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Potential changes in cooling degree day under different global warming levels and shared socioeconomic pathways in West Africa

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Supplementary material for this article is available online

Abstract

Increasing levels of climatic warming are expected to affect the global development of energy consumption. The cooling degree day (CDD) is one of the climate-driven indices that captures the impact of climate on energy demand. However, little is known about the spatiotemporal trends of CDD in relation to a changing climate and economy in West Africa and its main implications. Hence, in order to analyze how energy demand could evolve, this study aims to assess the changes in CDD under 1.5, 2.0, 2.5, and 3.0 °C global warming levels (GWLs), with and without population exposure and trends under the two representative concentration pathways (RCPs) of RCP4.5 and RCP8.5 for West Africa. A climate-reflective base temperature (T-base) is used and was determined using a piecewise linear regression method. Seasonal electricity consumption was derived using a decomposition feature. An ensemble of seven Global Climate Models (GCMs) were used for the future temperature projections. The future population was based on shared socioeconomic pathway outputs. Based on the analysis, the reported average T-base for the West African region is 24 °C. An increasing CDD trend was identified in all of the RCP scenarios, but is more pronounced in RCP8.5. RCP8.5 departs from the mean historical period of approximately 20% by 2100 with the standardized value. The same trend is observed under different GWLs as the warming level increased and was most striking in the Sahelian zone. Population exposure to CDD (labelled CDDP) increases with warming levels, but is more pronounced in highly agglomerated areas. The CDDP index best captures the spatial representation of areas with high cooling demand potential with respect to the demographic distribution. This study can serve to inform better energy demand assessment scenarios and supply planning against the backdrop of changing climate conditions in West Africa.

1. Introduction

Africa as a continent is the least contributor to overall global energy related greenhouse gas emissions (∼2%), while African countries are expected to be the most exposed to climate change effect as reflected in the 2019 Africa Energy Outlook (International Energy Agency (IEA) 2019). Given this high exposure and the low adaptive capacities of many countries across the continent, knowledge about the potential impacts across sectors, is therefore crucial for reducing the continent's vulnerability and building resiliency (Intergovernmental Panel on Climate Change 2014). All sectors of development are impacted by climate change, including the energy sector. In particular, both energy supply and demand are subject to climate change due unprecedented change observed in various weather parameters (Schaeffer *et al* 2012, Cronin *et al* 2018).

The continent is endowed with enormous renewable energy potentials including solar, wind and hydropower, of which most are sources of energy known for their high variability as a result of their sensitivity to change in the average weather condition (Cronin *et al* 2018). Furthermore, climate change impact access to fossil fuel endowments, and knowledge of them (Schaeffer *et al* 2012). A large multi-ensemble of global climate models' assessment over Africa showed a continuous and significant increase in mean temperature by end of the century (Almazroui *et al* 2020). In addition, the study of Zhang and Ayyub (2020) demonstrated that increasing temperatures reduces the capacity and efficiency of power generation, transmission, and distribution. Considering that the latter infrastructure components are essential for power delivery, the risk of power outages is increased under climate change and could result in serious economic effect for the continent. Beyond the power sector, gas transmission systems can be affected by factors such as floods, landslides, other extreme meteorological events, and geological hazards such as earthquakes and rockslides (Schaeffer *et al* 2012).

Moreover, a warmer climate amplifies demand owing to the need for cooling. These changes can have profound economic implications by affecting consumers through increased expenditure on energy commodities, on companies via higher fuel consumption and emissions in terms of fossil fuel use as well as effects on overall decision making processes, priorities and conventional adaptation measures as exposed by (Vincent *et al* 2019). Therefore, to ensure a holistic view of climate impact on final energy use, in addition to climate uncertainty, socio-economic implications should not be overlooked but be incorporated as exposed in the global analysis of Zhang *et al* (2021).

Climatic proxies for energy use in the literature are based on observing changes in cooling degree days (CDDs) and heating degree days indices, as a strong correlation is found between electricity consumption and degree days (Dowling 2013, Ciscar and Dowling 2014, Nateghi and Mukherjee 2017, Levesque *et al* 2018, Park *et al* 2018, van Ruijven *et al* 2019, Berardi and Jafarpur 2020, Mastrucci *et al* 2020, Steinberg *et al* 2020). As cooling and heating demand generally move in opposite directions, the net increase or decrease in energy consumption largely depends on a region's demand dominance (Li 2018). In tropical regions, for instance, heating is not required (Waite *et al* 2017, Li 2018). Given that West African countries are in the tropics and exhibit no discernible heating signal, hot days will be the main climate driver of electricity demand; hence, the CDD metric was selected as a climate-driven demand proxy for this study.

Furthermore, the calculation of degree days requires the use of a base temperature that varies from one region to another. The base temperature is defined as 'the outside temperature above which the demand for cooling units is needed in buildings to maintain human comfort' (Elizbarashvili *et al* 2018, Mistry 2019).

Chen *et al* (2018) conducted an extensive review of the different methodologies applied to determine the base temperature in the literature. Three main cases were found: "'(a) choosing the temperature threshold arbitrarily; (b) referencing a previous study in the same or a neighboring region; and (c) extracting it from a preliminary electricity-temperature plot'". In general, most studies use reference temperatures of 18 °C or 22 °C (Panigrahi and Behera 2017, Shi *et al* 2018, Spinoni *et al* 2021, Abebe and Assefa 2022).

Huang and Gurney (2016) conducted a sensitivity study of balance-point temperature (base temperature) in the U.S. and showed that the use of a fixed value against a context-specific value, leads to the overestimation of changes in energy consumption in most states. Their conclusion, could apply for other study areas, too. Hence, the third option mentioned above through a preliminary electricity-temperature plot analysis is chosen for this study to derive a study-area specific base temperature.

The first step in this study was to determine climate-reflective (context-specific) base temperatures for the West African region by analyzing several countries' base temperatures in different climatic zones. This will help in obtaining a robust CDD estimate that considers the regional climate system and reduces bias. It represents an added value to knowledge that this study provides compared to other studies focusing on the region.

Although the study used a segmented approach as recently explored in the literature (Chen *et al* 2018, 2019, 2020) and (Huang and Gurney 2016), it went one step further by using the seasonal component of energy consumption to refine the base temperature determination.

Secondly, to our knowledge this is the first study in the context of West Africa to assess the impact of climate change on CDD using high-resolution climate and energy data in the quest of reducing as much as possible bias.

Conversely, socio-economic factors are reflected through population considerations in CDD. Shi *et al* (2018) showed that CDD projections, with and without taking population factors into account, feature largely different indicators. Given this important difference, a population weighted approach of degree days is explored as well. High-resolution population data based on shared socioeconomic pathways (SSPs) (Jones and O'Neill 2016) were used to assess population exposure to CDD. The SSPs were developed by the research community and are part of a new scenario framework for climate impact studies and support mainly the Sixth Assessment Report (AR6) of the Intergovernmental Panel on Climate Change's (IPCCs).

Lastly, changes in cooling energy demand reflected by CDD in response to global warming levels (GWLs) of 1.5, 2, 2.5, and 3 °C, with and without population factor, were investigated. High-resolution climate projection data were derived from NASA's Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) datasets under representative concentration pathways (RCPs) of 4.5 and 8.5. The NEX-GDDP has been shown to perform better in Africa (Abiodun *et al* 2020), in contrast to the widely used Coordinated Regional Climate Downscaling Experiment datasets in climate impact studies including those of (Stanzel *et al* 2018, Quenum *et al* 2019, Sawadogo *et al* 2020).

The remainder of this paper is structured as follows. Section 2 presents the base temperature analysis and population-weighted calculation approach, as well as the climate and energy data gathered and processed. Section 3 discusses and presents the results. Section 4 provides a summary of the findings. Supplementary materials and figures are also presented.

2. Methods and data

2.1. Study area and climatic zones

This study was conducted in West Africa. West Africa features three main climatic zones, namely: the Sahelian, Soudanian, and Guinean (figure 1). Given the differences in climate, people's reactions to the temperature in each zone differ.

The West African region is one the continent's largest in terms of population (fastest-growing regions with an average increase of 2.4% a year) and faces a considerable electricity access deficit (IRENA 2015). In contrast, West Africa will likely lead the rapid economic growth expected on the continent in the coming years. Five out of the ten fastest-growing economies in 2019 were in West Africa: Côte d'Ivoire (the highest GDP growth rate: 7.3%), Ghana (7%), Benin (6.4%), Senegal (6.3%), and Niger (6.3%) (World Bank 2020). In spite of this, West Africa and the continent as a whole is affected by climate variability and climate change. Africa's exposure rate to increasing temperature has been faster than the global average (IPCC 2021). This is likely to impact the human response to electricity consumption. This study also aims to investigate human exposure to increasing warming.

2.2. Methodology

The overall methodological framework is summarized in the flowchart presented in figure 2.

2.2.1. Climate data and GWLs

The climate data (daily maximum and minimum temperatures) for the study were derived from the high-resolution (0.25° × 0.25°) NEX-GDDPs dataset across the RCPs RCP4.5 and RCP8.5. The dataset comprises 42 climate projections from 21 general circulation model (GCMs) runs for the period from 2006 to 2100, which were calculated within the Coupled Model Inter-comparison Project Phase 5 (CMIP5), with a historical experiment for each model from 1950 to 2005 (Bridget *et al* 2015).

The bias-correction spatial disaggregation method was applied on the NEX-GDDP dataset to overcome some limitations seen in global GCMs results (Jain *et al* 2019, Xu *et al* 2019). Data from seven (7) downscaled GCMs were used in this study and are presented in table 1. To maximize the robustness of the analysis, the multi-model means (MMMs) approach widely adopted in the literature (Yaro and Hesselberg 2016, Quenum *et al* 2019, Sawadogo *et al* 2019) was employed, as it helped to better capture the spatial variability and uncertainty of observations than individual models Jain *et al* (2019), Gusain *et al* (2020).

Given the limited number of weather stations points over the study area, ECMWF atmospheric reanalysis ERA5 datasets were used as an alternative, particularly for climate impact studies (Foli *et al* 2021). Currently, ERA5 data is available from 1950 with a 0.25° × 0.25° resolution (Hersbach *et al* 2020). The ERA5 temperature data was accessed from (AWS Open Data 2022). The Pearson correlation coefficient, root mean squared error, and mean absolute percentage error are used to compare and assess GCM results against ERA5 reanalysis data as used in similar assessments in the literature (Yao *et al* 2012, Jain *et al* 2019, Kim *et al* 2020, Li *et al* 2020). A description of each of the metrics is provided in the supplementary file (table sup 1).

The climate model data were re-gridded to a regular latitude–longitude grid of 0.25° to match the observation dataset using bilinear interpolation. The GWL period was derived for each GCM in order to assess the impact of global warming on CDD. The GWL period is generally defined as a '30-year span in which the climatology of the global mean temperature was higher than that of the pre-industrial baseline period (1861–1890) by the targeted global warming value'(Nikulin *et al* 2018, Abiodun *et al* 2020). In the study, the targeted global warming values are 1.5, 2.0, 2.5, and 3.0 °C.

The warming period for each model was derived from (Abiodun *et al* 2020) and are presented in table 2. Given that all GWLs for each GCM were achieved under RCP8.5, and for comparability purposes, an impact analysis was conducted that considered this pathway.

The ensemble model mean per GWL was compared against the control period (CtrlPeriod) from 1971 to 2000 in order to avoid overlapping years with the GWL period.

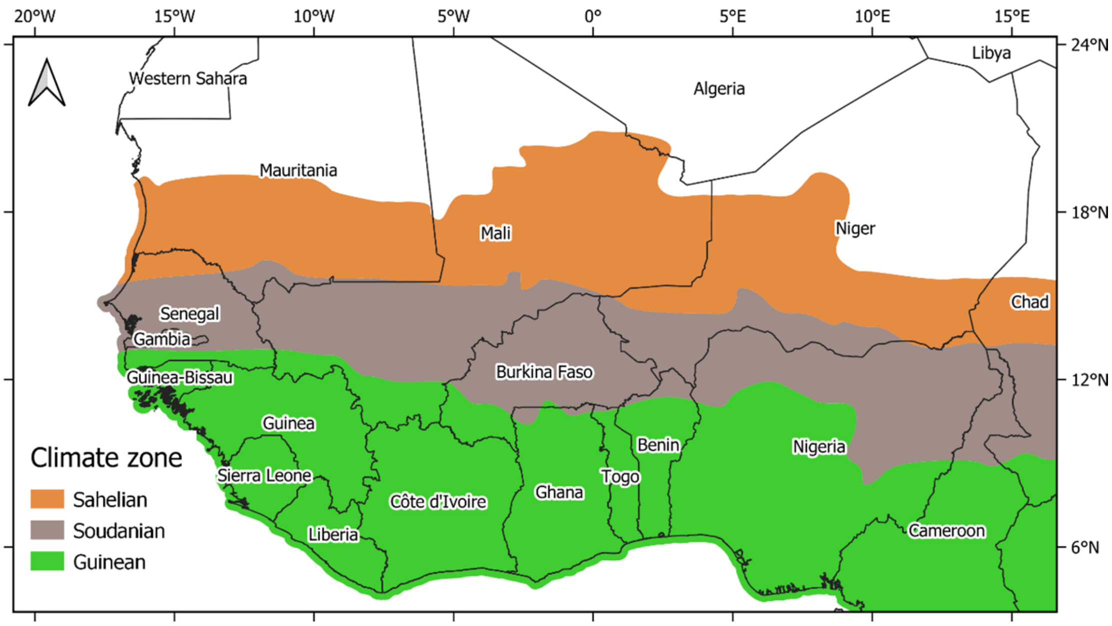

Figure 1. Climate zones in West Africa based on outputs of (ECOWAS Centre for Renewable Energy and Energy Efficiency 2017).

2.3. Electricity consumption data

Power consumption were obtained from local electricity utilities in the region with different temporal resolution. Table 3 provides a description of each dataset with their spatial and temporal resolution. The seasonal temperature and load profile of each country information is shown in figure 4.

2.4. Base temperature determination and degree day calculation

The degree day method is one of the most used methods for predicting seasonal energy consumption (Kalogirou *et al* 2014). The number of degree days was derived by computing the difference between the considered base temperature and the mean temperature for the different countries using ERA5 datasets, whereas only positive values are considered (Kalogirou *et al* 2014). The CDD was then calculated as follows:

$$\begin{gathered}\mathrm{CDD} = \sum_{i=1}^{n} (T_{\mathrm{mean}i} - T_{\mathrm{base}}), \\ (\text{for } T_{\mathrm{base}} > T_{\mathrm{mean}i}; \mathrm{CDD} = 0) \\ (\text{for } T_{\mathrm{base}} < T_{\mathrm{mean}i}; \mathrm{CDD} = (T_{\mathrm{mean}i} - T_{\mathrm{base}}))\end{gathered} \tag{1}$$

(*n:* number of days in one year, $T_{\mathrm{mean}i}$: mean temperature of day *i*, and T_{base}: base temperature, Shi *et al* 2018).

The base temperature for CDD is defined as the outside temperature below which the building does not require cooling (Elizbarashvili *et al* 2018). The most widely used method in determining Tbase are the energy signature and performance-line method (Krese *et al* 2012). For this analysis, the energy signature approach was used because it is more accurate than the performance lines as it requires high resolution electricity consumption data (Anjomshoaa and Salmanzadeh 2017). The base temperature is found by plotting the electricity consumption data versus the mean ambient temperature to identify some breakpoints.

Within this plot the intercept from which the seasonal electricity demand—due to the internal (e.g. occupants, lighting, equipment) and envelope (e.g. windows, doors, wall) gains, increases as temperature increases represents the base temperature (Krese *et al* 2012, Bhatnagar *et al* 2018). Hence, the Tbase is the breakpoint at which the lowest electricity consumption is achieved assuming that no cooling is needed (Chen *et al* 2018).

Notwithstanding that the base temperature can also vary spatially due to building characteristics, occupant profiles, and equipment usage (Huang and Gurney 2016), this study focusses on the temporal dimension of the base temperature.

To determine the region-specific base temperature capturing the climatic condition of the study area, a decomposition approach and piecewise linear modelling were used. The reason that drives this methodological approach through the decomposition procedure is on one hand to isolate the seasonal variability of the electricity consumption from the additional pattern in the overall consumption. Some of these factors includes economics and exhibiting different pattern and noise. Noise could also be linked to a sharp increase in demand for instance as a result of a public holiday inducing irregular pattern. Secondly, CDD is best to predict the seasonal consumption as mentioned above and demonstrated in the recent study of (Akara *et al* 2021), on the effects of weather on electricity consumption in West African cities.

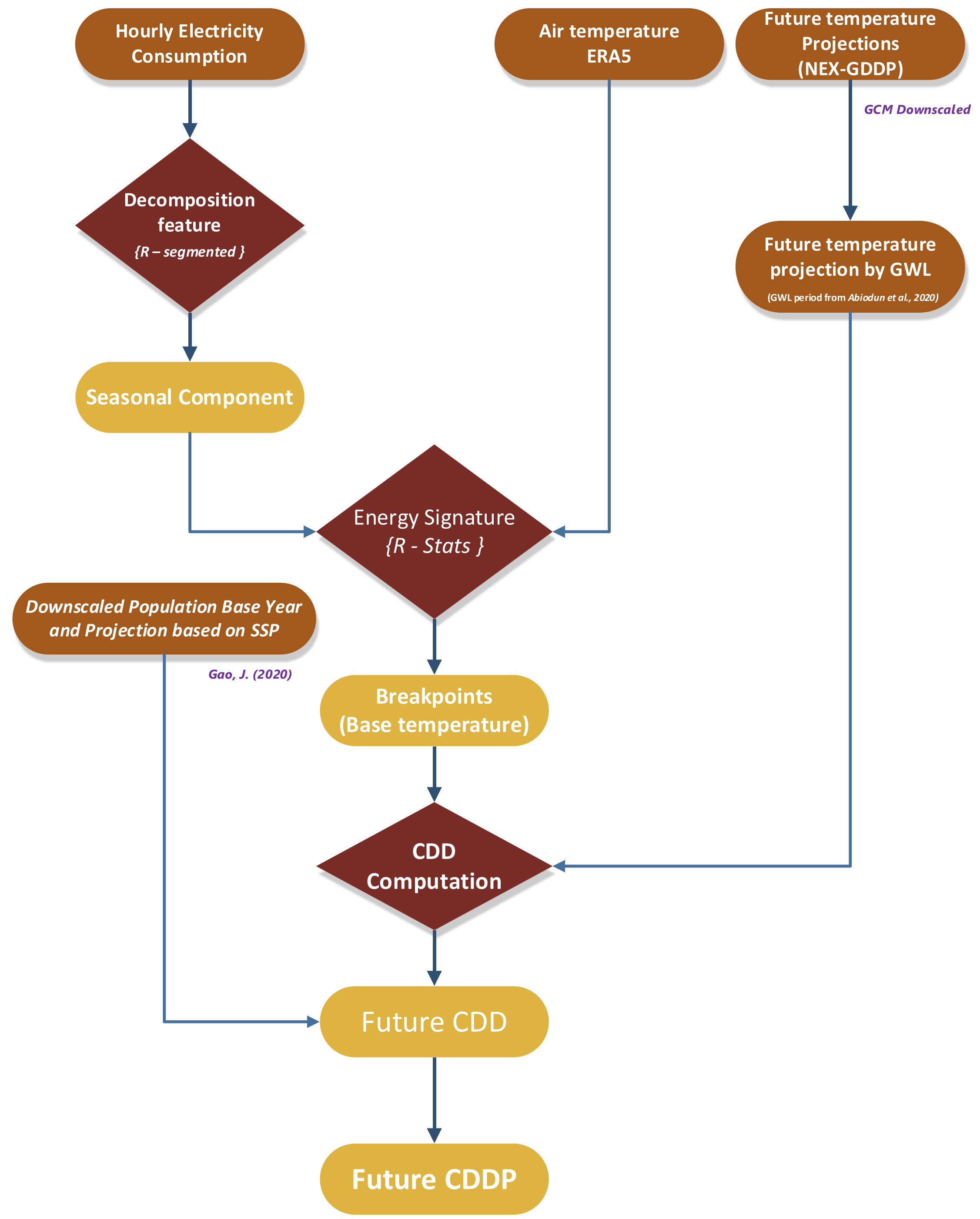

Figure 2. Methodology framework.

Therefore, to retrieve the seasonal component of the electricity consumption influenced by climatic factor and seasonality, a decomposition feature method was employed (Rosenhead *et al* 1963).

The classical seasonal decomposition by moving averages module in stats version 4.1.2 package in R (R Core Team 2019) was used to decompose the time series of electricity consumption into its seasonal, trend, and irregular components (illustrated in figure 3). The time series of electricity consumption are modelled as follows (Rosenhead *et al* 1963):

$$Y[t] = T[t] * S[t] * e[t] \tag{2}$$

where $T(t)$, $S(t)$, and $e(t)$ represent the trend, seasonal, and error components, respectively, and t each (hour/day). Each component of the time series are derived following the steps described in Meyer (2018). First, the trend component is determined by using a moving average and is removed from the time series $T(t)$. Second, the seasonal component $S(t)$ is derived by averaging each time unit over all periods and removed from the total electricity

Table 1. Climate models used for this analysis and downloaded from NASA NEX—Registry of Open Data on AWS.

Institution	Country	Model name	Resolution	Time horizon
Centre National de Recherches Meteorologiques, Centre Européen de Recherche et Formation Avancées en Calcul Scientifique	France	CNRM-CM5	22 km	1980–2100
Organization/Queensland Climate Change Centre of Excellence	Australia	CSIRO-Mk3.6.0	22 km	1980–2100
Institut Pierre-Simon Laplace	France	IPSL-CM5A-MR	22 km	1980–2100
Atmosphere and Ocean Research Institute	Japan	MIROC5	22 km	1980–2100
Max Planck Institute for Meteorology	Germany	MPI-ESM-LR	22 km	1980–2100
Norway Consumer Council	Norway	NorESM1-M	22 km	1980–2100
Geophysical Fluid Dynamics Laboratory	United States	GFDL-ESM2M	22 km	1980–2100

Table 2. General circulation model depicting global warming levels of 1.5, 2, 2.5, and 3 °C derived from Abiodun *et al* (2020). John Wiley & Sons. © 2019 Royal Meteorological Society.

			1.5		2		2.5		3	
NEX-GDDP models	Resolution	Experiment	Start	End	Start	End	Start	End	Start	End
CNRM-CM5	22 km	RCP8.5	2015	2044	2029	2058	2041	2070	2052	2081
CSIRO-Mk3-6-0	22 km	RCP8.5	2018	2047	2030	2059	2040	2069	2050	2079
IPSL-CM5A-MR	22 km	RCP8.5	2002	2031	2016	2045	2027	2056	2036	2065
MIROC5	22 km	RCP8.5	2019	2048	2034	2063	2047	2076	2058	2087
MPI-ESM-LR	22 km	RCP8.5	2004	2033	2021	2050	2034	2063	2046	2075
NorESM1-M	22 km	RCP8.5	2019	2048	2034	2063	2047	2076	2059	2088
GFDL-ESM2M	22 km	RCP8.5	2020	2049	2037	2069	2052	2081	2066	2095

Table 3. Description of the electricity consumption data.

Country	Spatial resolution	Temporal resolution		Source
Benin	Country aggregate	Hourly (2015–2020)	Daily aggregate of both country (2010–2020)	CEB is a bipartite utility established under the Benin-Togo Electricity Code responsible for power generation, transmission and development of electricity infrastructure for both countries (ECREEE and WorldBank 2019a, 2019f).
Togo	Country aggregate	Hourly (2015–2020)		
Senegal	Country aggregate	Hourly (2017–2020)		National Electricity Company of Senegal (SENELEC) owns approximately 50% of Senegal's installed capacity, with the remainder being generated independent Power Producers (IPPs). SENELEC has a monopoly on both the transmission and distribution of electricity (ECREEE and WorldBank 2019e).
Côte d'Ivoire	Country aggregate	Hourly (2017–2020)		Ivorian Electricity Company (CIE) in charge of electricity production, transmission and distribution of electricity throughout the country (ECREEE and WorldBank 2019c).
Niger	Region aggregates (Niamey, Tillabery, Dosso, Tahoua, Maradi and Zinder)	Hourly Load (2015–2020)		Nigerien Electricity Company (NIGELEC) is a public utility in charge of production (with others IPPs) and has complete monopoly over the transmission and distribution of electricity (ECREEE and WorldBank 2019d).
Burkina	Country aggregate	Hourly load (2018)		National Electricity Company of Burkina-Faso (SONABEL) responsible for electricity production, transmission, distribution, sales and imports (ECREEE and WorldBank 2019b). Data obtained from the author of (Sterl *et al* 2020).

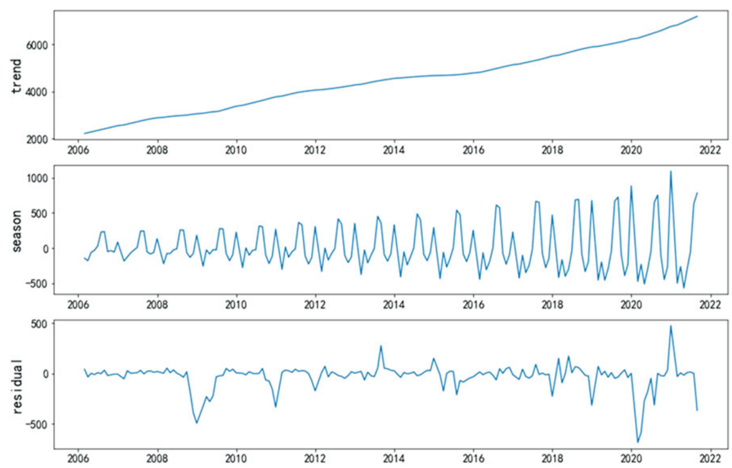

Figure 3. Example illustrating the trend, seasonal, and residual components of a monthly electricity consumption decomposed by seasonal-trend decomposition derived from Reproduced from Zhang and Rui (2021). CC BY 4.0.

consumption time series afterwards, too. The remaining part of the electricity consumption it the error component.

The seasonal component is plotted against temperature data. Breakpoints were suggested based on an estimate of regression models in segmented relationships detected in the linear predictor (seasonal electricity). For this analysis, the R package *segmented* was used, and the estimation approach is extensively discussed in (Muggeo 2003).

2.5. Population weighted approach using projections consistent with the SSP scenarios

The CDDP helps to capture the population exposure to CDD and assesses the impact of urbanization on. Population data were obtained from the global downscaled population base year and projection grids based on the SSPs, v1.01 (2000–2100) (Gao 2020). The dataset is spatially disaggregated at three level: global urban, rural, and total population. The population projections consist of ten-year intervals from 2010 to 2100 and 2000 representing the reference year with a resolution of 1 km, consistent with the SSPs narratives. Spatial interpolation was performed between decades to obtain a consistent annual development and subset was done over the study area. The population in 2000 was used as a reference for the control period from 1971 to 2000. The mean GWL population was computed with respect to the time spans listed in table 2.

The averaged values over 30 years of the population are multiplied by the averaged cooling degree-day values of MMM for each spatial cell to achieve CDDP (Chen and Sun 2020, Spinoni *et al* 2021) per GWL and by RCP pathways. Country-specific CDDP was obtained by masking the CDDP gridded data against country vector data (shapefile). The CDDP unit is labeled [W°Cday] which refers to a weighted degree day.

In this study, the population under the SSP5 scenario (growth-oriented world) is used given that all the different warming levels in all GCMs were achieved in RCP8.5 (table 2) and it is the SSP scenario where a radiative forcing of 8.5 W $m-2$ is projected by end of the 21st century (O'Neill *et al* 2016).

3. Results and discussion

3.1. Base temperature across the studied areas

Over the study area, daily data were collected for Benin, Togo, Côte d'Ivoire, Niger, and Senegal with different time frames. Figure 4 shows the seasonal trends in the temperature and load of the countries mentioned above. Benin, Togo, and Cote d'Ivoire are in the same climate zone, this explains why they display the same seasonal temperature profile, with two peaks in demand in March and December and the lowest record in August during the rainy season.

This shows the direct influence of weather conditions on consumer behavior. Over the Sahelian and Soudanian climate zones, the same observation can be made as Niger's and Burkina-Faso's temperature seasonal trends are the same with respect to peak and low periods of demand.

In contrast with the Guinean zone countries (Benin, Togo, Ivory Coast), the temperature is much higher, reaching a maximum country average of approximately 38.6 °C as we move up in latitude characteristics of the West African climate system. The temperature in Soudanian is warmer than that on the Guinea Coast and the warmest in the Sahelian (Ilori and Ajayi 2020). Peak loads were recorded during April and October and were lowest during August (figure 4).

However, in the case of Senegal, the average temperature and load profile were largely different because the internal sub-climate had a strong influence on the average temperature. Most of the

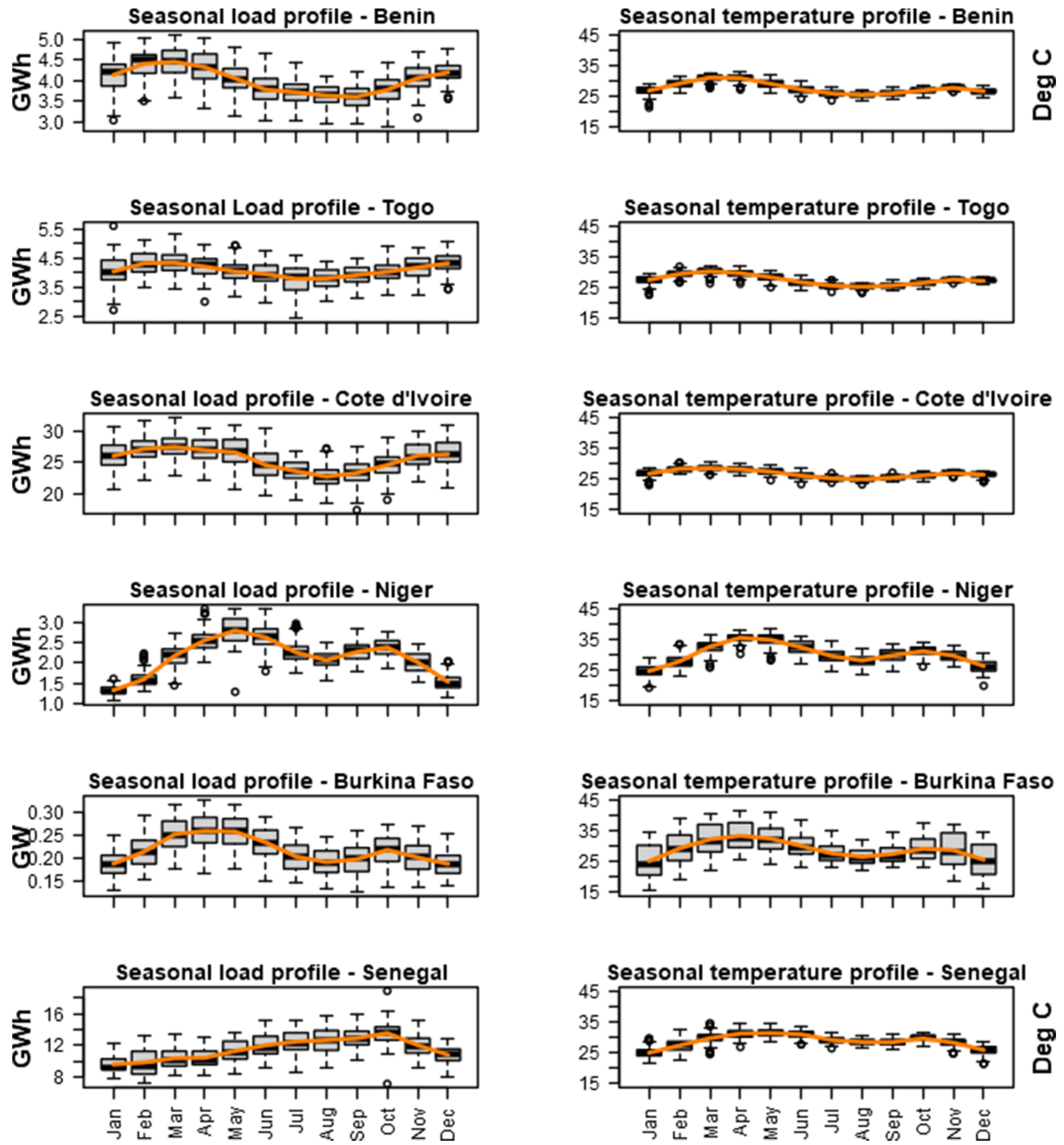

Figure 4. Seasonal load and temperature profile for Benin (2010–2020), Togo (2010–2020), Côte d'Ivoire (2017–2020), Niger (2015–2020), Burkina-Faso (2018) and Senegal (2017–2020). In brackets are the period of data used for the plot.

electricity demand in Senegal is consumed in large cities that border the west coast and have different climate systems compared to the rest of the country, which is influenced by the hot Sahelian climate, as shown in figure 5.

Seasonal temperature profiles of synoptic weather stations in big cities such as St Louis, Dakar, and Cap Skiring areas (Menne *et al* 2012) follow the country seasonal load profile and clearly indicate the influence and weight of big cities' climate and demand on the overall electricity consumption. This demonstrates the disparity between the average country temperature and load profile.

For each country, the temperature was plotted against the seasonal component of the load profile using the method described in the methodology section. Breakpoints were estimated to infer the base temperature using the R Segmented linear regression. It provides through an iteration process, an estimation of slopes and breakpoints along with standard errors that best fit the original dataset. Tbase breakpoint is selected based on one of the following two criteria. In the case that a 'V' shape is more or less captured by the model, Tbase represents the temperature at which the lowest electricity consumption is observed in accordance to Chen *et al* (2018). In the other cases, Tbase is located at the breakpoint where electricity starts increasing as temperature increases. The base temperature breakpoint for each country is illustrated in figures 6 and 7 (right plot with dotted vertical line) and summarized per climatic zone in table 4.

This is then used in the CDD computation (see figure 8).

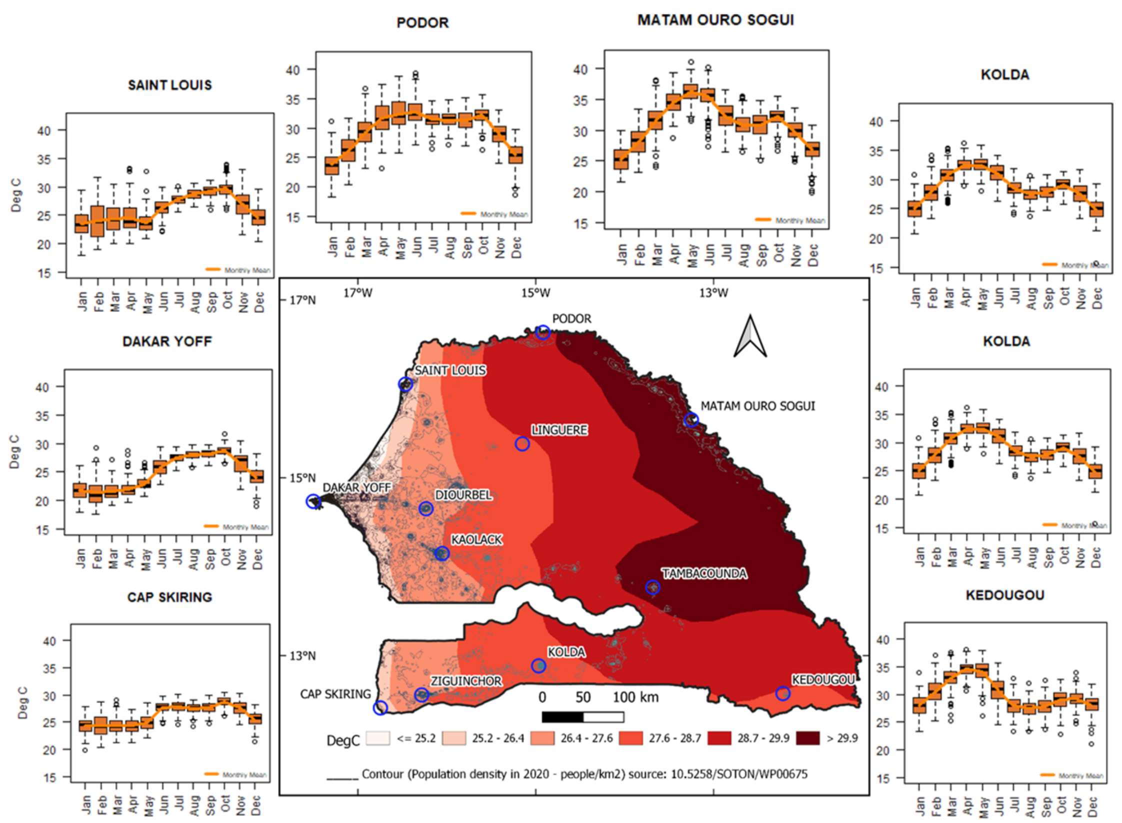

Figure 5. Seasonal trend of temperature per weather synoptic stations in Senegal, highlighted in red are temperature profile of big cities (Menne *et al* 2012), Senegal population density of 2020 derived from (WorldPop and CIESIN 2018).

Table 4. Base temperature per country and climatic zone.

Countries	Criteria	Tbase (°C)	Avg. Tbase (°C)	Climate zone
Niger (Niamey)	Breakpoint from which load increases with temperature	24.10	24.10	Sahelian
Burkina	''V'' shape and lowest electricity achieved	25.82	24.465	Sudanian
Senegal		23.11		
Côte d'Ivoire		23.68	24.37	Guinean
Benin-Togo		25.06		
Mean			24.35	

Note: Niamey region data used to represent the entire country of Niger; Benin-Togo represents bulk electricity consumption for both countries.

Segmented models output for each of the country analyses are provided in table sup 7 to show the slope, intercept and breakpoints found.

4. Model evaluation

Global climate models were evaluated by computing the CDD with Tbase = 24 °C, determined previously over the control historical period (1971–2000) in comparison with the observation data (using ERA5 temperature data). The good performance of the climate models in spatial and temporal scale allowed us to rely on them for future projections to measure the impact of climate change. The performance analysis of the climate models is presented in details in the supplementary results. The Soudanian zone displayed a relatively high Tbase compared with the Guinean and Sahelian zones. We decided to use an average temperature of 24 °C to represent the West-Africa Tbase to accommodate all the data constraints and for simplicity purpose.

As figure 8 shows, CDD is going to increase by an average anomaly factor of 20% in RCP8.5, and 10% in RCP4.5 by the end of the century as compared to the historical period. The climatological average over the historical period was approximately 1193.44 °Cday, it will reach around 2072 °Cday and 2932 °Cday by 2100 in RCP4.5 and RCP8.5, respectively. In all scenarios, the results show that CDD is likely to increase more than the historical period and more than double in RCP8.5.

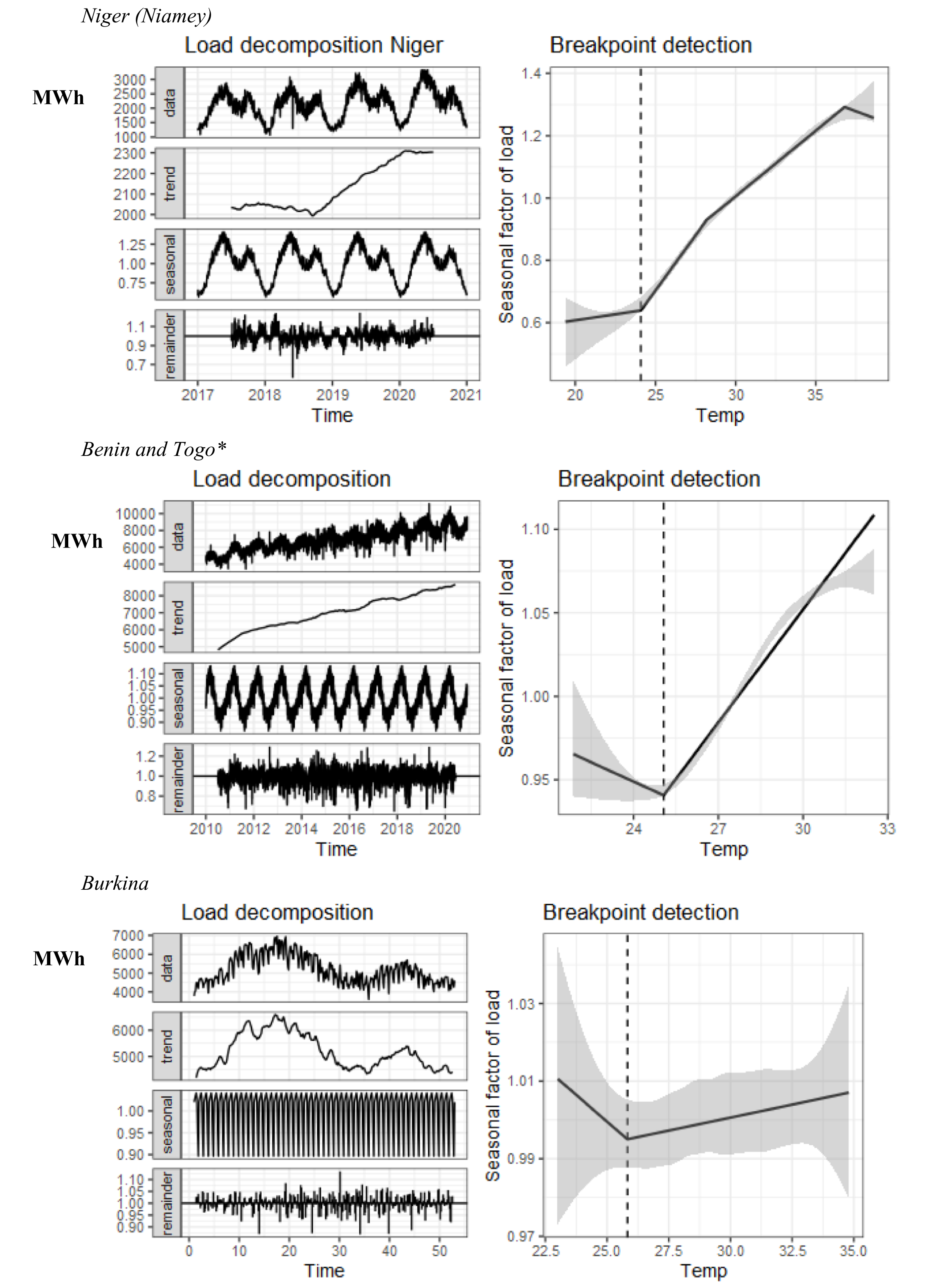

Figure 6. Load decomposition and breakpoints (red circles) per country, *Benin and Togo: combined daily electricity consumption data was obtained from 2010–2020, Burkina (2018 data), dotted line shows the base temperature breakpoint.

However, it is worth mentioning that, until 2038, the trend for both RCPs remained mostly identical or very much closer. After 2038, RCP8.5 started increasing faster than RCP4.5, which is a more stabilized scenario. The gap grew even larger from 2080 to 2100 (figure 8).

4.1. Changes of CDD under the four different warming thresholds

The changes in CDD under different GWLs were assessed using the RCP8.5 scenario. A study by Abiodun *et al* (2020) showed that for all models used in this study, all warming levels were

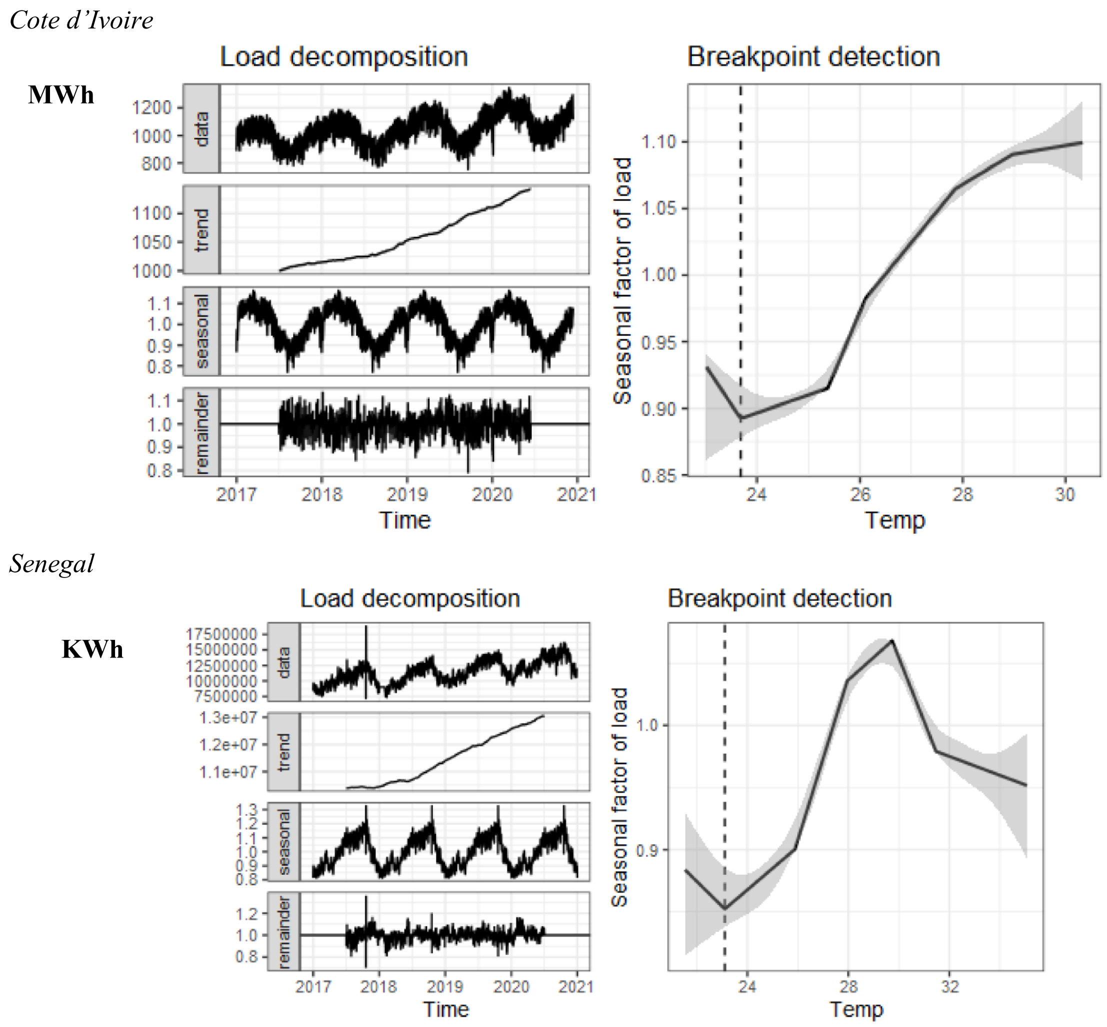

Figure 7. Load decomposition and breakpoints (dashed line) per country (Senegal and Côte d'Ivoire).

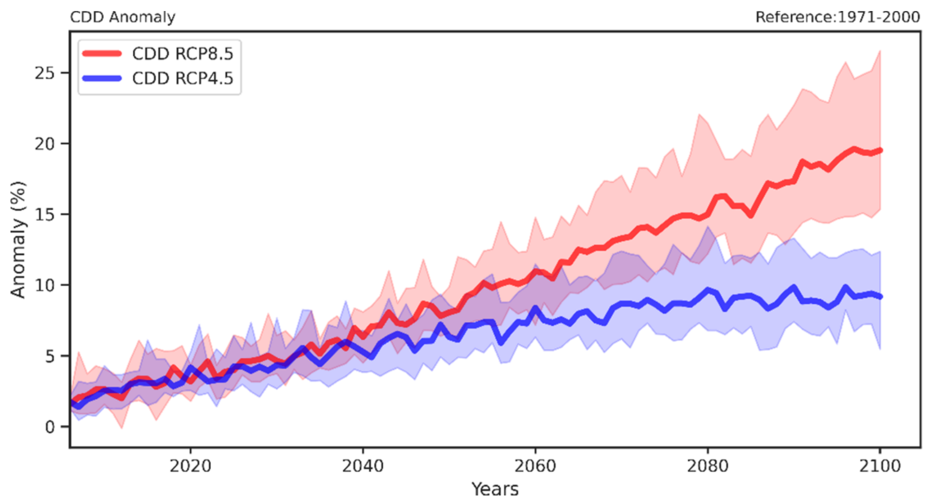

Figure 8. Future trend of CDD over West-Africa from 2006 to 2100, Anomaly = 100* [(Projection-observation)/standard deviation (observation)]. Observation is the average CDDs from 1971 to 2000. The shading indicates the range of simulations (maximum and minimum).

reached under RCP8.5 and this radiative forcing is suitable to explore the worst case scenario (Vuuren *et al* 2011). Figure 9 presents CDDs per GWLs (1.5, 2.0, 2.5 and 3.0 °C) and absolute changes using the Multi Model Ensemble (MME) mean.

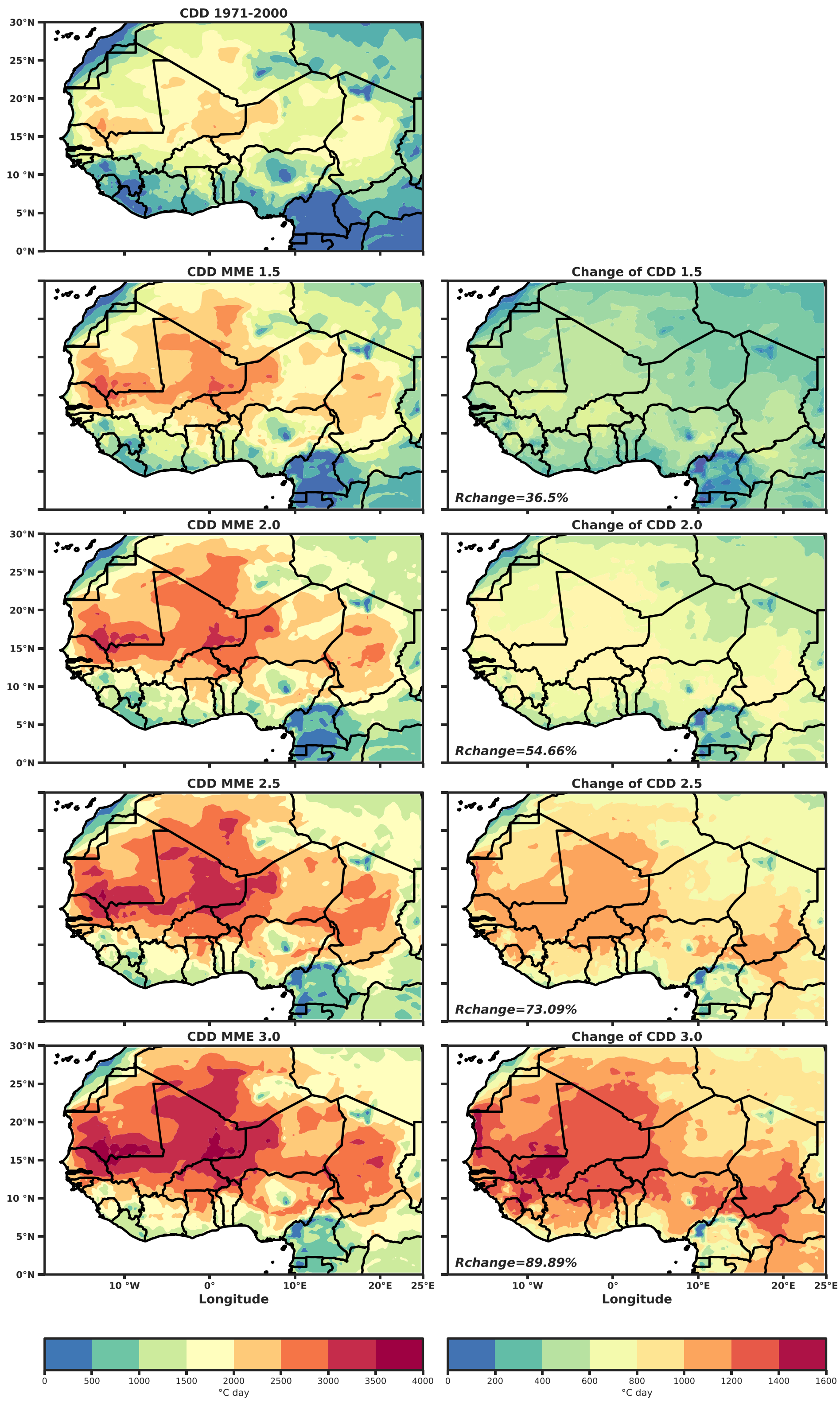

Figure 9. Cooling degree day per global warming levels and percentage changes.

The study area mean CDD is roughly 1193, 1629, 1845, 2065, 2266 °Cday, for 1.5, 2.0, 2.5 and 3.0 °C, respectively. As the warming levels increase, CDD increases in the order of 36%, 55%, 73% and 90% as compared to the historical levels (figure 9).

In addition, by climatic zone, it can be observed from figures 9 and figure sup 3, that the magnitude of change is much more pronounced in Sahel than that of other climatic zones and lowest in Guinean zone. While in all warming levels, the mean in the

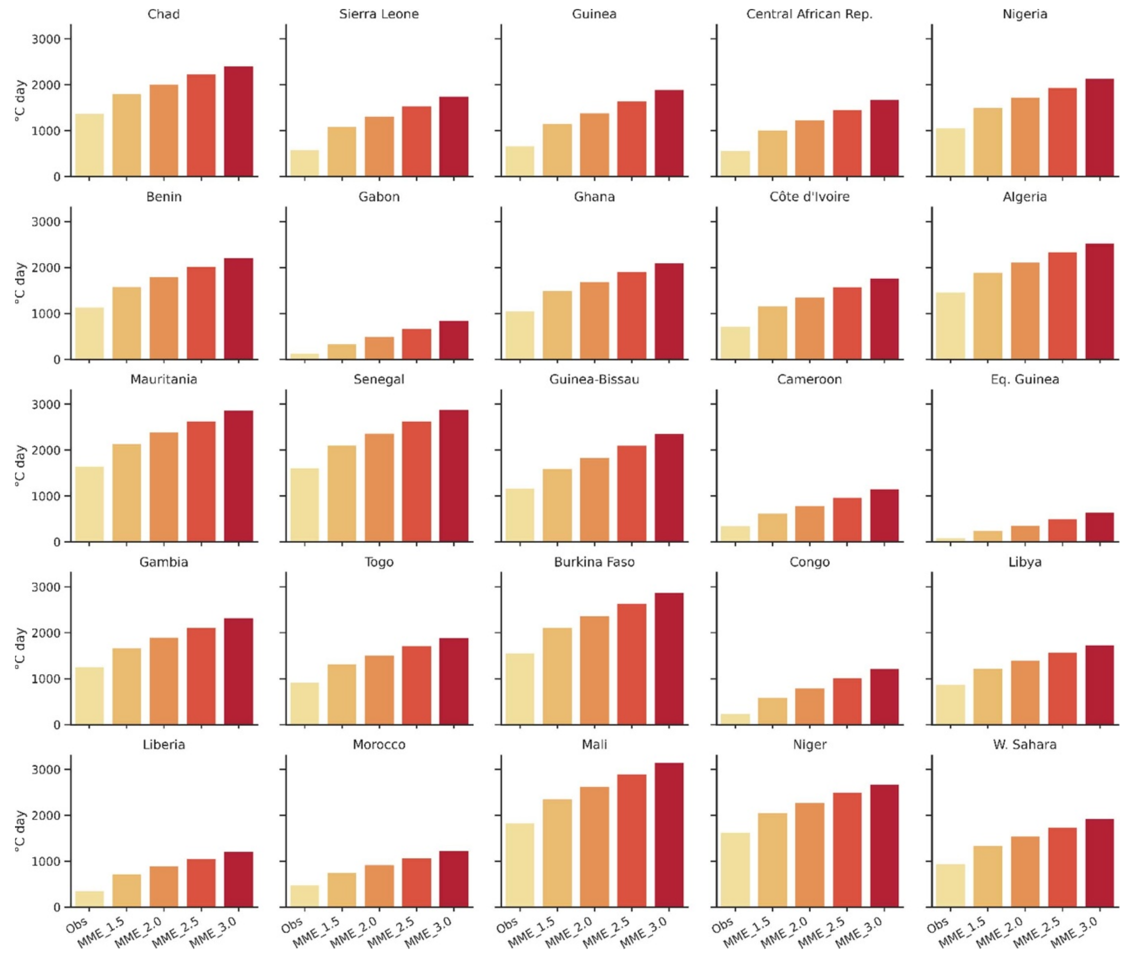

Figure 10. CDD by country and GWL (1.5, 2.0, 2.5 and 3.0 °C) under RCP8.5; MME: multi-model ensemble means. Obs: historical CDD.

Guinean zone is below the overall study area average (30% lower), in Soudanian and Sahelian zones, an increase of 130% and 170% respectively above the average is recorded (table sup 4).

Countries in the Sahel will have a higher CDD in the future; therefore, an increasing energy demand for cooling can be expected as warming increases (figure 9). Likewise, the projection of Parkes *et al* (2019) over Africa demonstrates an increasing intensity of heat stress events in Sahelian Africa as GWLs increase.

Furthermore, figure 10 sheds more light on this observation, where countries with the highest number of CDD such as Mali, Burkina Faso, Senegal, Mauritania, Niger, Algeria, and Chad, are located in the Sahel. Under GWL 3.0 °C for example it is recorded respectively, 3150, 2883, 2880, 2867, 2679, 2533, 2418 °C days (table sup 5). However, it is noteworthy that these countries are some of the largest in the continent in terms of land area and population resulting in high cumulative amounts at national level.

In all countries, CDD increases in all the warming levels and even more than 150% in some countries. In terms of changes compared with the historical period, countries such as Liberia, Cameroon, Sierra Leone, Central African Rep., Guinea and Morocco display the highest relative change. For instance, considering a GWL of 3.0 °C, Liberia CDD is projected to be 1215 °Cday, while it was 358 °Cday historically, representing a three times fold increase (table 5). This shows that those countries will be highly exposed to extreme temperatures compared to the past, and therefore, it is likely that the energy demand required for cooling will increase drastically in the projected climate trend. However, to account for human exposure to CDD, CDDP is required.

4.2. Impact of population weighting per country on changes of CDD

The population-weighted approach of CDD (CDDP) per country helps to measure the urbanization effect on CDD values. The distribution of CDDP across West Africa and per GWL was computed and is shown in figure 10. CDDP is more intense around big cities in West Africa, denoting a strong effect of concentrated areas compared to other areas (figures 11(b) and (c)). Under GWL 3.0 °C cities such as Cotonou (5% of Benin population in 2022), Bobo Dioulasso (5% of Burkina-Faso 2022), Kano (2% of Nigeria population 2022), Lagos (7% of Nigeria population

Table 5. Relative change of cooling degree day by country per GWL as compared with the historical period [%].

Country	MME 1.5	MME 2.0	MME 2.5	MME 3.0
Liberia	105%	151%	198%	240%
Cameroon	76%	122%	175%	226%
Sierra Leone	84%	122%	160%	195%
Central African Rep.	77%	114%	154%	191%
Guinea	72%	106%	144%	182%
Morocco	56%	90%	121%	154%
Cote D'Ivoire	62%	90%	119%	147%
Togo	44%	65%	86%	105%
Guinea-Bissau	36%	57%	80%	102%
Nigeria	42%	62%	82%	101%
Ghana	43%	62%	82%	100%
Libya	40%	59%	79%	98%
Benin	39%	58%	77%	94%
Burkina Faso	36%	52%	69%	85%
Gambia	33%	51%	68%	85%
Senegal	30%	46%	62%	78%
Chad	31%	46%	62%	75%
Mauritania	29%	45%	59%	73%
Algeria	29%	45%	60%	73%
Mali	28%	43%	58%	71%
Niger	26%	40%	53%	65%

Relative change = 100* [(Warming—observation)/observation].

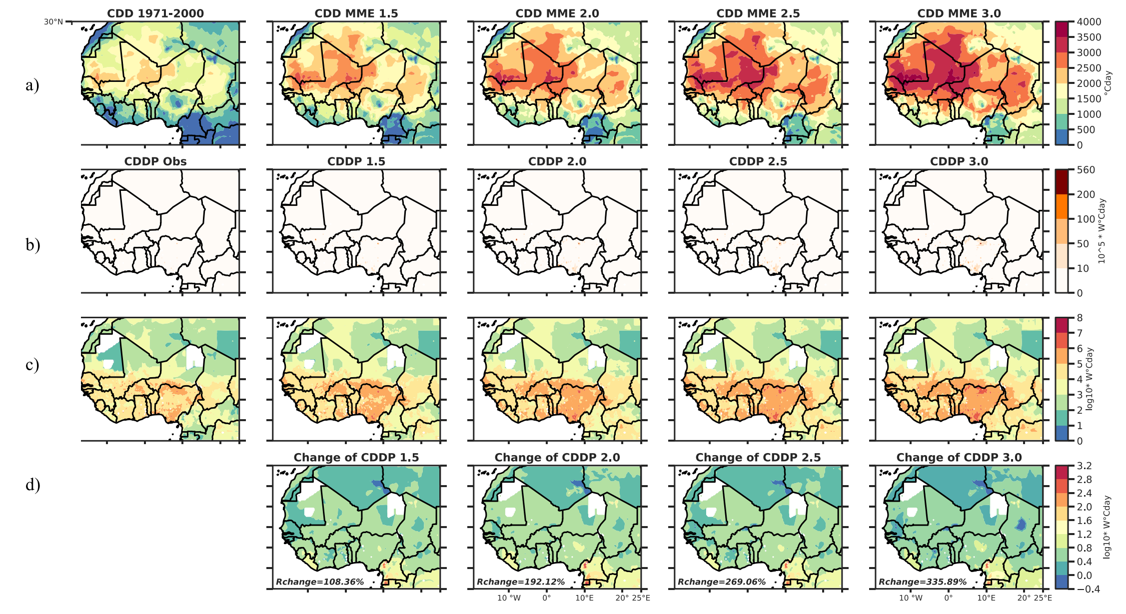

Figure 11. Spatial distribution of population weighted cooling degree days (CDDP) over West-Africa and by global warming levels (1.5, 2.0, 2.5, 3 °C), (a) observed CDD (1971–2000) and under different GWLs, (b) observed CDDP (1971–2000) and under different GWLs, (c) log. Transformation of (b), (d) change of CDDP under different GWLs (i.e. CDDP1.5-CDDP Obs), Rchange (relative change = [CDDP 1.5-CDDP Obs/CDDP Obs]), W°Cday (weighted degree day) MME: multi-model ensemble mean.

2022), and Dakar (19% of Senegal population 2022) (United Nations 2019). These cities can be perceived in figure 11(b). These areas are the hubs of higher electricity demand and contribute significantly to the overall national consumption.

Table 6 presents a descriptive statistic of CDDP computed over the study area domain and shows this strong disparity given the difference the large difference between the mean and the standard deviation (std).

Statistically, the regional CDDP std computed by warming levels are more than seven times greater than the average for all the warming levels (table 6). For instance, while the mean historical CDDP was 246 074 W°Cday, the std was approximately 182 003 W°Cday. There is a huge gap between big metropolises and the rest of the areas. Approximately 15% of grid points were above the CDDP mean representing the largest spots (85th percentile in table 6).

Table 6. Descriptive statistics of population weighted cooling degree days over the study area (0° N–30° N; 20° W–20° E).

	CDDP OBS	CDDP 1.5	CDDP 2.0	CDDP 2.5	CDDP 3.0
MEAN	2.5×10^4	5.1×10^4	7.2×10^4	9.1×10^4	1.1×10^5
STD	1.8×10^5	3.8×10^5	5.5×10^5	7.0×10^5	8.4×10^5
10%	6.2×10^1	1.4×10^2	1.7×10^2	1.9×10^2	2.1×10^2
75%	1.4×10^4	2.9×10^4	3.9×10^4	4.8×10^4	5.4×10^4
80%	2.3×10^4	4.7×10^4	6.3×10^4	7.8×10^4	8.9×10^4
95%	3.5×10^4	7.0×10^4	9.5×10^4	1.2×10^5	1.3×10^5
MAX	9.8×10^4	2.0×10^5	2.9×10^5	3.6×10^5	4.3×10^5

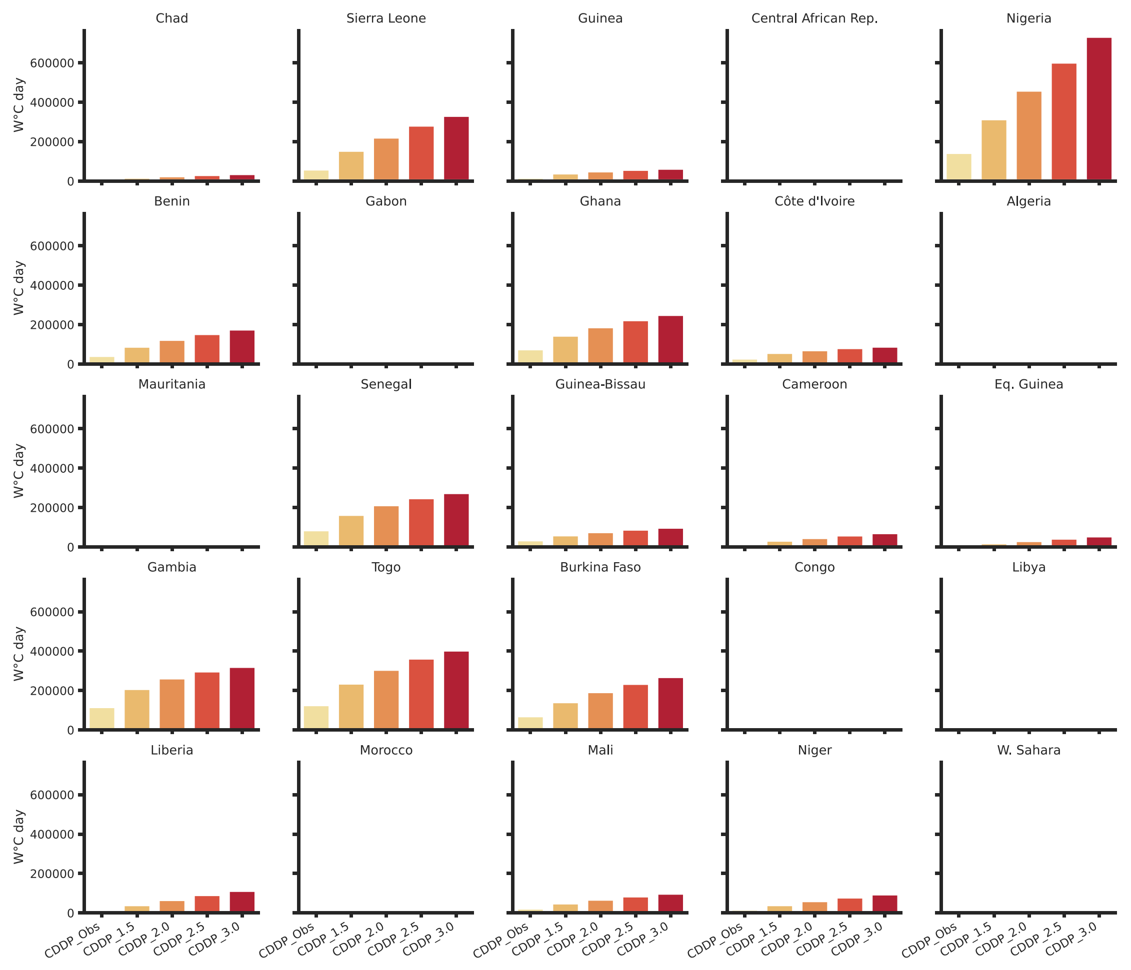

Figure 12. Population weighting of cooling degree-days per global warming levels under RCP8.5 and SSP5 population dataset. CDDP Obs: historical CDDP (1971–2000), W° Cday (weighted degree day).

Thus, strong disparities exist between some areas and other regions. To obtain a smoother plot, log transformations were applied to the CDDP to exclude extreme values. The CDDP was more pronounced in areas from 15° N downward (figure 11(c)). Population dynamics in this sub-region and increasingly warmer climate likely explain this distribution in figure 11(c), ranging from 1 to 8 Log10 W° Cday. Other areas are below 4 W° Cday, especially higher latitude (above 15° N) in the Maghreb—northern region of Africa. Moreover, as warming levels increase, CDDP increases with a relative change of 108%, 192%, 269%, and 335% respectively in 1.5, 2.0, 2.5 and 3.0 °C GWLs compared with the historical period. This change is greater in countries such as Liberia, Sierra Leone, Nigeria Niger and Equatorial Guinea (figure 11(d) and table sup 6).

Figure 12 presents CDDP per country and GWL. Countries such as Nigeria, Togo, The Gambia, Sierra Leone, Burkina Faso, Senegal, Ghana, Benin, and Mali are projected to accumulate high CDDP. Demand for cooling will likely be higher for these countries.

In summary, even though there is a strong influence of regional climate on CDDP, as seen in figure 9, the population adjusts this climate driven distribution. The result of the CDDP demonstrates that it captures better areas known for high consumption in the study area. Therefore, it can be used to complement other factors to improve energy demand estimate, which a topic for future research.

In accordance to recent studies (Shi *et al* 2018, Spinoni *et al* 2021), CDD projections with and without considering population differs spatially as well as quantitatively. The spatial distribution of CDD weighted with population is much more pronounced in agglomerated areas with high population density. Therefore, the energy systems will face an additional demand for cooling needs as populations increase and as the urbanization trend continue to rise with increasing warming (Parkes *et al* 2019). The results show that Nigeria has a larger CDDP and will likely lead to greater future demand in the region especially in big cities. This observation is aligned with the studies of Parkes *et al* (2019) and Deroubaix *et al* (2021), where largest increase in CDD will occur in densely populated regions, particularly in a country like Nigeria.

5. Conclusion

This study aimed to reduce the uncertainty in the estimation of CDDs in West Africa. By providing an estimation of a context-specific Tbase, using high-resolution bias-corrected climate model outputs and electricity consumption data in various climate zones. And explored the changeover different RCP scenario and GWLs.

Given, the different climatic zone in West-Africa one would expect large difference in the base temperature per zone. But the results indicated close value to 24 °C which is therefore considered for the entire study area for the analysis.

The projected future increase in CDD exceeds in all scenarios at least +120 °Cday (while +140 °Cday in RCP8.5) annually as compared to past period mean. The results obtained are in line with the study of Deroubaix *et al* (2021) who are taking a Tbase of 22 °C showing a projected future increase exceeding +300 CDD in large parts of the tropics, and exceeding +400 CDD in Amazonia, including the Sahel, as in Spinoni *et al* (2021).

The CDD increases with increasing warming levels with a growth rate of about 36%, 55%, 73% and 90% in 1.5, 2.0, 2.5 and 3.0 °C GWL respectively compared to the historical CDDs. The projected future increase in cooling exceeds on average +435 °Cday over all GWLs, and much more pronounced in the Sahel followed by the Soudanian zone. Countries such as Mali, Mauritania, Burkina Faso, Senegal, and Niger had the highest CDDs. This observation follows the historical trend studied in Biardeau *et al* (2020) where the highest CDDs globally are found in Northern Africa along the Sahelian zone. Hence the Sahelian zone will likely experience a high demand for cooling needs, given climate projections. Guinean zonal mean is lower compared with other climatic zones and as well as below the study area mean.

The spatial distribution of CDDP is largely different from CDD (see figures 9 and 12). Although the CDD shows the areas with a high accumulation of degree days (based on surface temperature distribution), the CDDP filters out spot areas that would likely exhibit a high demand induced by population distribution and exposure to a number of degree days.

As a result, the color distribution of the CDDP plot is scattered and accentuated in only a few areas. A larger CDDP was observed in densely populated areas and spots of high electricity consumption. Hence, CDDP can allow to identify areas that are likely to exhibit a high demand for cooling in the future. CDDP would be a great input for assessing the climate-economy impact of demand and its spatial distribution.

Therefore, future demand assessments should consider this index in addition to other factors.

6. Limitations and perspectives

The paper identifies areas that are expected to see the greatest increase in energy demand for cooling under different GWL. This information is crucial for energy supply planner as this will help in determining best the spatial distribution and operation of production units to minimize losses to supply areas of high consumption.

Another important factor that could add a duplicative effect to expansion needs for energy infrastructure is the increasing rate of access to electricity in the region, which might drive access to cooling devices, thereby leading to a higher demand. This is also highlighted in the discussion of the study of Biardeau *et al* (2020), referring to Bangladesh, where electricity access now reaches 80%, up from 20% in 2000. Moreover, recent projections of air conditioning showed southern and western African countries will achieve significant penetration by 2050 (Davis *et al* 2021, Falchetta and Mistry 2021). Several countries in West Africa such as Sierra Leone, Ghana and Nigeria will depict several-fold increases in air conditioning according to recent study projections (Davis *et al* 2021). Whereby for Sierra Leone is projected to develop from near 0% to 10% in 2050 (Davis *et al* 2021).

Furthermore, income is found to have a large impact on adoption of air condition units (Davis *et al* 2021, Falchetta and Mistry 2021). Therefore, considering a combined effect of a warming climate and West Africa region regaining its pre-covid economic growth as mentioned in the introduction, it can result in a considerable increase in cooling demand in the upcoming years. Besides, differences in income levels are a source of inequality and affects adaptive capacity to warming for low-income households and can result in negative implication on physical and mental health, and productivity (Andrijevic *et al* 2021, Davis *et al* 2021, Mastrucci *et al* 2022).

This aspect has started to be discussed and appear in recent literature on implications for cooling demand (Andrijevic *et al* 2021, Davis *et al* 2021, Falchetta and Mistry 2021, Pavanello *et al* 2021, Mastrucci *et al* 2022).

It is worth mentioning others factors that bias CDD as a cooling potential measure such as, cross-country variation of household sizes and building construction type that are ignored in degree day used in the study as indicated (Li *et al* 2019, Biardeau *et al* 2020, Andrijevic *et al* 2021) and can be furthered in future research.

Combining the above factors including electrification, technological factors, market penetration of cooling devices and economic dynamics with CDDP will likely provide a much more correct estimate of cooling demands. Even as recent studies (Falchetta and Mistry 2021, Mastrucci *et al* 2022) have attempted to address this gap by combining several factors including socio-economic with satellite data to model spatially explicit estimates of potential cooling demand, this is still an open research area that needs to be further explored.

The analysis assumes seasonal component of the electricity consumption is driven by only temperature although it follows the same temperature pattern. Notwithstanding some others cyclical effects (non-climatic) that this seasonal variation can embody but not discussed in this study and future research can explored. Limited years of electricity consumption data were obtained from some utilities and this could potentially affect energy signature output strength.

The study did consider having two countries per climate zone to palliate to this lack of data. In addition, the study considers consistent data of Niamey region to represent the entire country (Niger). The above challenge showed the need of collecting high-temporal resolution data to improve accuracy. Nevertheless, this study provides the basis for future study with an estimate of Tbase for West Africa which can supports climate related impact topics on energy demand in the study area.

The degree-day projections in this study are based on downscaled GCMs datasets from the CMIP5 experiment while CMIP6 has now been released. In CMIP6 the main set of future climate projections is based on the SSP-RCP framework (van Vuuren *et al* 2012), defined and coordinated by the Scenario Model Intercomparison Project (ScenarioMIP) (Tebaldi *et al* 2021). This allows for further research by having one dataset that includes both climate and economic pathways in which internal climate features have been improved.

Data availability statement

All climate datasets were directly obtained from the Registry of Open Data on Amazon Web Services and processed using Amazon Elastic Compute Cloud (Amazon EC2). Bias-corrected climate projection datasets are available at https://registry.opendata.aws/nasanex/ and subset for this study area available at 10.5281/zenodo.7562110. ECMWF ERA5 reanalysis was accessed from https://registry.opendata.aws/ecmwf-era5. Senegal cities temperature data were derived from the Daily Global Historical Climatology Network version of 3.29 (Menne *et al* 2012). It can be assessed from NOAA National Climatic Data Center with the following link http://doi.org/10.7289/V5D21VHZ.

Code availability

All the code used for the analysis and outputs in the manuscript is available at https://github.com/ODOU/Cooling-Degree-Day-in-West-Africa.

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