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1 **Recent trends in urban electricity consumption for cooling**
2 **in West and Central African countries**

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12 **Abstract**

13 In the present work, we estimate the factors that explains the day-to-day and long-term variability of the per-capita
14 electricity consumption in twelve cities of West and Central Africa, especially its sensitivity to weather. Whatever
15 the local climate, temperature is an important driver, explaining from 25% to 70% of variability. The percentage
16 contribution of temperature to the annual consumption is often greater than 20%. Air humidity is another important
17 factor, especially in Sahelian cities where its seasonality is large. It explains up to 6.8 % of day-to-day consumption
18 variability in Dakar. The thermal sensitivity is significantly lower than that in OECD countries but when normalized
19 by the base consumption, it is similar. Each additional degree of temperature produces a 3-4% increase of the base
20 consumption in Mindelo and Dakar, 6-10% in most Sahelian and tropical cities. The percentage consumption
21 increase induced by a 10 percentage points increase in air humidity can be also significant: in Sahelian and in some
22 tropical cities, it ranges from 30 to 90% of the percentage consumption increase per degree of temperature rise.
23 For most cities finally, the base consumption and the normalized weather sensitivities are significantly increasing
24 over time, making the electricity demand behavior highly non-stationary.

25

26

27 **Keywords:** Africa, electricity load, weather sensitivity, energy consumption, temperature, humidity, trends

28

29 1 Introduction

30 To achieve efficient planning and management of electricity systems, utilities require accurate forecasts and
31 projections of the electricity consumption and of its weather sensitive part (e.g.[1,2]). This issue becomes more and
32 more challenging worldwide as the sensitivity of electricity systems to weather conditions is increasing rapidly [3].
33 This increasing sensitivity is explained by the massive development worldwide of renewable energy production
34 (hydro, solar, wind) and by an increasing energy demand for cooling as a result of climate warming. [4–6]. The
35 increasing share of electricity consumption for cooling is expected to be exacerbated in large cities where
36 temperature increase is expected to be larger as a result of the urban heat island effects (urbanized areas
37 experiencing significantly higher temperature than surrounding rural areas; e.g. [7]).

38 According to Waite et al. [8], heating, ventilation and air conditioning already accounts for 35% of total primary
39 energy in the United States, and are expected to reach similar proportions in other regions worldwide in the next
40 years. The future evolution of the consumption and its drivers is also of concern in emerging countries, mostly
41 located in regions with tropical to subtropical climates such as those in South Asia and Sub-Saharan Africa. In
42 these regions, population and economic growths, urbanization and increasing level of life increase the need for
43 more energy-intensive services and technologies (e.g., food processing and storage, lighting and thermal comfort).
44 Boosted by the heat island effect and poor building isolation, mega-cities in emerging countries are already seeing
45 their electricity consumption going up during hot and humid conditions that they experience at certain seasons or
46 almost year-round. Such conditions are expected to become more frequent and intense in future climate [9,10].

47 A number of studies have been conducted worldwide in the past decades to characterize and model the relationship
48 between electricity consumption and weather conditions at the country, city, block or even building scale [8,11–16].
49 If the consumption first depends on different economic, social and demographic factors such as population, local
50 Gross Domestic Product (GDP), energy prices, or local manufacturing levels, it also depends on weather.
51 Temperature is by far the main driver of the weather-sensitive part of the consumption, for heating in cold weather
52 and for ventilation and cooling in hot conditions [17]. The temperature-consumption relationship is non-linear as
53 consumption for cooling (resp. heating) only exists when the air temperature is above (resp. below) a given high
54 (resp. low) “comfort” temperature threshold. These thresholds vary depending on the considered system or region;

55 they roughly range from 12 to 16°C for heating and from 18 to 24°C for cooling (e.g. [8,18–20]). To account for
56 this non-linearity, the consumption for heating (resp. cooling) is typically estimated from Heating Degree Days
57 (HDDs) (resp. Cooling Degree Days (CDDs)), obtained from the deviation of the air temperature below (resp.
58 above) the considered comfort threshold. Consumption may also depend on other weather variables such as air
59 humidity, solar radiation, brightness, cloudiness, or wind speed. However, most were found to explain less the
60 variations in consumption than the temperature variable, which limited their integration in prediction schemes. One
61 exception is the air humidity that is known, together with air temperature, to be an important driver of human comfort
62 or discomfort conditions [10,21], and thus to have a significant, although moderate, influence on electricity
63 consumption. As such, humidity, either relative or specific, has been used as an additional explanatory variable of
64 the electricity consumption (e.g. [15,22,23]). Similar to temperature, the effect of humidity on consumption is
65 sometimes assumed to start above a given temperature [15] or humidity [22,23] threshold.

66 The weather sensitivity of the electricity consumption remains poorly characterized in many regions across the
67 globe, especially in emerging countries. This work aims to fill this gap and explore the weather sensitivity of the
68 daily electricity consumption for a set of large cities located in West and Central Africa. More especially, it seeks to:
69 1) characterize the climatic and non-climatic factors that determine the day-to-day variations of electricity
70 consumption in those cities; 2) estimate the sensitivity of the per-capita consumption to air temperature, air humidity
71 and wind speed and their evolution with time; 3) estimate the fraction of the consumption that can be explained by
72 the weather and 4) explore how these features compare across cities and vary within the various climate contexts
73 across the region. To normalize the comparison between locations, we will consider the percentage increase in the
74 consumption per degree of temperature rise (DTR) and introduce the humidity-to-temperature sensitivity ratio.

75 The paper is organized as follows. Section 2 describes the modelling framework used for the analysis. The cities
76 and the data used in this study are presented in Section 3. Results are described in Section 4 and discussed in
77 Section 5. The conclusion is given in Section 6.

78 2 Analytical framework

79 To characterize the different factors of variability of the consumption and especially its weather sensitivity, we
80 consider a non-stationary adaptation of the change point regression model described in Refs [8,14,15]. With this
81 modeling framework, the predictions of daily electricity consumption per-capita are based on both climatic and non-
82 climatic predictors, and structurally accounts for long-term drift in their influence on the consumption. Since the
83 electricity consumption of West and Central African cities do not show any discernible heating signal, the
84 dependence to temperature is here only accounted for via the CDDs. The model could however easily include
85 HDDs in configurations where electricity is also used for heating purposes.

86 2.1 Model of per-capita electricity consumption

87 The model for the per-capita consumption for day t , $C(t)$, reads as follows:

$$88 \quad C(t) = C_0(t) + \sum_{i=0}^6 \gamma_i \cdot Y_i(t) + \sum_{n=1}^N \beta_n(t) \cdot X_n(t) + \varepsilon(t), \quad (1)$$

89 where $C_0(t) + \sum_{i=0}^6 \gamma_i \cdot Y_i(t)$ is the component of the electricity consumption that is non-sensitive to the weather
90 conditions; $\sum_{n=1}^N \beta_n(t) \cdot X_n(t)$ is the sensitive-to-weather component, and $\varepsilon(t)$ an error term.

91 Regarding the non-sensitive component, $C_0(t)$ is the base per-capita consumption for a (not holiday) Monday
92 [W/capita]. The term $\sum_{i=0}^6 \gamma_i \cdot Y_i(t)$ is used to estimate the base per-capita consumption for the other days from
93 the Monday's consumption. $Y_i(t)$ is a binary variable defined for $i = 0, \dots, 6$ with $Y_i(t) = 1$ if the current day t
94 corresponds to the i^{th} type-of-day and $Y_i(t) = 0$ otherwise; $i = 0$ for "Mondays", 1 for "Tuesdays", 2 for "Wednesdays",
95 ... and 6 for the non-working days (i.e., Sundays, religious and public holidays). The coefficients γ_i are the type-of-
96 day dependent factors [W/capita]; they determine the base per-capita consumption for days other than Mondays
97 (e.g. the base per-capita consumption is $(C_0 + \gamma_1)$ for Tuesdays, $(C_0 + \gamma_6)$ for non-working days, etc...). Note that
98 since C_0 is the base per capita consumption for Mondays, γ_0 is always equal to 0 (i.e., the sum in equation 1 could
99 start at $i=1$).

100 Regarding the sensitive-to-weather component, N is the number of weather predictors and $X_n(t)$ is the value of
101 the n^{th} weather predictor for day t . The coefficients $\beta_n(t)$ are the sensitivities of the consumption to the weather
102 predictors. They can be a function of time.

103 In the following, we consider different models with 1 or 3 daily weather predictors, namely the CDDs, a relative
104 humidity index, and the mean wind speed. In a 3-predictor configuration, the coefficients $\beta_0(t)$, $\beta_1(t)$ and $\beta_2(t)$ are
105 the temperature-, humidity- and wind-sensitivities of the consumption, expressed in $[W/^\circ\text{C}/\text{capita}]$, $[W\%/ \text{capita}]$
106 and $[W/(\text{m/s})/\text{capita}]$ respectively. In a first approximation, they can be interpreted as an estimate of how much
107 more (or how much less) electricity is required to keep people “comfortable” as air temperatures, relative humidity
108 and/or wind speed change.

109 In the common formulation (e.g. [14]) the base consumption C_0 is modelled as a non-linear function of time to
110 account, when relevant, for the time evolution of the mean daily per-capita consumption; the other coefficients of
111 the model are assumed to be constant. In the more general case, all coefficients can vary over time. Change over
112 time of the β_n coefficients, undertaken in this study, highlights a change in weather sensitivity. Change over time of
113 the γ_l coefficients, although not included here, could show a change in the weekly pattern of the electricity
114 consumption. We here model the low frequency temporal evolution of the base consumption and of the weather
115 sensitivity coefficients using (different) smooth functions that are defined as

$$116 \quad f_k(t) = A_k \cdot g_k(t - t_0) \quad (2)$$

117 with A_k a constant, t_0 a reference date in the period and $g_k(t)$ a polynomial trend model such as $g_k(0)=1$. The constant
118 A_k is then the value of the considered coefficient (weather sensitivity or type-of-day dependent factor) for the
119 reference date t_0 . When a same reference date t_0 is used for different cities, this makes the values A_k obtained for
120 C_0 and for the k^{th} predictor comparable between the different locations considered.

121 As shown later, the sensitivity to weather coefficients tends to be higher when the base consumption C_0 is higher.
122 To normalize the comparison across locations, we will also discuss the percentage increase in daily electricity
123 consumption per degree of temperature rise (DTR). It corresponds to the β_0/C_0 ratio expressed in percentage of the
124 base consumption C_0 per DTR. This relative thermal sensitivity is often used for operational purposes to
125 characterize the response of electricity systems to temperature changes (e.g.[7]). We also define the humidity-to-

126 temperature sensitivity ratio (β_1/β_0), which corresponds to the ratio (in percent) between the consumption increase
127 induced by a 10% of relative humidity rise and the consumption increase induced by a 1°C temperature rise. This
128 enables the comparison among different locations and the comparison with the thermal sensitivity, which has never
129 been done so far.

130 **2.2 Weather predictors**

131 Different weather predictors can be considered in the model (equation 1). In the present work, we consider surface
132 wind speed, relative humidity and CDDs.

133 For wind speed $W(t)$, we use the mean daily value as predictor. For relative humidity, following Guan et al. [22], we
134 use a relative humidity index $IR(t)$ defined as the positive deviation of the relative humidity from a fixed threshold
135 R_0 :

$$136 \quad IR(t) = \max [R(t) - R_0, 0]. \quad (3)$$

137 The CDDs for a given day is typically defined with the positive deviations of the daily air temperature from a constant
138 threshold temperature T_0 . Following Scapin et al. [14], CDDs for a given day t is estimated with the positive
139 difference between $T_{eff}(t)$, a so-called effective temperature estimated for that day t and the threshold temperature
140 T_0 .

$$141 \quad CDD(t) = \max [T_{eff}(t) - T_0, 0], \quad (4)$$

142 where $T_{eff}(t)$ is defined as a weighted average of the effective temperature of the previous day $T_{eff}(t-1)$ and the air
143 temperature of the current day $T(t)$. The temporal evolution of the effective temperature follows the fluctuations of
144 the air temperature, although with smoother variations. This formulation allows accounting for the potential lag
145 between weather and consumption due to the building thermal inertia and to the temporal adaptation of individuals
146 to weather variations [1,14]. $T_{eff}(t)$ can be expressed as:

$$147 \quad T_{eff}(t) = \delta \cdot T_{eff}(t-1) + (1 - \delta) \cdot T(t), \quad (5)$$

148 where δ is expressed as $\delta = \exp(-dt/K)$ with $dt = 1$ day and K a time constant (in days) traducing the temporal inertia
149 of the system. The larger the inertia constant, the larger the memory of the system and the smoother the temporal

150 variations of the resulting effective temperature. The inertia constant K is expected to be larger for areas where
151 buildings have larger thermal inertia obtained for instance from improved insulation.

152 **2.3 Model Estimation**

153 The model requires the estimation of different parameters. K , the inertia parameter used to calculate the effective
154 temperature and the different thresholds used to calculate the weather-related predictors (i.e. T_0 for CDDs or R_0 for
155 humidity), can be optimized for each location, thanks to ad-hoc sensitivity analyses. The other parameters (i.e., C_0 ,
156 γ_i and β_n) are obtained via least square optimization of deviations between predicted and observed daily
157 consumptions.

158 **2.4 Experimental setup**

159 To shed light on the influence from each predictor and modelling assumption, we compare different model versions.
160 Our reference model (model A) is a model where predictors are CDD (estimated from effective temperatures), wind
161 speed and relative humidity; and where weather sensitivity coefficients are modelled as a function of time. Weather
162 sensitivities are kept constant over the period in model B. In models C and D, only CDD is used as predictor (with
163 respectively time varying or constant thermal sensitivity).

164 For all models, the base consumption C_0 is modelled as a function of time. For the sake of robustness, a 2nd order
165 polynomial is considered for C_0 and, when a time dependency is considered for the weather sensitivities, a linear
166 trend is used. If for a given location only two years of consumption data are available, a linear trend is also set for
167 C_0 . If only one year of data is available, the coefficients are kept constant for all predictors (the trend model $g(t)$ is
168 a constant).

169 **3 Cities and data**

170 **3.1 Cities**

171 We consider large cities from twelve countries in West and Central Africa. They are located within contrasted
172 climatic zones: 1) oceanic (Mindelo and Dakar); 2) Sahelian (Bamako, Ouagadougou, Niamey and Kano); 3)

173 tropical humid (Abidjan, Accra, Cotonou, Lomé, Yaoundé, Libreville). The three corresponding climate regimes are
174 illustrated with the annual cycles of air temperature, air humidity and wind for Dakar, Ouagadougou and Abidjan in
175 Figure 1. They are largely determined by the West African Monsoon [24,25] which provides humid air masses and
176 drives the rainy season and the highly seasonal patterns of most weather variables in the region.

177 The twelve cities are amongst the largest cities in the region. Their 2014 population varies from roughly 800,000
178 inhabitants for Libreville (Gabon) and Cotonou (Benin) to almost 4.5 million for Abidjan (Cote d'Ivoire) (see Table
179 A1, Appendix). As many other cities in the region, they are developing rapidly. Their economic growth was around
180 4.2% in 2015 [16]; their urbanization rate increased between 0.7 % to 2.7 % per year from 2000 to 2015 and their
181 national gross domestic product between 9.2 % and 2.1% in 2015 [16]. The consumption in most cities has
182 increased significantly the past decades as a result of population growth and also from the increase of the per-
183 capita consumption that is not stationary, except for a very few cases (e.g., Dakar). This increase applies for both
184 the mean consumption and its intra-annual variability. This is for instance illustrated with the increasing seasonal
185 amplitude for Ouagadougou in Figure 2. The general features of the per-capita consumption temporal pattern (long
186 term trend, seasonality, sub-daily variability) are presented for all cities in the Supplementary Material (SM) (Section
187 2 & Figure SM5 to SM8).

188 3.2 Weather data

189 The meteorological gage network in the region is sparse, and operating gages are not always nearby the locations
190 of interest or they neither monitor the required weather parameters nor cover the period for which consumption
191 data are available. Consequently, the weather time series (2000-2019) required for the analysis were extracted for
192 each location from the 0.25° resolution ERA5 meteorological reanalyses [26].

193 Weather predictors considered are the daily mean temperature, T in [°C], the daily relative humidity of the air, R in
194 [%], and the speed of wind, W in m/s at 2-meter elevation. $R(t)$ was estimated from the air temperature and dew
195 point temperature T_d with the Magnus formulae [27,28].

$$196 \quad R(t) = 100 \cdot \exp\left(m \cdot \left(\frac{T_d(t)}{T_d(t) + T_1} + \frac{T(t)}{T(t) + T_1}\right)\right) \quad (6)$$

197 Where $m = 17.27$, $T_1 = 237.7^\circ\text{C}$, are constant and $T(t)$ and $T_d(t)$ are in $^\circ\text{C}$. A summary description of the climatology
198 of the considered weather predictors is given for all locations in the SM (Figure SM2 to SM4 and Table SM1).

199 3.3 Population

200 The temporal evolution of the population is required to estimate the per-capita consumption for each day of the
201 studied periods. It was estimated for each city based on available census data for census years (Table SM1) in or
202 near the period, assuming a constant growth rate r between two consecutive census years. The population
203 estimated for year y , $P(y)$, reads:

$$204 \quad P(y) = P(y_1) \cdot [1 + r]^{(y - y_1)} \quad \text{with} \quad r = [P(y_2)/P(y_1)]^{(1/(y_2 - y_1))} - 1, \quad (7)$$

205 where $P(y_1)$ and $P(y_2)$ are the population estimates available for the two consecutive census years y_1 and y_2 .

206 3.4 Electricity load

207 Load data were obtained from the online database of Waite et al. [8] or collected from National Electricity Distribution
208 Companies of each country (Table A1 & A2, Appendix). Hourly load data were available for Libreville, Yaoundé,
209 Lomé, Accra, Dakar and Mindelo. For all the other cities, hourly loads were estimated from country-level hourly
210 loads and monthly ratios of peak consumption at city-level feeders compared to peak consumption for the national
211 grid as a whole. Measured/estimated hourly data were then processed to produce, for each city, time series of daily
212 per-capita consumption. A comprehensive description of collected load data is given in SM (Table SM2 & SM3).

213 As a result of different practices of the national electricity companies, consumption data can be quite variable in
214 terms of definition, quality and integrity. Possible limitations of the analysis due to data are discussed in SM (Section
215 3). For some cities, some discontinuities / breaks are observed in the per-capita consumption trend (not shown).
216 Different social and economic factors can often be identified for these configurations. Such breaks are not modelled
217 in this work and we extracted for each city a subperiod for which the time evolution in the per-capita consumption
218 is relatively smooth and progressive (pseudo-stationary). Depending on the city, the subperiods retained for the
219 analysis cover 1 to 10 years (Table SM3).

220 4 Results

221 We first describe the model coefficients and the model prediction skill obtained for each city. We then show how
222 the weather sensitivities vary within the region and how they evolved over the recent years. The model prediction
223 skill is estimated with the Explained Variance (EV), i.e. the proportion (in %) of total variance in the data explained
224 by the model. The EV for a perfect model is equal to 100%.

225 To ease the comparisons, the same values of K , T_0 and R_0 and/or H_0 are used for all cities ($K = 1.5$ days, $T_0 = 22^\circ\text{C}$,
226 $H_0 = 22^\circ\text{C}$, $R_0 = 50\%$). These values have been found to be regionally optimal and, whatever the location, they only
227 lead to non-significant loss in prediction skill when compared to predictions obtained from locally-optimal
228 parameters. The threshold temperature also matches with the one used in a number of similar works worldwide
229 (see, e.g., [8,19,20]). The low value obtained for the temporal inertia coefficient K may be due to the “leaky”
230 envelopes of buildings in the region, which are sometimes intentionally designed to accommodate natural
231 ventilation [8].

232 4.1 Explained variance

233 Except for Abuja and Accra, the EV of the model for the daily per-capita consumption is high to very high (Evd1 in
234 *Table 1*). It ranges from 57/59% for Mindelo/Cotonou, 72.1% for Yaoundé to around 85% for Dakar, Libreville, Lomé
235 and even more for Bamako, Ouagadougou, Niamey, Abidjan. It is 2 to 10 percentage points (pp) higher when the
236 city-scale consumption is considered (Evd2 in *Table 1*) and even much larger when daily predictions aggregated
237 to monthly values are compared to monthly observations (Evm1 and Evm2 in *Table 1*). For most cities, the model
238 reproduces very well the observed seasonal and day-to-day variations (Figure SM12).

239 Except for Abuja, the cumulated contribution of the three weather predictors to daily EV for the daily per-capita
240 consumption prediction is always greater than 24 pp (Σw in *Table 1*). It is larger than 50 pp for half of cities and
241 especially high for Dakar and the Sahelian cities where it is up to 70 pp. Most of the contribution is obtained from
242 CDDs (EVT in *Table 1*) but the contribution of relative humidity (EVH in *Table 1*) is not negligible. Including humidity
243 in the model increases the EV by 2 pp on average, and up to 4.3, 4.9, 5.9 and 6.8 pp in Abidjan, Niamey, Bamako
244 and Dakar respectively. This contribution is rather remarkable for cities like Abidjan, or Cotonou where the variability

245 of humidity is rather small all along the year. Except for Cotonou and Dakar where it is 1.3 and 1.5 pp respectively,
246 the contribution of wind is conversely negligible.

247 In many cities, the type-of-day is also an important explanatory factor. Its contribution to total daily variance ranges
248 from 10-15 pp in Dakar, Bamako, Ouagadougou, Abidjan, Accra, Cotonou to 23, 31, 33 and even 43 pp in Libreville,
249 Yaoundé, Mindelo and Lomé respectively (see EVD in Table 1). The latter high values are obviously to be related
250 to the large working day / non-working day contrasts highlighted in the weekly profiles of those cities (See Type-
251 Of-Day coefficients in Table 2 and Figure SM5). As illustrated in the sub-daily consumption profiles of Figure SM7,
252 the large decrease observed on Saturdays and then Sundays/Holidays is mostly due to a reduced consumption
253 during the business hours.

254 **4.2 Base consumption and weather sensitivities**

255 The base Monday per-capita consumption C_0 varies by a factor 6 from one city to the other (Table 2, Figure 3a).
256 The highest values are observed for Libreville/Yaoundé and Cotonou (resp. 181, 158 and 135 W/cap.) followed by
257 Mindelo, Dakar and Abidjan (resp. 98, 95 and 62 W/cap.). It is between 30-40 W/cap. for Bamako, Ouagadougou,
258 Niamey, Accra and Lomé and drops to 6 W/cap. for Abuja.

259 The sensitivity coefficient to wind is significant in a few cities only, namely Dakar, Bamako, Ouagadougou, Abidjan,
260 and to a lesser extent in Yaoundé. For Dakar, the only city where both the significance is high and the contribution
261 of wind to explained variance is greater than 1 pp, the sensitivity to wind is negative, which was expected, due to
262 the cooling effect that wind is known to bring during hot periods [1]. Because of its low impact on consumption in
263 almost all locations, wind will be mostly disregarded in the following.

264 Conversely to wind, the significance of the sensitivity coefficients to CDDs and to air humidity is very high for all
265 cities (with the exception of that for humidity in Abuja). For both variables, the sensitivities vary a lot from one city
266 to another. For temperature, it varies from 0.2-0.4 W/°C/cap. for Abuja/Accra to 1.5-3 for Mindelo, Sahelian cities
267 and Lomé and from 4-5 for Dakar/Yaoundé to 8-13 W/°C/cap. for Abidjan/Cotonou and Libreville.

268 The sensitivity to humidity is expected to be positive as, for high temperatures, the thermal discomfort is expected
269 to increase when humidity increases. This is the case for most cities considered here, with the exception of

270 Ouagadougou, Accra and Yaoundé (this point is further discussed in SM-Section 3). For the cities where the
271 contribution of humidity to explained variance is greater than 2% points and with the exception of Yaoundé, the
272 sensitivity varies between 0.15-0.35W%/cap. in the oceanic / Sahelian cities (Mindelo, Dakar, Bamako, Niamey)
273 to 0.6-0.7W%/cap in the tropical ones Abidjan-Cotonou.

274 The type-of-day induced variations of the consumption are small when compared to those induced by weather. In
275 the Sahelian cities for instance, the 8°C increase observed on average between the cold and warm seasons
276 induces a 50 to 60% increase of the consumption. The 60% increase of relative humidity observed between the
277 dry and wet seasons induces a 20 to 40% increase in Bamako and Niamey. For comparison, the consumption,
278 roughly the same for the different working days, is 2 to 13% lower for Saturdays and 4% to 22% lower for Sundays
279 and public holidays.

280 **4.3 Relative thermal sensitivity and humidity-to-temperature sensitivity ratio**

281 As described above and summarized in *Figure 3b-d*, the thermal sensitivities have often higher values in the coastal
282 cities of the tropical region than in Sahelian ones. The relative thermal sensitivity (percentage increase of base
283 consumption per DTR) does not vary as much (*Table 3* and *Figure 4a*). Each additional degree of temperature
284 produces a 3-4% increase of the base consumption in the oceanic climate cities, 6-8% in most Sahelian and tropical
285 cities (the lowest / highest values, 1% - 11%, being for Accra/Abidjan respectively). The regional variations are thus
286 significantly smaller than those of the raw thermal sensitivity (i.e., the coefficient of variation (CV) between cities is
287 82% for β_0 , it drops to 56% for β_0/C_0).

288 Similarly, the humidity-to-temperature sensitivity ratio varies much less across locations than the raw sensitivity to
289 humidity (the CV is 51% for β_1/β_0 ; 86% for β_1) (*Figure 4b*). The β_1/β_0 ratio even tends to be the same for a number
290 of locations suggesting some proportionality between both sensitivity coefficients at regional scale. Finally, we found
291 that the percentage per-capita consumption increase induced by a 10% increase in air humidity roughly
292 corresponds to 70% of the percentage consumption increase induced by a 1°C increase of temperature (30 to 90%
293 depending on the city).

294 **4.4 Contribution of cooling to electricity consumption**

295 The prediction model allows estimating the percentage contribution of cooling to electricity consumption over any
296 time period (e.g. a given day, year....) (e.g. Waite et al. [8]). According to model A (Table SM4), the percentage
297 cooling contribution of temperature to the mean annual consumption is rather low in oceanic cities and in Yaoundé,
298 Accra (smaller than 10%) but conversely rather large for all other cities, being often greater than 25% (up to 31-
299 37% in Bamako and Niamey). The cooling contribution of temperature to the consumption varies in time. For days
300 where the maximum daily consumption has been observed, the estimated contribution of cooling is a few
301 percentage points higher than the contribution mentioned above. Except for oceanic cities, Yaoundé, Accra where
302 it is weaker and around 5%-15%, it is far from negligible, from 20-30% for Cotonou, Libreville, 30-35% for
303 Ouagadougou, Abidjan, Lomé and up to 43% for Bamako and Niamey.

304 **5 Discussion**

305 **5.1 Trends in weather sensitivities**

306 An important factor of the daily per-capita consumption variability is its non-stationarity and long-term trend. In
307 model A, the weather sensitivities and the base consumption can have different (positive) trends. The contribution
308 to explained variance given by the trend on the base consumption (EVC0 column in *Table 1*) is low to very low in
309 Dakar, Yaoundé and Lomé (0.8, 0.5 and 2.9 pp), but significant in Libreville (5.2), Bamako (8.3), Cotonou (11.2) to
310 large in Ouagadougou (18), Niamey (21.7) and Abidjan (27.7). The contribution to explained variance given by the
311 trend on weather sensitivity coefficients is much less in comparison (0.5 pp in average) but it is up to 1 - 2.6 pp in
312 Bamako / Cotonou / Niamey (see difference of EVd1 between model A and model B where only a trend on the
313 base consumption is accounted for; *Table 3*). It is also worth noting that for all cities but Cotonou, the relative trends
314 in weather sensitivities are higher than the ones of the base per-capita consumption (Figure SM9-11). For instance,
315 the relative thermal sensitivity β_0/C_0 is actually almost doubling over the considered period in Niamey (8 years) and
316 Yaoundé (5 years).

317 The sensitivity of the electricity consumption to weather is commonly estimated using a change point regression
318 model where the consumption is considered to be the sum of a base consumption and of different factors related
319 to weather or other explanatory variables such as the type-of-day. In this approach, if the long-term drift of the
320 consumption is often accounted for (e.g., with a trend function modeling the base consumption C_0 as a smooth
321 function of time or GDP), the sensitivities to weather are typically assumed constant over time (e.g. [14,18,29]). As
322 shown here, this is definitively not the case for West African cities. In the general case, it is also likely that this
323 assumption does not hold. The economic growth that drives the trend in base consumption is for instance expected
324 to come together with an increase in air conditioning equipment in both private and public buildings (e.g. [8] for
325 India and other cities worldwide). The sensitivity to weather is also expected to increase as a result of climate
326 warming, degradation in indoor comfort conditions, and, in turn, new acquisition and increased use of cooling
327 systems (e.g. [30] for Spain, [14] for Italy). Despite, the increasing sensitivity of electricity consumption to weather
328 has been disregarded in prediction models until now. An exception is of the work by Akara et al. [16] (the authors
329 assume that all factors (the base consumption, weather sensitivities, type-of-day factors) follow a same trend, which
330 seems to be a reasonable assumption at first). Our results confirm that trends in weather sensitivity can be non-
331 negligible and should be accounted for in such cases. They further show that a non-stationary change point
332 regression model should be considered where each coefficient has its own trend model to account for potentially
333 different temporal dynamics in the drivers of changes (cf. illustration Figure 5).

334 Detrending the consumption data in a preliminary pre-processing step has been sometimes carried out so that the
335 analysis can be produced with stationary data. Note however that with the ongoing change in regional climates
336 worldwide, part of this long-term increase could also result from changes in climate conditions (e.g. regional
337 warming increases CDDs). In such a configuration, detrending the data before the analysis is likely to produce
338 erroneous results and interpretations. The periods considered in the present work (for which no significant changes
339 in weather conditions has been detected, not shown) make such an influence likely small. Nonetheless, the
340 formulation retained for the model considered here does not require any preliminary detrending and would thus
341 allow to disentangle the effects of changes in climate conditions from those of socio-economic factors.

342 **5.2 Comparison with other studies**

343 The thermal sensitivity of the electricity consumption was found to vary significantly depending on local climate
344 conditions and the socio-economic context of the considered area. In a similar comparative work, Waite et al. [8]
345 considered the cooling responses of hourly electricity consumption from 17 cities in South Asia, the Middle East
346 and Africa (non-OECD), and those from 18 mature urban economies in the United States and Japan (OECD). The
347 per-capita cooling electricity responses were found to range from 0 to 13 W/°C/capita in non-OECD countries
348 compared to 15 to 151 W/°C/capita in the OECD case. Our results are obviously in line, with thermal sensitivity
349 from 0.2-0.4 W/°C/cap. for Abuja/Accra, 2-5 for oceanic, Sahelian cities and Yaoundé to 8-13 W/°C/cap. for Abidjan,
350 Cotonou and Libreville. The deviations between the weather sensitivities from non-OECD and OECD countries (10
351 to 20 times larger) confirm the strong potential for a significant increase in weather sensitivities in West Africa in
352 coming years.

353 In a review of fifteen studies, Santamouris et al. [7] assessed the relative thermal sensitivity across various regions,
354 mostly comprised of OECD countries, and found values ranging from 0.5% and 8.5%; the highest values being
355 reported from United States because of the high penetration of air conditioning. In our work, it ranges from 1% for
356 Accra to 12% in Abidjan. The contrast between results obtained for West Africa cities and cities considered in
357 Santamouris et al. [7] is thus much less than the one mentioned previously for the raw thermal sensitivity by Waite
358 et al. [9].

359 To our knowledge, the sensitivity of the electricity consumption to the weather variables other than temperature has
360 poorly been assessed. For cities located in the Sahelian region or near the ocean, we found that an increase in
361 relative per-capita consumption induced by a 10% increase in humidity, roughly corresponds to 70% of the increase
362 induced by a 1°C increase of temperature (30 to 90% depending on the city). This humidity-to-temperature
363 sensitivity ratio is remarkably similar to the one that can be estimated from the results obtained by Bonkaney [29]
364 for Niamey and three other smaller cities in Niger (70 to 90% for Zinder, Maradi, Agadez). This characterization
365 would obviously be worth investigating in other regions worldwide.

366 The increasing sensitivity to weather for cooling over time was highlighted in a number of previous works, although
367 rarely quantified [14,18,31,32]. A comparison of our results with other studies is thus rather difficult. However, the

368 pace of the changes is sometimes mentioned. For instance, during the 1990-2013 interval, the relative thermal
369 sensitivity of the Italian electricity consumption increased by a factor 3 [14]. In West African cities, the rate of change
370 is similar in most cases, if not higher: in a number of cases, thermal sensitivity has doubled within a 4- to 7-year
371 window. Our modelling framework assumes that changes are progressive but they can of course be abrupt as a
372 result of specific triggering weather sequences. In Italy for instance, the sensitivity increased sharply in the 2003-
373 2005 period, likely a consequence of the heat wave that took place in Europe during the 2003 summer and caused
374 a strong increase in the spread of air conditioning systems in the residential sector [14]. A careful monitoring of the
375 evolution of consumption patterns in the coming years will be especially valuable to better understand and anticipate
376 the dynamics of change in West Africa.

377 6 Conclusion

378 This research gives an unprecedented description of the recent trend in per-capita electricity consumption across
379 twelve West and Central African cities. The trend is explicitly split into two components: the base consumption with
380 its variations based on the day of the week, and a weather sensitive component, which determines the day-to-day
381 variability based on several weather predictors (temperature, humidity and wind speed). The results align with the
382 already identified relationship between weather and electricity consumption: day-to-day and seasonal variations in
383 daily per-capita consumption are mainly due weather variability at these time scales. Temperature is by far the
384 main driver of variability in all investigated cities, explaining from 25% to 70% of the daily consumption variability.
385 Except for the oceanic city Mindelo and for Yaoundé/Accra, the contribution of the weather sensitive component to
386 total consumption is greater than 20% at the annual scale, and is even larger for daily consumption maxima.
387 Besides temperature, air humidity is shown to be an important factor, mostly in Sahelian cities where its seasonality
388 is large. The increase in explained variance when including humidity (and wind in Dakar) in the prediction model is
389 significant.

390 The weather sensitivities are significantly lower than those in OECD countries (but the relative weather sensitivities
391 much less). For the cities considered here, however, they all highlight significant change over time, which could
392 likely reduce this gap in the next years/decades. The different factors of variability present their own trends, and
393 they should ideally be accounted for separately in a non-stationary prediction model.

394 The results obtained for some cities suggest that the data quality issue is a potentially critical issue for such analysis
395 (Section 3 in SM). Both local consumption and weather data may not be available at the city scale. Proxies can be
396 obtained from country scale consumption data and from meteorological reanalyses data but they may be rather
397 poor estimates of their true local counterparts. Nevertheless, such proxies allow a first estimate of all coefficients
398 required for a prediction model, especially weather sensitivities and type-of-day factors.

399 Our results provide a better understanding of how the electricity consumption in major African cities depends on
400 current weather conditions (air temperature and humidity) and also how it varies across the region due to regional
401 climate variations. For most cities, a non-stationary prediction model allows to have a good prediction of the
402 multiscale variations of the consumption (from day-to-day to seasonal variations). This turns to be promising for the
403 various actors in the energy sector in West and Central Africa, including energy producers, national electricity
404 companies and eventually the West African Power Pool that aims to improve electricity balancing at the regional
405 scale. On the one hand, the possibility to easily forecast temperature and humidity variations a few days ahead in
406 the region could improve electricity consumption forecasts and in turn improve the grid management. On the other
407 hand, our results can be also used to develop future projections of the electricity consumption patterns and
408 variability in the region, from ad-hoc climate, demographic and urbanization projections (e.g. [2,33,34]).

409 The methodology and the non-stationary prediction model developed here can be applied to other regions
410 worldwide, in emerging countries especially where significant trends in consumption patterns are typically observed,
411 and to other systems. For the West and Central Africa region, the application to larger administrative areas but also
412 smaller cities would be definitively useful for local energy actors. It would be also worth investigating the possibility
413 to improve the model prediction accuracy by modelling the consumption at higher temporal (e.g., hourly) and spatial
414 resolution (e.g., district) or by estimating the likely different cooling responses of the different types of sectors of
415 the considered city (residential, administrative, industrial, ...).

416

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419 presentations and discussion): G.K.A. Data collection, data quality check, database elaboration: G.K.A. Software

420 development, formal analysis, writing - original draft preparation: G.K.A., B.H. Review and editing: G.K.A., B.H.,
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511

8 Figures

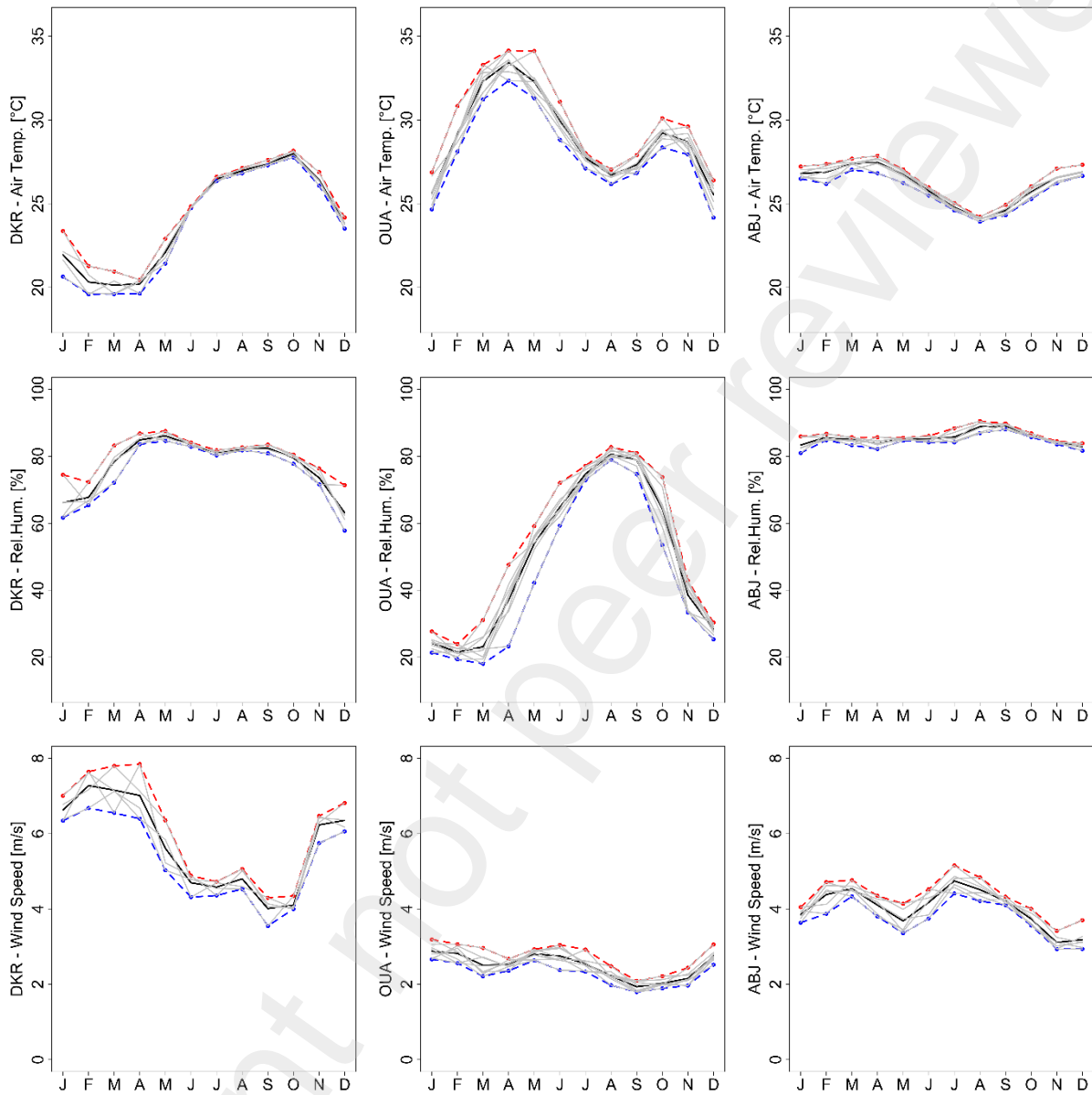


Figure 1: Mean annual cycle of monthly temperature [T_m - $^{\circ}\text{C}$] (1st row); air relative humidity [RH-%] (2nd row) and wind speed [Ws-m/s] (3rd row) for Dakar (left), Ouagadougou (middle) and Abidjan (right) for 2011-2014, 2010-2017, 2012 -2017 resp. Mean value in black. One grey line for each year of the period. Blue / red: minimum / maximum monthly values (other cities in Figures SM2-4)

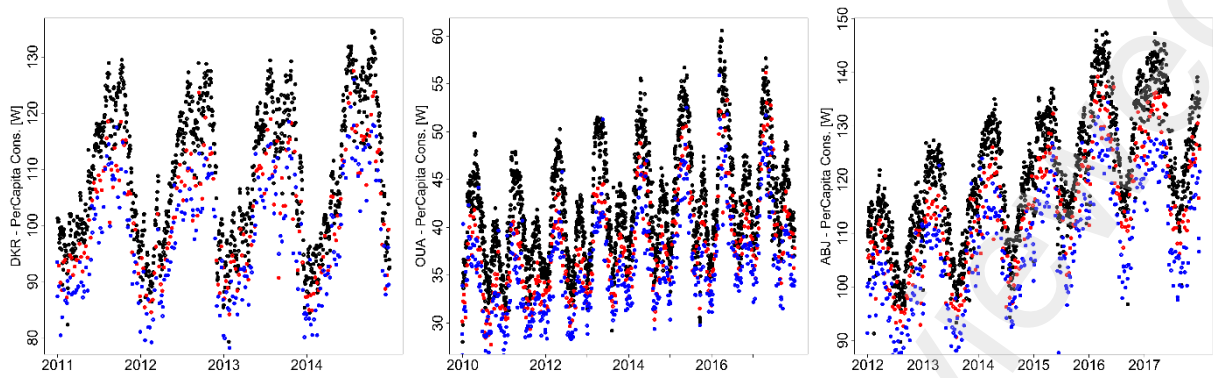


Figure 2: Per-capita daily consumption [W/Capita] for Dakar (left), Ouagadougou (middle) and Abidjan (right). Black/red/blue dots: working days/Saturdays/non-working days (other cities in figure SM6).

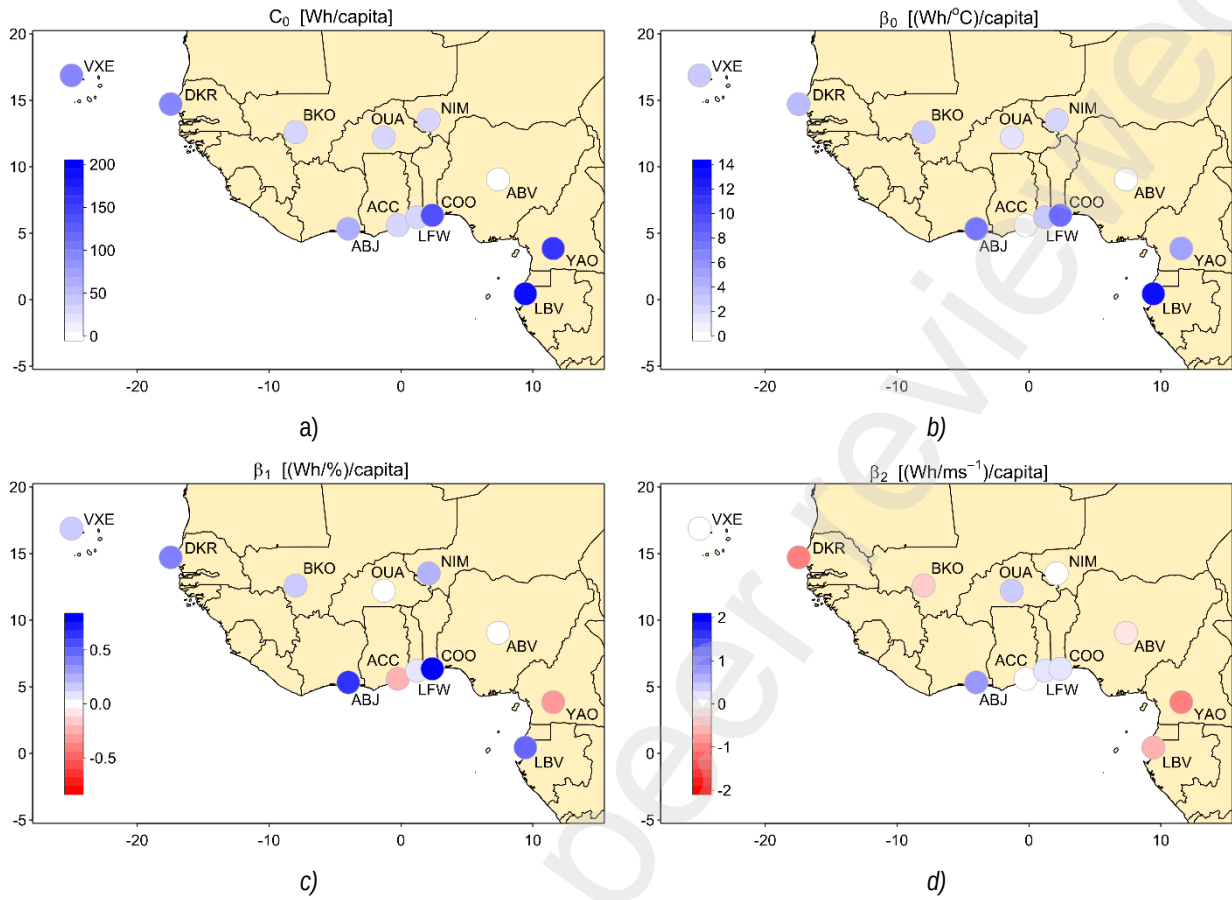


Figure 3: a) Base electricity consumption for a Monday in year 2014 (C_0) and sensitivity factor related to b) temperature (β_0), c) relative humidity (β_1) and d) Wind Speed (β_2). The ID for each city is given in Table 1.

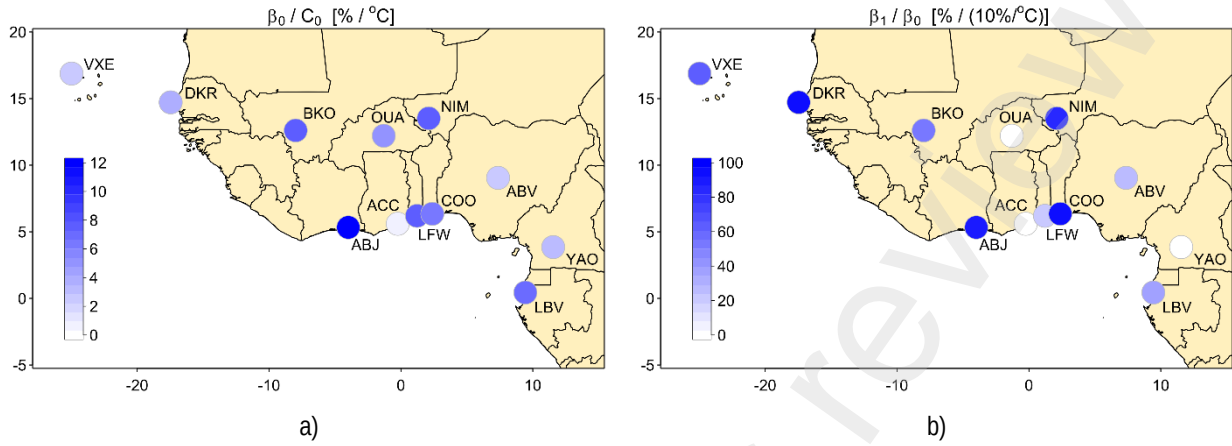


Figure 4: a) Relative temperature sensitivity (β_0/C_0 in [% per degree of temperature rise]): percentage increase of the daily electricity consumption per degree of temperature rise ; b) humidity-to-temperature sensitivity ratio (β_1/β_0 in [%], percentage increase induced by 10% of relative humidity rise expressed in percentage of the percentage increase induced by a 1°C temperature rise; only positive ratio values have been plotted).

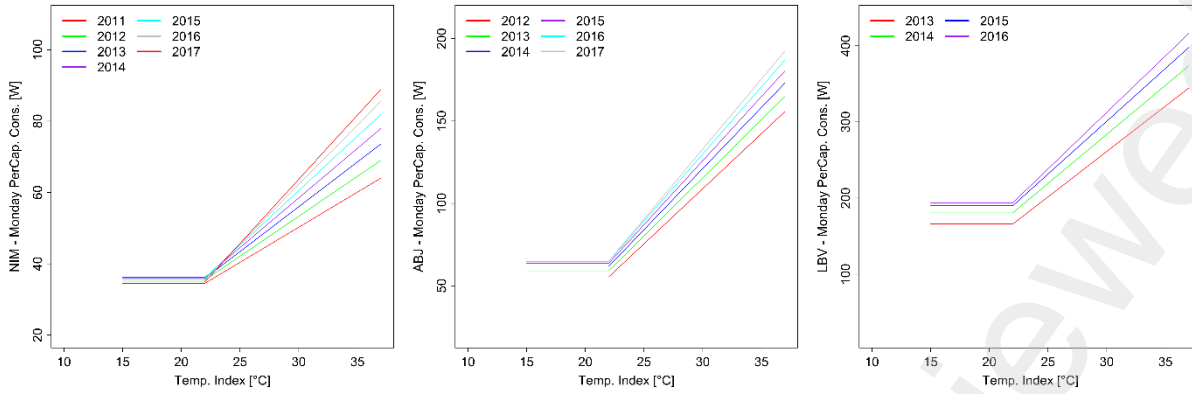


Figure 5 : Thermal component of the non-stationary change point regression model: year-to-year cooling electricity response to temperature change for a Monday (Niamey, Abidjan, Libreville). Relationship derived from the evolution of both the base consumption $C_0(t)$ and the thermal sensitivity $\beta_0(t)$ (other cities in Figure SM12)

9 Tables

Table 1. Model A : Explained Variance (%) for daily (EVd) and monthly (EVm) prediction for the per-capita consumption (EVd1, EVm1) and for the city-scale consumption (EVd2, EVm2). Percentage points (pp) of total variance explained by the time evolution of the base consumption $C_0(t)$ (EVC0); by the type-of-day (EVD) by the temporal variations (daily+trends) of temperature and corresponding CDDs (EVT), relative humidity (EVH) and wind (EVW) and by all weather predictors ($\Sigma w = EVT+EVH+EVW$). Cities are presented by climate regime, from NW to SE locations (cities with a star have only one year of consumption data).

City	ID	EVd1	EVd2	EVm1	EVm2	EVC0	EVD	EVT	EVH	EVW	EVW	Σw
Mindelo*	VXE	56,9	58,1	89,3	90,1	-	33,2	21,9	1,9	0,0	0,0	23,8
Dakar	DKR	84,0	87,0	92,1	93,9	0,8	11,6	63,5	6,8	1,3	1,3	71,6
Bamako	BKO	87,5	93,5	94,2	97,5	8,3	9,4	63,8	5,9	0,1	0,1	69,8
Ouaga	OUA	87,8	95,7	93,4	98,4	18,0	15,9	53,4	0,3	0,1	0,1	53,8
Niamey	NIM	90,6	92,9	96,2	97,2	21,7	3,9	60,0	4,9	0,2	0,2	65,1
Abuja*	ABV	12,4	28,2	-41,9	18,2	-	1,8	10,0	0,2	0,5	0,5	10,7
Abidjan	ABJ	89,1	93,4	95,7	97,8	27,7	15,8	41,1	4,3	0,1	0,1	45,5
Accra*	ACC	39,4	43,7	36,3	42,7	-	13,7	21,8	3,9	0,1	0,1	25,8
Lomé	LFW	85,1	92,6	95,7	98,9	2,9	43,5	38,0	0,7	0,1	0,1	38,8
Cotonou	COO	59,1	59,4	84,9	85,2	11,2	17,8	25,9	2,8	1,5	1,5	30,2
Libreville	LBV	84,7	87,1	93,3	95,0	5,2	23,0	55,8	0,4	0,3	0,3	56,5
Yaoundé	YAO	72,1	86,2	77,6	94,7	0,5	30,7	37,9	2,9	0,1	0,1	40,9

Table 2. Coefficients of Model A : C_0 : base per-capita consumption for a Monday [W/capita], γ_i , $i=0..6$ type-of-day dependent factors [W/capita] (by construction, $\gamma_0=0$); β_0 , β_1 and β_2 : temperature-, humidity- and wind-sensitivities in [W/°C/capita], [W%/capita] and [W/(m/s)/capita]. Coefficients are given for the reference date: $t_0 = 01$ July 2014. Significance of coefficients are indicated with | '***', | '**', | '*', | ' ' for PValue < 0.001, < 0.01, < 0.05, and > 0.05 resp.. β_0/C_0 is the percentage increase of daily consumption per degree of temperature rise in [%/°C]; β_1/β_0 is the humidity-to-temperature sensitivity ratio (see main text for definition, *simplified unit in % here).

	C_0 (base)	β_0 (CDDT)	β_1 (RHum)	β_2 (wind)	γ_1 (Tues.)	γ_2 (Wed)	γ_3 (Thu.)	γ_4 (Fri.)	γ_5 (Sat.)	γ_6 (Holy.)	β_0/C_0	β_1/β_0
	[W/cap.]	[W/°C/cap.]	[W%/cap.]	[W/(m/s)/cap.]	[W/cap.]	[W/cap.]	[W/cap.]	[W/cap.]	[W/cap.]	[W/cap.]	[%/°C]	[%]*
Mindelo*	98 ***	2.9 ***	0.18 ***	-0.006	1.1	1.6	1.7	2.8 **	-3.8 ***	-10.3 ***	3,0	62
Dakar	95 ***	3.8 ***	0.35 ***	-1.04 ***	1.9 ***	2.4 ***	2.1 ***	1.6 **	-5 ***	-9 ***	4,0	92
Bamako	39 ***	2.9 ***	0.14 ***	-0.37 ***	1.0 ***	1 ***	0.86 ***	0.54 *	-4.3 ***	-6.2 ***	7,4	52
Ouaga	30.5 ***	1.6 ***	-0.03 ***	0.46 ***	0.5 **	0.7 ***	0.44 **	0.27	-3.6 ***	-5.4 ***	5,2	-19
Niamey	36 ***	2.8 ***	0.22 ***	-0.03	-0.10	-0.10	-0.30	-1.3 ***	-4.9 ***	-5.8 ***	7,8	79
Abuja*	5.8 ***	0.16 ***	0.00	-0.16	0.06	-0.20	-0.19	-0.11	-0.26	-0.27	3,3	0
Abidjan	62 ***	7.4 ***	0.64 ***	0.74 ***	2.2 ***	2.7 ***	2.3 ***	2.4 ***	-4.6 ***	-10.6 ***	11,9	86
Accra*	38 ***	0.44 ***	-0.24 ***	-0.08	0.29	0.7 *	0.65 *	0.66 *	-0.23	-1.5 ***	1,1	-54
Lomé	37 ***	2.9 ***	0.07 ***	0.14 *	1.6 ***	1.8 ***	1.6 ***	1.4 ***	-4.7 ***	-8 ***	7,8	24
Cotonou	135 ***	8.1 ***	0.73 ***	0.11	1.8	2.0	2.0	2.2	-10.9 ***	-18.8 ***	6,0	90
Libreville	181 ***	12.9 ***	0.46 ***	-0.51 *	2.9 ***	2.8 ***	1.6 *	0.34	-14.3 ***	-23.7 ***	7,1	36
Yaoundé	158 ***	4.9 ***	-0.33 ***	-0.87 **	3.2 ***	4 ***	3.4 ***	3.8 ***	-3.4 ***	-12.7 ***	3,1	-67

Table 3. Explained Variance of Models (Evd)

City	A	B	C	D
Mindelo*	56,9	56,9	55,1	55,1
Dakar	84,0	83,7	76,5	76,3
Bamako	87,5	86,8	82,1	81,4
Ouaga	87,8	86,9	87,0	86,2
Niamey	90,6	88,0	87,3	84,9
Abuja*	12,4	12,4	11,7	11,7
Abidjan	89,1	88,8	86,9	86,8
Accra*	39,4	39,4	34,6	34,6
Lomé	85,1	85,1	84,8	84,8
Cotonou	59,1	57,8	56,2	55,2
Libreville	84,7	84,2	84,5	84,1
Yaoundé	72,1	71,7	69,7	69,3