsible for producing and generating the electricity over the country.

The weather variables data are obtained from the automatic weather station in AGRHYMET and the Meteorological service of Niger (DMN). These data include the air temperature, the maximum temperature, the minimum temperature, the relative humidity, the wind speed, and the solar radiation.

The DED depicts seasonal variation and an increasing trend (Figure 2). The latter might be due to socio-economic development while the former is a result of weather fluctuations.

The observed outliers which mostly occurred during the rainy season are due network failure due to strong winds. Indeed, the very low value of demand observed on 28th August 2005, 1st July 2008 are due to the collapse of pylons on Birnin Kebbi's line which provides about 68% of electricity supply resulting to blackouts in several localities. On the other hand, the minimum values observed on November 2010 resulted from the revisions of the thermal plant PC4 in Niamey in order to increase its production capacity.

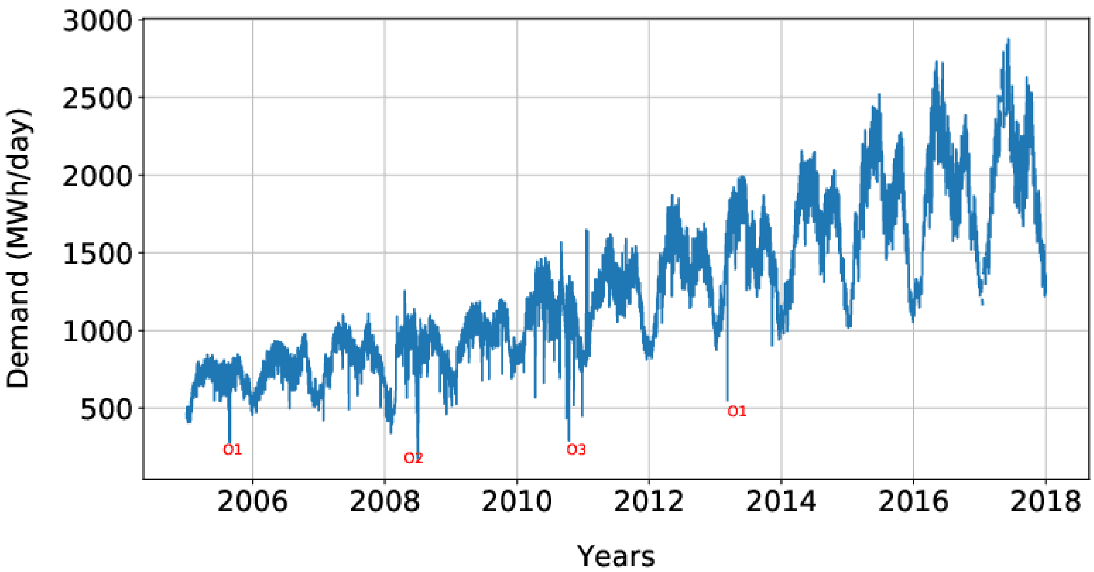


Figure 3: Time series of daily electricity demand for Niamey (2005-2017). O1, O2, O3, and O4 are the outliers.

Several studies have shown that the relationship between electricity and temperature is nonlinear and thereby used two branches in studying the relationship (*Valor et al., 2001; Ahmed et al., 2012; Yi-Ling et al., 2014; Shin and Do, 2016)*). For convenience, can be introduced with concept of Degree Days (DD): The Cooling Degree Days (CDD) and the Heating Degree Days (HDD). While HDD provides an indication of the sensible heating requirements for a particular location, the CDD provides the same but for sensible cooling requirements (Giannakopoulos and Psiloglou, 2006). The difference between the two branches is usually identified on electricity-temperature scatter plots using the base temperature, which is the temperature point where the electricity shows no sensitivity to temperature. However, unlike the studies of Giannakopoulos and Psiloglou (2006) and Valor et al., (2001), in this study, the relationship between the electricity demand and temperature is quite linear and presents its minimum value around 22ºC (Figure 3). Hence, this value will be used to calculate the CDD.

From Figure 3, the base temperature for this study is about 22°C; hence, this value is used to define the CDD and HDD in Equation (1) & (2):

$$CDD = max(T - 22, 0) \qquad (1)$$

Where CDD is the cooling degree-days, T the air temperature (°C), and 22 the temperature at which the electricity shows no sensitivity to air temperature (i.e. base temperature).

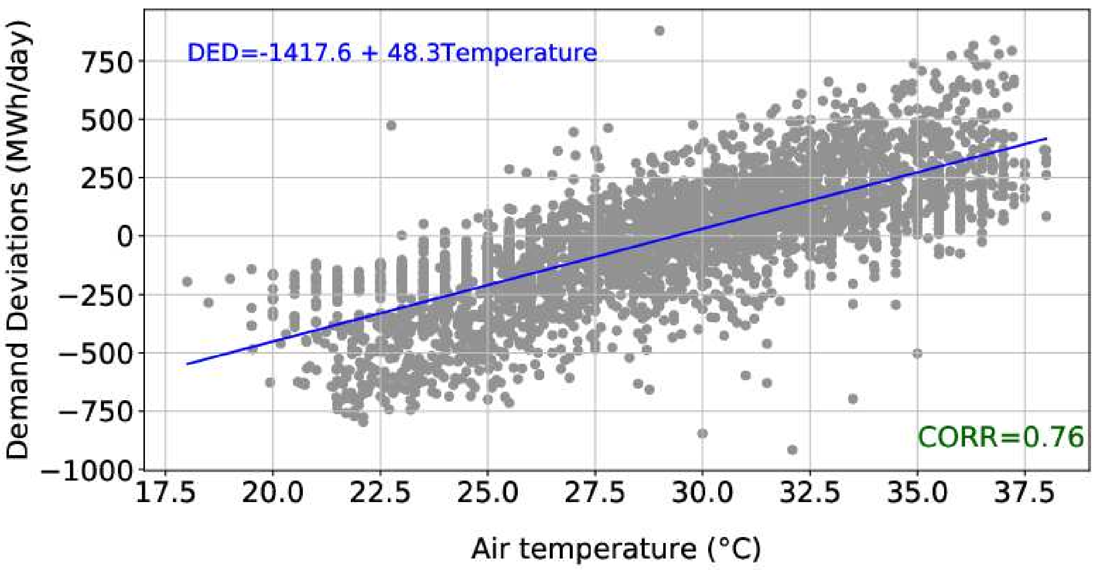


Figure 3: Scatter plot of detrended electricity demand and air temperature (red line indicated the best fit and blue line shows the base temperature)

Another feature is the heat index (HI) reflecting an increased operation of air conditioning during hot and humid summer days. Indeed, the effect of relative humidity on electricity demand is supposed to be relevant in conjunction with warm and hot temperature only, because the perceived temperature can be higher in such meteorological conditions and thus the use of cooling appliances increases (Apadula *et al.*, 2012). Following Steadman, (1979), the HI formula can be defined as follow:

$$HI = C_0 + C_1 * T + C_2 * H + C_3 * TH + C_4 * T^2 + C_5 * H^2 + C_6 * T^2H + C_7 * TH^2 + T^2H^2 \quad (2)$$

Where HI is the heat index (°C), T is the air temperature (°C); H is the relative humidity (%) and $C_i$, the constants. The HI has been applied only when the temperature is equal or exceeds 27 and simultaneously the relative humidity higher than 40%. Such meteorological conditions occur only in summer months (JJAS) in Niger where the mean temperature is greater than 27°C and the relative humidity relatively higher than 40%.

If the above conditions are not satisfied, the HI is set equal to the maximum temperature.

Finally, in order to take into account, the thermal oscillation within a day, we introduce the diurnal temperature range, which is defined in Equation 4:

$$DTR = T_{max} - T_{min} \quad (3)$$

The descriptive statistics of climate variables are summarized in the Table 1.

Table 1: descriptive statistics of the climate variables used in this study

| | Tmean (°C) | Tmax (°C) | Tmin (°C) | Humidity (%) | Radiation (Watt/m$^2$) | Wind (m/s) | DTR (°C) |
|---|---|---|---|---|---|---|---|
| Mean | 29.4 | 36.8 | 22.3 | 34.6 | 260 | 2.4 | 14.4 |
| Std. | 3.8 | 3.9 | 4.7 | 22.2 | 46 | 1.3 | 4.4 |
| Max | 18 | 45.2 | 32.2 | 89 | 560 | 10.2 | 25 |
| Min | 18 | 24 | 9 | 4 | 0 | 0 | 2.8 |

### 2.1.4 CORDEX data

The simulated daily temperature, humidity, radiation, and wind from the CORDEX simulation dataset were analyzed for the study. 14 multi-model simulations datasets produced by four CORDEX Regional Climate Models (RCMs: RCA, CCLM, REMO and ALADIN) were used in this study. The RCM and GCMs downscaled are given in Table (2). To assess the impacts of a warming level on climate variables, we calculated the difference between the projected future values (for the warming level) and the historical values (i.e. GWL minus historical). For more information on the definition of GWL period, we refer the readers to (Nikulin et al., 2018).

Table 2: names of GCMs and downscaling RCMs simulations used in this study

| RCMs | GCMs | Period of Global Warming Level | | | |
|---|---|---|---|---|---|
| | | 1.5 | 2.0 | 2.5 | 3.0 |
| RCA | CCCMA | 1999-2028 | 2012-2041 | 2024-2053 | 2044-2053 |
| | CNRM | 2015-2046 | 2029-2058 | 2041-2070 | 2052-2081 |
| | CSIRO | 2018-2047 | 2031-2059 | 2040-2069 | 2050-2079 |
| | HadGEM | 2010-2039 | 2033-2062 | 2042-2071 | 2051-2080 |
| | IPSL | 2002-2031 | 2016-2045 | 2027-2056 | 2036-2065 |
| | MIROC | 2019-2048 | 2034-2063 | 2047-2076 | 2058-2087 |
| | MPI | 2004-2033 | 2021-2050 | 2034-2063 | 2046-2075 |
| | NCC | 2019-2048 | 2034-2063 | 2047-2076 | 2059-2088 |
| CCLM | CNRM | 2015-2044 | 2029-2058 | 2041-2070 | 2052-2081 |
| | HadGEM | 2010-2039 | 2023-2052 | 2033-2062 | 2042-2071 |
| | ICHEC | 2005-2034 | 2021-2050 | 2034-2063 | 2047-2076 |
| | MPI | 2004-2033 | 2021-2050 | 2034-2063 | 2046-2075 |
| ALADIN | CNRM | 2015-2044 | 2029-2058 | 2041-2070 | 2052-2081 |
| RACMO | ICHEC | 2003-2032 | 2021-2050 | 2035-2064 | 2046-2075 |

## 2.2 Methods

We establish the historical relationship between electricity demand and climate variables using the Multiple Linear Regression (MLR) Model. Prior the model development, the trend (due to socio-economic development) and the seasonality (due to weekends, holidays effect) were removed following the procedure of Apadula *et al.* (2012). The general linear regression model is given in equation 5:

$$DED_t = \beta_0 + \beta_1 t + \beta_2 t^2 + \beta_3 I_W + y_t \tag{4}$$

Where $DED_t$ is the aggregated demand for electricity, t is the time variable (t=0,1,2,3…), $I_W$ is the dummy variable taking the value 1 if the observation of the demand corresponds to holidays (Weekends included) and 0 otherwise, and $y_t$ is the electricity demand due to weather fluctuations. The DED has been detrended by removing the deterministic part (time variable due to socio-economic development and dummy variable due to holidays effect).

In addition, we used the Principal Components Analysis (PCA) to find the key weather variables that are highly correlated with the working-days demand deviations (WDDD, demand after removal of trend and seasonality). Then, we develop the MLR using the PCA results (WDDD is used as response variable and the climates variables are used as independent variables). Moreover, we check the basics linear models' assumptions using the residual plots (homogeneity of the variance, and histogram of residuals) to find out whether or not the model complies with the basic assumptions of linear models. These methods have been already used in previous study to check linear model assumptions (Aranda et al., 2012; Bianco et al., 2009). In addition, the coefficient of determination $R^2$, the Root Mean Square Error, and the Mean Bias Error are used to assess the accuracy of the model.

Furthermore, to evaluate the performance of the simulation datasets, in reproducing the climate of Niger, we compared the simulated climate data for the period 1971-2000 (hereafter, reference period) with the Princeton Global Forecasting (PGF) data for the same period. However, the evaluation focuses on the variables needed for building the model. Furthermore, to assess the impact of climate change at various global warming levels (GWL1.5, GWL2.0, GWL2.5, and GWL3.0), we subtract the climate data in the reference period from that in GWL periods. The GWL period is defined as 30-year period in which the climatology of global mean temperature is higher than that of the pre-industrial baseline period (1861-1890) (Nikulin et al., 2018). As observed in Table (2), this period varies with GCMs simulations.

# 3 Results and discussions

## 3.1 Relationship between DED and climate variables

Table (3) provides the loading of the principal Component Analysis using the PC1 and PC2. As stated earlier, the PCA is used in this study to group the key climate variables that are highly correlated with the electricity demand. From these results it is noticeable that the PC1 is highly correlated with the energy, Temp, Tmin, Tmax, Radiation, and HI. In other words, there is a process that couples an increase of the energy demand with these climate variables. Therefore, the PCA result suggests that the CDD, Tmax, Tmin, and HI are highly correlated with the DED.

Table 3: Loadings of PCA results.

| | PC1 | PC2 |
|---|---|---|
| Energy | **0.817** | -0. 363 |
| CDD | **0.970** | -0.188 |
| Temp | **0.971** | -0.190 |
| Humidity | | **-0.851** |
| Radiation | **0.594** | 0.109 |
| Tmax | **0.928** | 0.324 |
| Tmin | **0.787** | -0.580 |
| HI | **0.816** | 0.491 |
| Wind | 0.161 | -0.367 |
| DTR | | **0.954** |
| Proportion of variance | *0.469* | 0.243 |
| Cumulative variance | 0.469 | 0.713 |

## 3.2 Evaluation of Multiple Linear Regression (MLR) models

Multiple Linear Regression (MLR) model was developed based on de-trend electricity and climate variables that highly correlate with the DED to establish the functional relationship between the DED and climate variables. The regression coefficients and their corresponding p-values are given in Table (4) while the resulting regression model in equation 6.

$$y = -599.2 + 77.27CDD + 3..09RH - 12.07HI + 13.14Tmax - 0.33Rad - 37.38Wind \quad (5)$$

The performance of the model is then assessed through its ability to estimate historical values of observed electricity demand. Following the approach of (Braun et al., 2014), we splitted the datasets into two set: The first part (80% of the data) was used to train the model while the second part (20% of the data) was used to validate the model. Figure 4a presents the time series of observed and estimated electricity demand while the Figure 4b shows the scatter plots between the observed and estimated DED. The model achieves a good correlation coefficient (r=0.899), high coefficient of determination ($R^2$=0.808) and relatively low mean square error

(RMSE=140.87MWh/day). This indicates that the model performs well in estimating the DED based on the meteorological variables only and without including impact non-meteorological variable of the DED. Table (4) indicates that all the model parameters are significant.

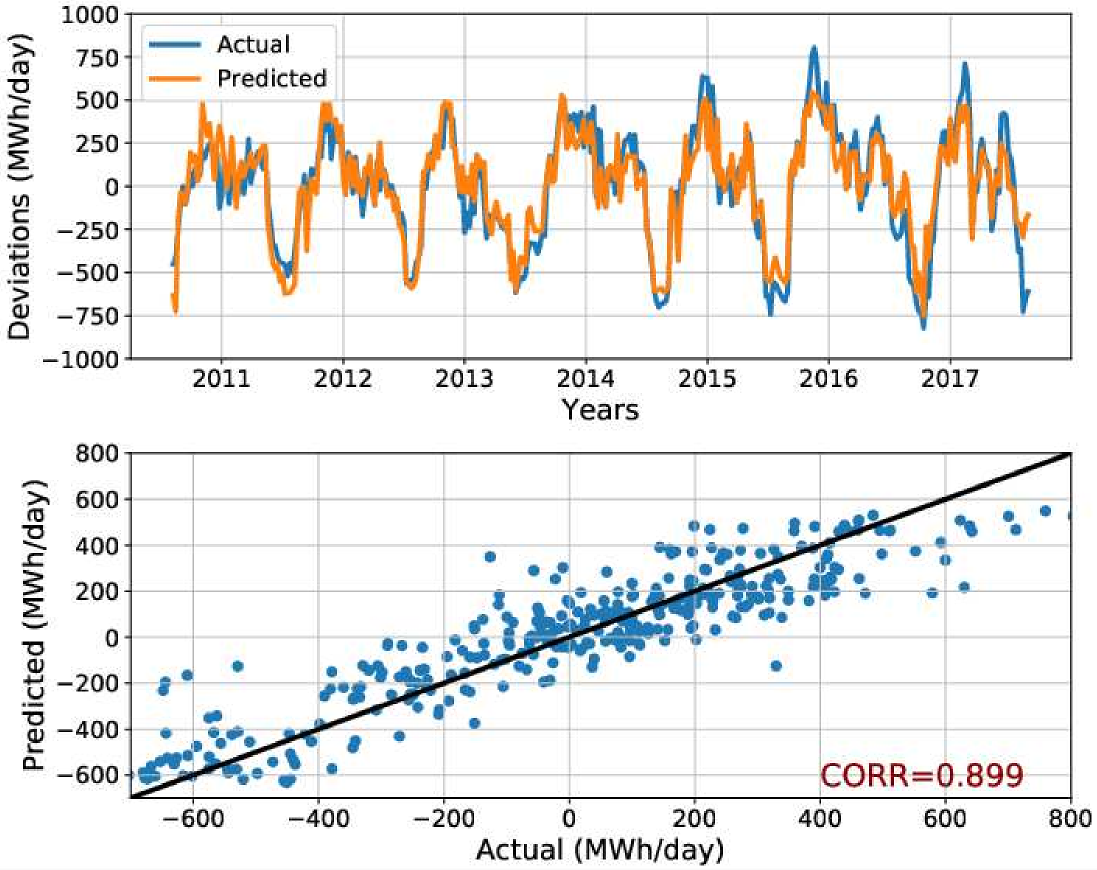


Figure 4: Times series of observed and estimated DED (upper panel) and scatter plot of observed and estimated DED (Lower panel). CORR is the correlation coefficient between observed and estimated DED

Table 4: Regression coefficients and P values of the MLR results

| Variables | Coefficients | P values |
|---|---|---|
| Intercept | -599.2 | 0.000 |
| CDD (°C) | 77.27 | 0.000 |
| HI (°C) | -12.08 | 0.000 |
| Humidity (%) | 3.09 | 0.000 |
| Rad (watt/m$^2$) | -0.33 | 0.000 |
| Wind (m/s) | -37.38 | 0.000 |
| Tmax (°C) | 13.14 | 0.000 |

| Regression statistics | | |
|---|---|---|
| $R^2$ | RMSE | MAE |
| 0.808 | 140.87 | 107.57 |

Furthermore, we check the assumptions of linearity to find out whether the model complies with the basic assumptions of linear regression model. The residual error from the regression model is the different of the observed electricity demand and the fitted values. The residuals error should be normally distributed to comply with the basic assumptions of regression models (Bianco et al., 2009; Aranda et al., 2012). Residuals plot show that there is no specific pattern or relationship between the residual and the fitted values (Figure 5a) and the distribution follows approximately the normal distribution (Figure 5b). Consequently, we can conclude that the models comply with the basic assumptions of regression models. Therefore, the model can be used to project the impact of climate change on DED.

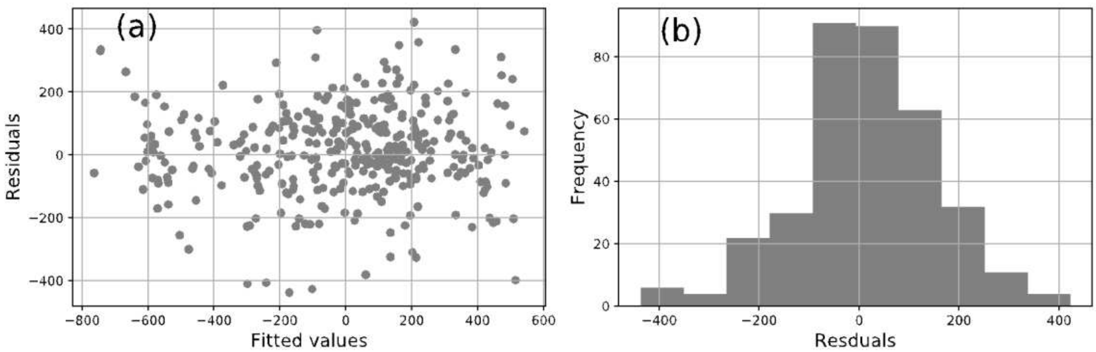


Figure 5: Scatter plot of the residuals versus the fitted values (left panel) and the histogram of the residuals plot (right panel)

## 3.3 Evaluation of CORDEX simulations

Figure 6 shows that the RCMs reproduce well the annual cycle of daily energy demand and the climate variables (CDD, Tmax, Heat Index, radiation, and wind). In most cases the observed annual cycles lie within the RCMs ensemble spread except for CDD for which the RCMs models fail in reproducing the peak value observed in May and October and also for wind where the RCMs fail in reproducing the minimum values of wind speed observed April. Furthermore, both observed and simulated cycles show high values of DED, CDD, HI, and Tmax in April-June and October, and high values of wind in June-July, reflecting the seasonal movement of the Inter-tropical

Discontinuity (ITD) and December-February, reflecting the prevailing harmattan conditions. In both the observed and simulated curves, the minimum values of solar radiation occur in August while the maximum values occur in March-April.

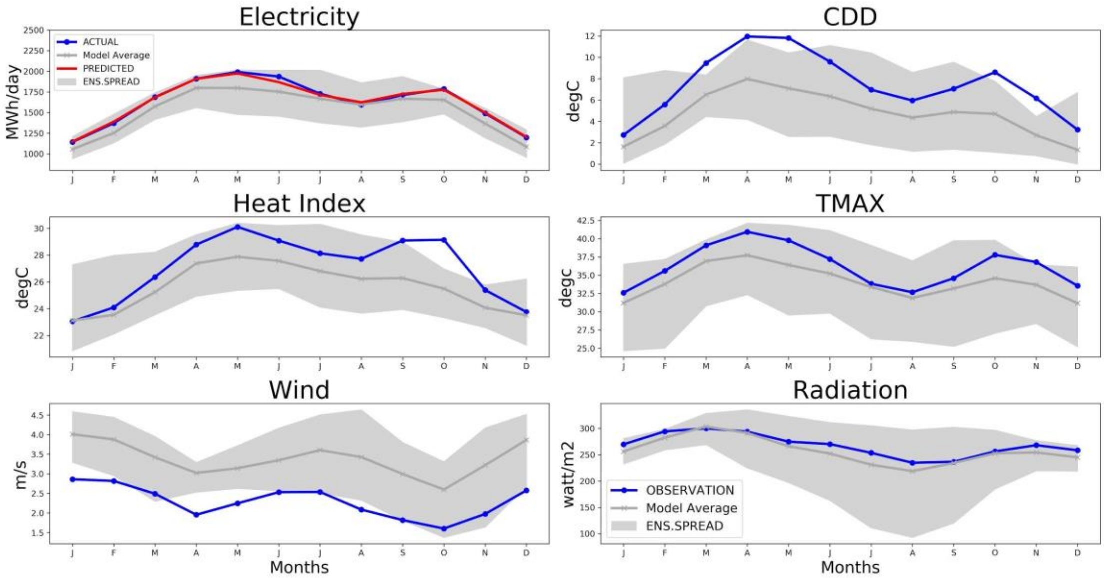


Figure 6: annual cycle of daily energy demand and the relevant climate variables used to build the Multiple Linear Regression model in Niger as depicted by observation and CORDEX RCMs ensemble

Despite, the good performance of the RCMs ensemble to reasonably reproduce the annual cycle of the climate variables (Figure 6), the models struggle to reproduce the spatial distributions of some climate variables (Figure 7). For instance, the observation features a maximum CDD (>8°C) over the southwestern part of the country. The RCMs ensemble mean fails to adequately reproduce this pattern (r≈0.51); instead it shows a relatively uniform distribution of the number of CDD across the country (2-6°C). Thus, the bias in simulating the CDD is up to -3°C Similarly, the same could be also observed for the Tmax and HI where the observation features a maximum value of Tmax (≈40°C) and HI (≈28°C) over the Southwestern part of the country. But the RCMs have not been able to adequately reproduce these patterns (r=0.47 for HI and r=0.5 for Tmax). Hence, the bias in simulating the Tmax is up to -5 over the central part of the country while it is for HI +1°C over the Northern and -1°C over the southern part. Moreover, the RCMs ensemble mean completely fails in reproducing the spatial variability of the observed radiation and Wind (r≈0). While the observation features a maximum radiation over the northern part of up to 300W/m$^2$, the RCMs ensemble mean shows a maximum value of about 280W/m$^2$ over a narrower area. The associated bias is up to -50W/ m$^2$, suggesting that the models highly underestimate the solar radiation. Contrary, the models overestimate the wind speed with a bias up to 1.5m/s. While these biases might result from the deficiency of RCMs, they may also come from the deficiency of the PGF data used for the validation. For instance, PGF data is a hybrid observation-reanalysis dataset created by combining global observation datasets and reanalysis datasets (NCEP-NCAR) (Sheffield et al. 2006). Hence because of the very low density of the observational network over the country, the PGF data might not be able to capture the spatial variability of the climate variables. Notwithstanding, it may capture the day-to-day variation of most of the climate variables used in this study

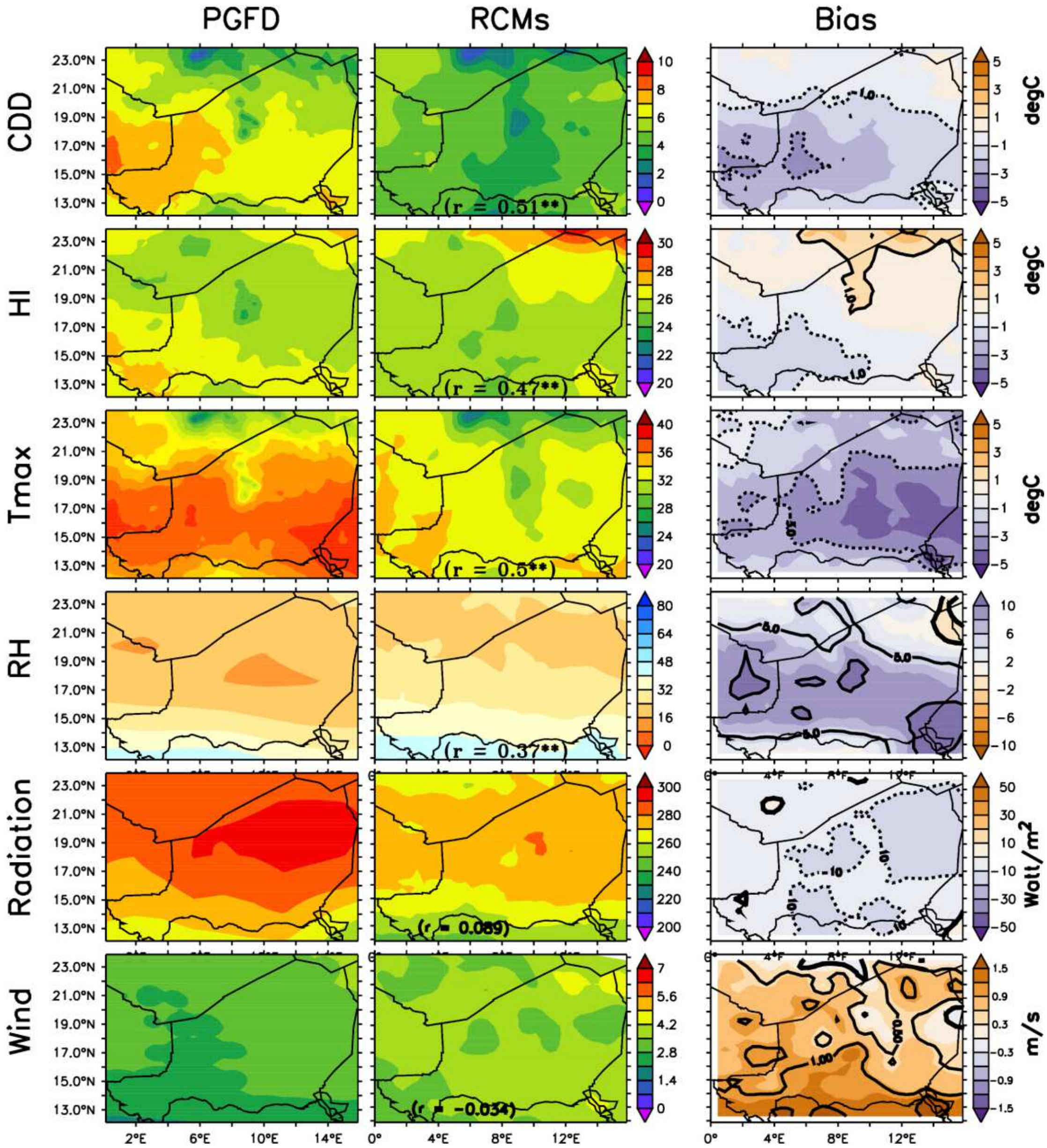

Figure 7: spatial distribution of climate variables over Niger as depicted by PGFD and CORDEX RCMs ensemble mean in reference period (1971-2000). The climate variables are CDD (°C), HI (°C), Tmax (°C), Humidity (%), Radiation (Watt/m$^2$) and Wind (m/s). r denotes the spatial correlation and asterisk (*) denotes significant at 95% confidence level.

## 3.4 Projected changes

The CORDEX ensemble models project an increase in daily electricity over the entire country for all the GWLs (Figure 8a-d). However, the magnitude of the increase varies across the country and grows with increasing of GWLs. For instance at GWL1.5, the changes are rather homogenous (between 4 and 8% increase in DED) over the entire country. In addition, the changes are robust (i.e. statistically significant at 99% confidence level). However, for GWL2.0, DED increase varies across the country, from 4 to 8% in the central part of the country to 8-12% in the remaining part of the country. Compared with changes at GWL1.5, an additional increase (up to 3%) in DED is observed over most part of the country. Conversely, a further increase in warming level beyond 2° will enhance the DED over the entire country, such that, at GWL3.0, most part of the country becomes hotspots of increase in DED due to climate change. This suggests that failing to keep the global warming level below or at 2° (level set by the Paris agreement) may have serious consequences on DED over the entire country. Indeed, an additional increase (up to 9.5% compared to GWL1.5) could be over most part of the country, with the highest increase around Niamey. The increase in DED over the entire country is robust (i.e. statistically significant at 99% confidence level) at all the GWLs. These findings are consistent with the notion climate change will increase the electricity consumption in tropical countries (Santamouris *et al.*, 2015; Scapin *et al.*, 2015; Huang and Hwang, 2016; Ang et al., 2017 among others).

Moreover, Figure 8 shows that the projected changes in DED are consistent with the changes in CDD, Tmax, HI and humidity variables. For instance the increase in DED may be attributed to the increase of CDD, Tmax, HI and humidity. This is expected since high CDD will require more DED for cooling purposes. In fact, Figure 5e-h indicates that the spatial correlation between the changes in DED and CDD is very high (>0.9) and significant (99% confidence level) at all the GWLs. Moreover, the increase in CDD is in agreement with the result of (Klutse et al., 2018) who found an increase in temperature over the region as a result of climate change. In the same way, DED increase is also followed by the increase in HI and Tmax. Indeed, high Tmax would result to increase the electricity demand peaks, hence contributing to increase the overall DED. So the Tmax is an important factor that influences the DED. For instance the spatial correlation between the changes in DED and CDD is high (>0.9) and significant (99% confidence level) at all the GWLs. Finally, the changes in DED are also in agreement with the changes of humidity since our previous work has established that the humidity and DED are negatively correlated (*Bonkaney et al., 2019)*. So a decrease in relative humidity will lead to an increase in DED, which is observed in Figure 8a-d. Nonetheless, for both of radiation and wind, the projected changes are not consistent with changes observed in DED. For instance, one might have expected a decrease in radiation result in a decrease in DED, because of the positive relationship between DED and radiation (Table 3). But the reverse is the case. This might be due to fact that the impact of the other climate variables (CDD, Tmax, HI, and humidity) overwhelms the impact of radiation on DED. Indeed, the spatial correlation between DED and the radiation is weak (r<0.5) and not significant. Similarly, an increase in wind speed could also have resulted to a decrease of DED because of the negative relationship between DED and wind (Table 3), but this is not the case. This can also be explained by the fact the wind has weak influence on electricity demand. The spatial correlation between wind and DED is weak (r<0.3) and not statistically significant.

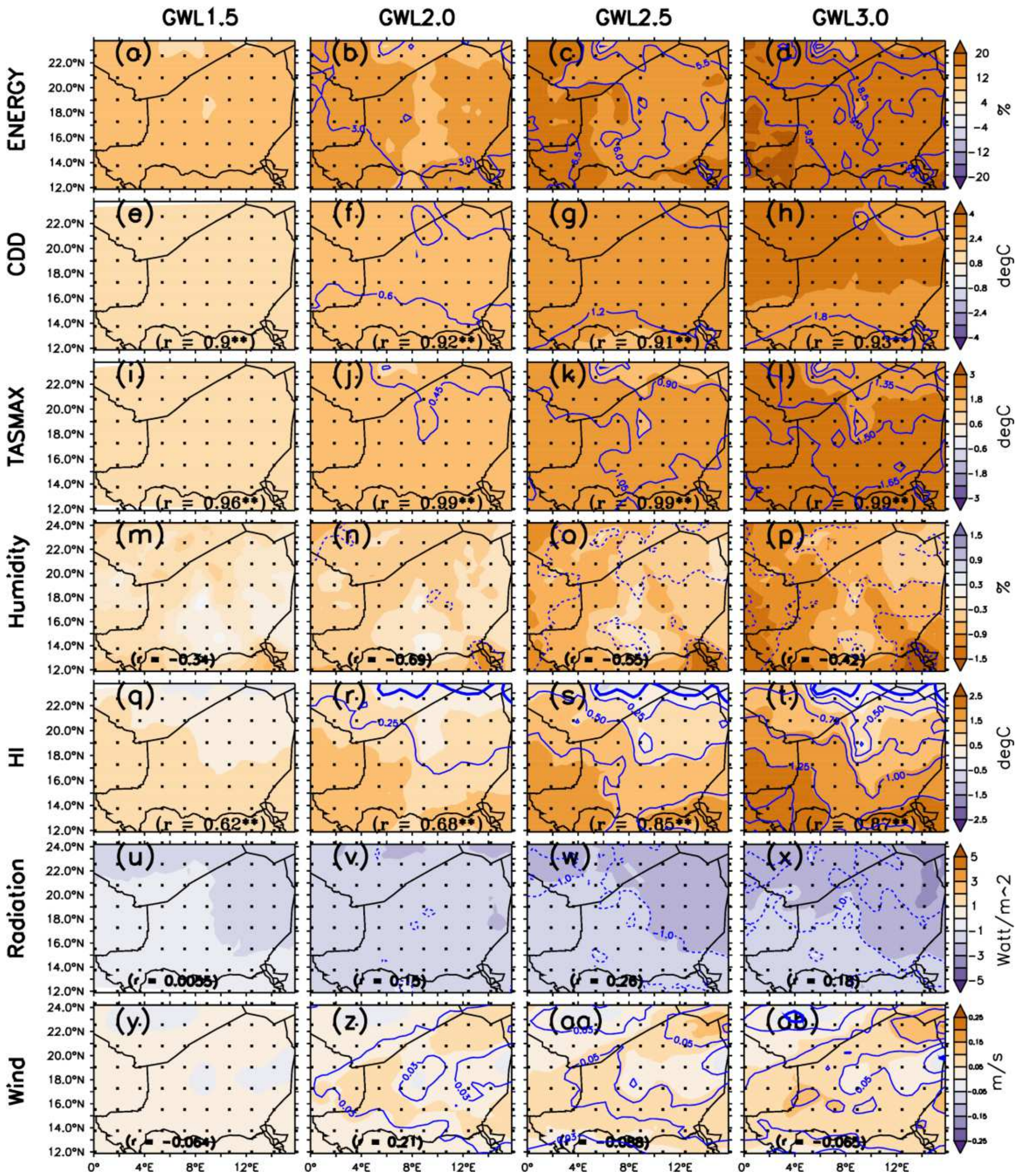


Figure 8: Projected changes in DED (panel: a-d), CDD (e-h), humidity (i-l), HI (m-p), DTR (q-t), Radiation (u-x), and wind (y-ab) at different global warming level (GWL1.5, GWL2.0, GWL2.5, and GWL3.0). The dots indicate where at least 85% of the simulations agree on the sign of the changes and the changes are statistically significant.

However, it is worth studying the impact of global warming on DED for individual months are considered. Figure 9 shows that the impact of climate change differs from one month to another. Positive values indicate an increase while negative values depict a decrease. Some variables such as DED, CDD, HI would have a net increase for all the months at all the GWLs. The highest increase in DED and CDD are observed during the hot period (March-June and October-November) where the lowest are in cold period (December-February and august). Hence, the impacts of global warming may be more severe in hot periods than the cold period. However, for the HI, the highest increase is rather observed in April-June whereas the lowest increase is in December-February. Conversely, for the variables such as humidity, radiation and wind, both positive and negative values can be observed depending on the months considered and the specific GWL. For example, the highest decrease in relative humidity is observed in May-July with the magnitude of decrease increasing with GWLs. But an increase is observed in September for all the GWLs and August for the GWL1.5 and GWL2.0. Regarding the radiation, a general decrease can be observed except in July where the changes are positive. However, in June, the projections show a decrease for GWL1.5 and GWL2.0 and a slightly increase for GWL2.5 and GWL3.0. Looking at the wind, projections show an increase for April-October and slightly decrease in November-February.

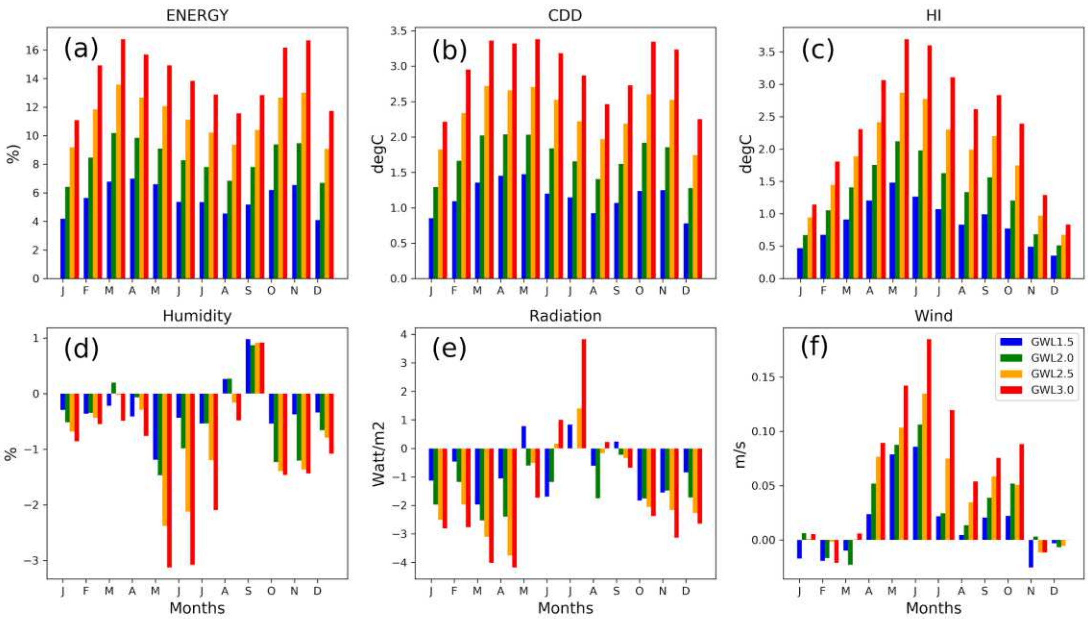


Figure 9: Projected changes in a-) DED, b-) CDD, c-) HI, d-) Humidity, e-) radiation, f-) Wind under different GWLs considering individual months.

The level of agreement among the models on the projection (a measure of robustness in the projected changes in the electricity demand over Niger), depends on the GWLs and the various variables (Figure 10). In general, agreement among simulations is better for the projections of Tmax, DED, CDD, and HI than RH, Radiation and Wind projections. For instance, almost all the simulations agree on the projections of the Tmax, DED, CDD, and HI for all the GWLs. This indicates that the projections of DED, CDD, and HI are robust at all the GWLs. The ensemble median of DED indicates an increase of about 5%, 7%, 12% and 15% for GWL1.5, GWL2.0, GWL2.5, and GWL3.0 respectively. The least agreement among the simulations is observed for the Radiation where the simulations do not agree on the projections of these variables for any of the GWLs. Nevertheless, the ensemble median of radiation indicates a decrease for this variable, with the magnitude of the decrease increasing with global warming level. However, for the humidity and wind, more than 75% of the simulations agree on the projections at GWL2.5 and GWL3.0. Hence, this indicates that changes in both wind and humidity are only robust for the warming level above 2°. It may also be noted that for all the variables, the spread among simulations increases with increasing global warming (Figure 10).

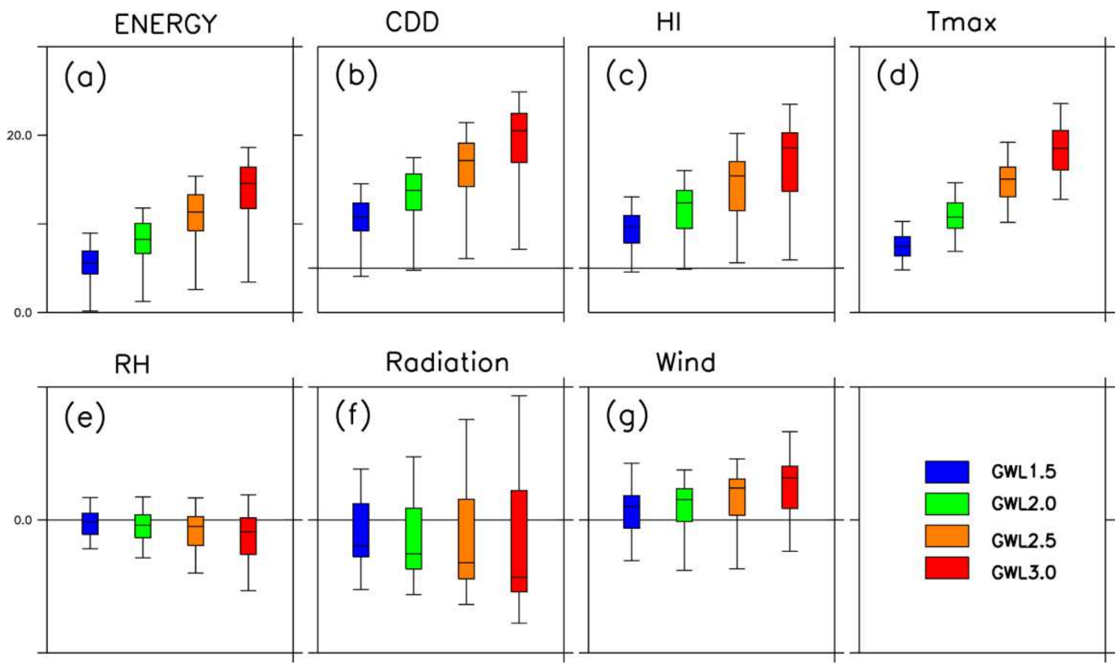


Figure 10: Projected changes in a-) DED, b-) CDD, c-) HI, d-) DTR, e-) RH, f-) Radiation, and g-) Wind at specific GWLs in Niamey.

## 4 Conclusion

As part of the efforts to understand and quantify the impact of climate change on key economic sectors, this study has investigated the potential impacts of gradually global warming on electricity demand in Niger. The Principal Component analysis (PCA) was utilized to group the key climate parameters that influence the electricity demand.

Then the Multiple Linear Regression (MLR) model has been developed to predict the electricity demand based on the PCA results. Moreover, for the projections, 14 multi-model regional climate simulations from the Coordinated Regional Climate Downscaling Experiment (CORDEX) at four specific Global Warming Levels (GWL1.5, GWL2.0, GWL2.5 and GWL3.0) have been analyzed. The results are summarized below:

- The principal component analysis (PCA) result revealed that the climates variables such as the air temperature, maximum and minimum temperature, relative humidity (RH), heat index (HI), cooling degree-days (CDD), radiation and wind are highly correlated with the detrended electricity demand.
- The stepwise regression results suggest that only the variables such CDD, humidity, heat index, radiation, wind and Tmax are statistically significant at 99% confidence level. The accuracy of the regression results shows high value of coefficient of determination $R^2$ (0.808) and a reasonable root mean square error (140.87MWh/day). Moreover, the residual plots indicated that the residuals from the regression model are normally distributed, suggesting that the model comply with the assumptions of regression models.
- The CORDEX simulations realistically reproduce the annual cycle of the DED and climate variables used in this study and in most cases; the observed annual cycle is within the RCMs ensemble spread. However, discrepancies do exist between the individual simulations.
- The CORDEX simulations project an increase in DED, Tmax, HI, CDD, and Wind and a decrease in humidity, and radiation at all GWLs. The highest increase in DED is projected in hot period (Mach-June) and October-November.
- The simulations agree on the projections of DED, HI, CDD at all GWLs. Conversely, there is no agreement among simulations for the radiation at any of the global warming levels. However, more than 75% of the simulations agree on the projections of wind and humidity at GWL2.5 and GWL3.0.

To provide more robust information for policymakers, the results of this study can be improved in different ways. First, besides the factors related to climate, other factors such as population, GDP, policy, consumer's behavior, urbanization and so on may also determine the future electricity demand. For instance, climate influences the electricity demand through the response of people to weather (Valor et al., 20 01). In other words, depending on the weather conditions, people will increase or decrease the demand. Secondly, the current study used aggregated electricity demand including the residential, commercial and industrial sectors since disaggregated data were not available. So, future may look on the impacts of the global warming on different sectors. Thirdly, conducting biases corrections on GCMs and RCMs simulations may further reduce the disagreement among the models for the projections of humidity, radiation, and wind. Such considerations will make the results more relevant for policy makers. Nevertheless, the present study has demonstrated the capability of the CORDEX models in reproducing the annual cycle of the climate variables used in this study and showed the impacts of climate change on electricity demand in Niamey at various global warming levels.

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