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

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Abstract

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

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

1 Introduction

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

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

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

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

The weather sensitivity of the electricity consumption remains poorly characterized in many regions across the globe, especially in emerging countries. This work aims to fill this gap and explore the weather sensitivity of the daily electricity consumption for a set of large cities located in West and Central Africa. More especially, it seeks to:

- 1) characterize the climatic and non-climatic factors that determine the day-to-day variations of electricity consumption in those cities;
- 2) estimate the sensitivity of the per-capita consumption to air temperature, air humidity and wind speed and their evolution with time;
- 3) estimate the fraction of the consumption that can be explained by the weather and
- 4) explore how these features compare across cities and vary within the various climate contexts across the region.

To normalize the comparison between locations, we will consider the percentage increase in the consumption per degree of temperature rise (DTR) and introduce the humidity-to-temperature sensitivity ratio.

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

2 Analytical framework

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

2.1 Model of per-capita electricity consumption

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

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

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

Regarding the non-sensitive component, $C_0(t)$ is the base per-capita consumption for a (not holiday) Monday [W/capita]. The term $\sum_{i=0}^6 \gamma_i Y_i(t)$ is used to estimate the base per-capita consumption for the other days from 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 corresponds to the i^{th} type-of-day and $Y_i(t) = 0$ otherwise; $i = 0$ for "Mondays", 1 for "Tuesdays", 2 for "Wednesdays", ... and 6 for the non-working days (i.e., Sundays, religious and public holidays). The coefficients γ_i are the type-of-day dependent factors [W/capita]; they determine the base per-capita consumption for days other than Mondays (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 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 start at $i=1$).

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

In the following, we consider different models with 1 or 3 daily weather predictors, namely the CDDs, a relative 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 the temperature-, humidity- and wind-sensitivities of the consumption, expressed in $[W/^\circ C/capita]$, $[W\%/capita]$ and $[W/(m/s)/capita]$ respectively. In a first approximation, they can be interpreted as an estimate of how much more (or how much less) electricity is required to keep people “comfortable” as air temperatures, relative humidity and/or wind speed change.

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

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

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 A_k is then the value of the considered coefficient (weather sensitivity or type-of-day dependent factor) for the reference date t_0 . When a same reference date t_0 is used for different cities, this makes the values A_k obtained for C_0 and for the k^{th} predictor comparable between the different locations considered.

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

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

2.2 Weather predictors

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

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

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

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

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

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

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

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

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

2.3 Model Estimation

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

2.4 Experimental setup

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

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

3 Cities and data

3.1 Cities

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

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

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

3.2 Weather data

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

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

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

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 of the considered weather predictors is given for all locations in the SM (Figure SM2 to SM4 and Table SM1).

3.3 Population

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

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

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

3.4 Electricity load

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

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

4 Results

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

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

4.1 Explained variance

Except for Abuja and Accra, the EV of the model for the daily per-capita consumption is high to very high (Evd1 in Table 1). It ranges from 57/59% for Mindelo/Cotonou, 72.1% for Yaoundé to around 85% for Dakar, Libreville, Lomé and even more for Bamako, Ouagadougou, Niamey, Abidjan. It is 2 to 10 percentage points (pp) higher when the city-scale consumption is considered (Evd2 in Table 1) and even much larger when daily predictions aggregated to monthly values are compared to monthly observations (EVm1 and EVm2 in Table 1). For most cities, the model reproduces very well the observed seasonal and day-to-day variations (Figure SM12).

Except for Abuja, the cumulated contribution of the three weather predictors to daily EV for the daily per-capita consumption prediction is always greater than 24 pp (Σw in Table 1). It is larger than 50 pp for half of cities and especially high for Dakar and the Sahelian cities where it is up to 70 pp. Most of the contribution is obtained from CDDs (EVT in Table 1) but the contribution of relative humidity (EVH in Table 1) is not negligible. Including humidity 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 and Dakar respectively. This contribution is rather remarkable for cities like Abidjan, or Cotonou where the variability

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

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

4.2 Base consumption and weather sensitivities

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

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

Conversely to wind, the significance of the sensitivity coefficients to CDDs and to air humidity is very high for all cities (with the exception of that for humidity in Abuja). For both variables, the sensitivities vary a lot from one city 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 and Lomé and from 4-5 for Dakar/Yaoundé to 8-13 W/°C/cap. for Abidjan/Cotonou and Libreville.

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

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

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

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

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

Similarly, the humidity-to-temperature sensitivity ratio varies much less across locations than the raw sensitivity to 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 of locations suggesting some proportionality between both sensitivity coefficients at regional scale. Finally, we found that the percentage per-capita consumption increase induced by a 10% increase in air humidity roughly corresponds to 70% of the percentage consumption increase induced by a 1°C increase of temperature (30 to 90% depending on the city).

4.4 Contribution of cooling to electricity consumption

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

5 Discussion

5.1 Trends in weather sensitivities

An important factor of the daily per-capita consumption variability is its non-stationarity and long-term trend. In model A, the weather sensitivities and the base consumption can have different (positive) trends. The contribution to explained variance given by the trend on the base consumption (EVC0 column in Table 1) is low to very low in 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 large in Ouagadougou (18), Niamey (21.7) and Abidjan (27.7). The contribution to explained variance given by the 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 Bamako / Cotonou / Niamey (see difference of EVd1 between model A and model B where only a trend on the base consumption is accounted for; Table 3). It is also worth noting that for all cities but Cotonou, the relative trends in weather sensitivities are higher than the ones of the base per-capita consumption (Figure SM9-11). For instance, the relative thermal sensitivity β_θ/C_0 is actually almost doubling over the considered period in Niamey (8 years) and Yaoundé (5 years).

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

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

5.2 Comparison with other studies

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

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

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

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

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

6 Conclusion

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

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

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

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

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

Author Contributions: conceptualization and methodology: G.K.A, B.H. Contacts and exchanges with national electricity companies and administrative institutions (data inquiry, at site visits and exchange, work progress presentations and discussion): G.K.A. Data collection, data quality check, database elaboration: G.K.A. Software

development, formal analysis, writing - original draft preparation: G.K.A., B.H. Review and editing: G.K.A., B.H., A.D., B.F. Fund acquisition: A.D., B.H.

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Data availability statement : Weather data from ECMWF are freely available from the Copernicus Climate Data Store [26]. Load data were obtained from the database built by Waite et al. [8] and from National Electricity Companies for the other locations. Load data are confidential for most locations. The contact persons from the appropriate organisations in Africa are available upon request.

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8 Figures

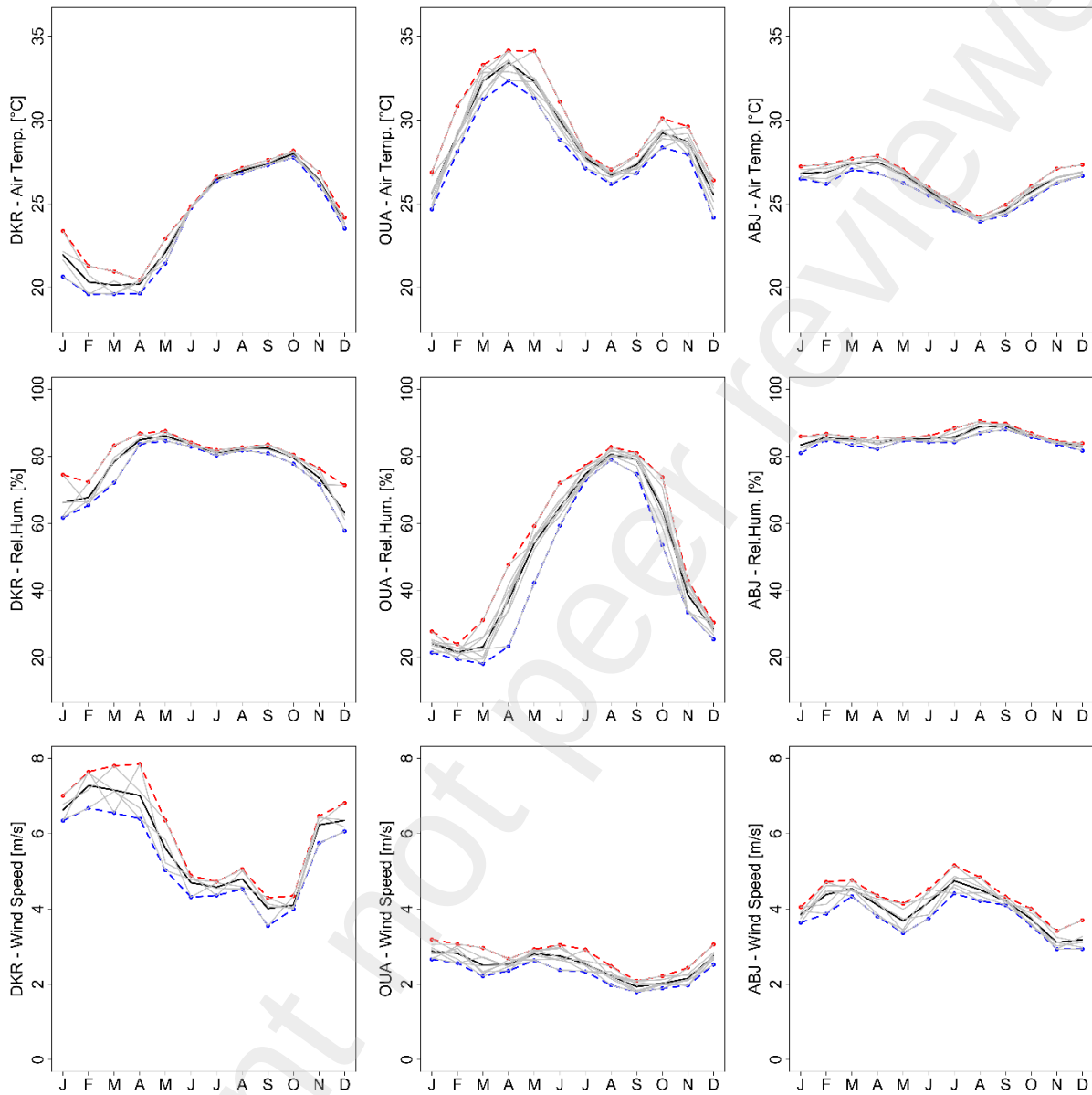


Figure 1: Mean annual cycle of monthly temperature [T_m -°C] (1st row); air relative humidity [RH-%] (2nd row) and wind speed [Ws-m/s] (3rd row) for Dakar (left), Ouagadougou (middle) and Abidjan (right) for 2011-2014, 2010-2017, 2012 -2017 resp. Mean value in black. One grey line for each year of the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

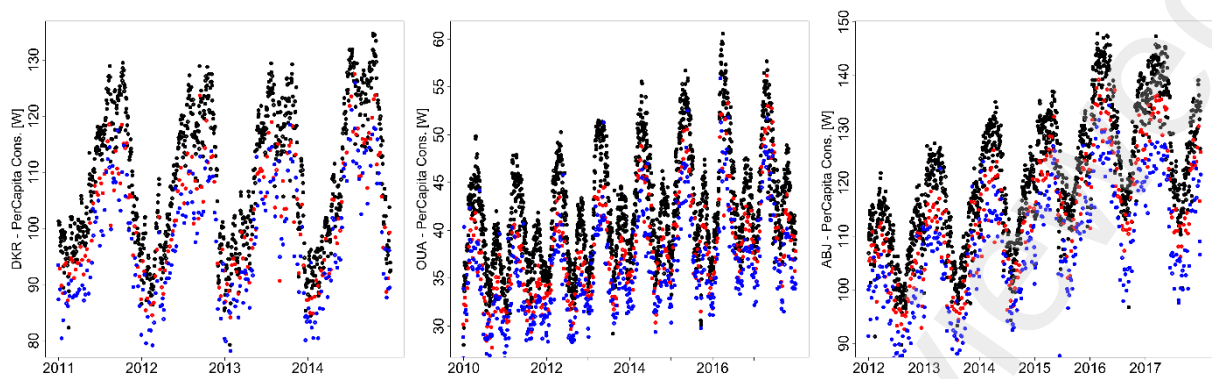


Figure 2: Per-capita daily consumption [W/Capita] for Dakar (left), Ouagadougou (middle) and Abidjan (right). Black/red/blue dots: working days/Saturdays/non-working days (other cities in figure SM6).

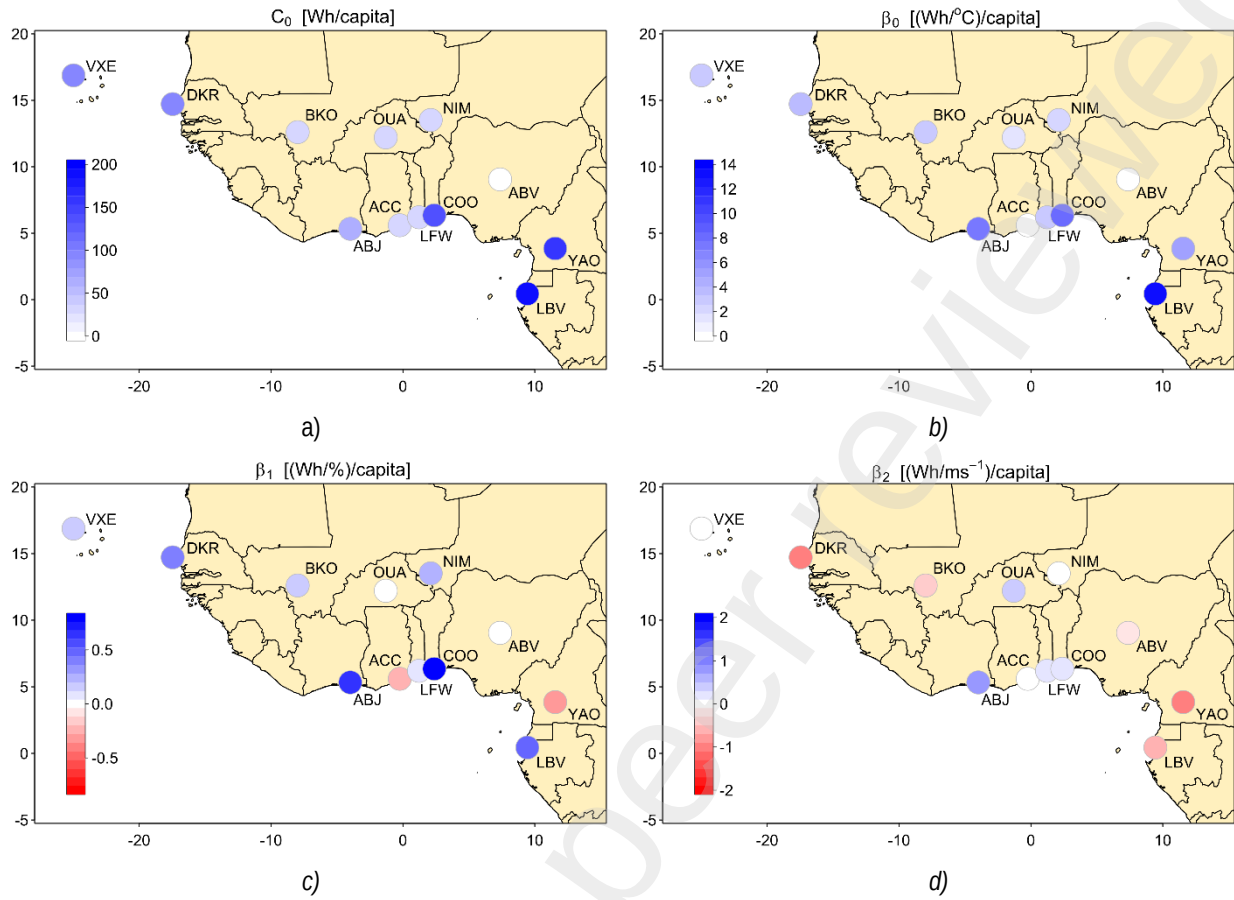


Figure 3: a) Base electricity consumption for a Monday in year 2014 (C_0) and sensitivity factor related to b) temperature (β_0), c) relative humidity (β_1) and d) Wind Speed (β_2). The ID for each city is given in Table 1.

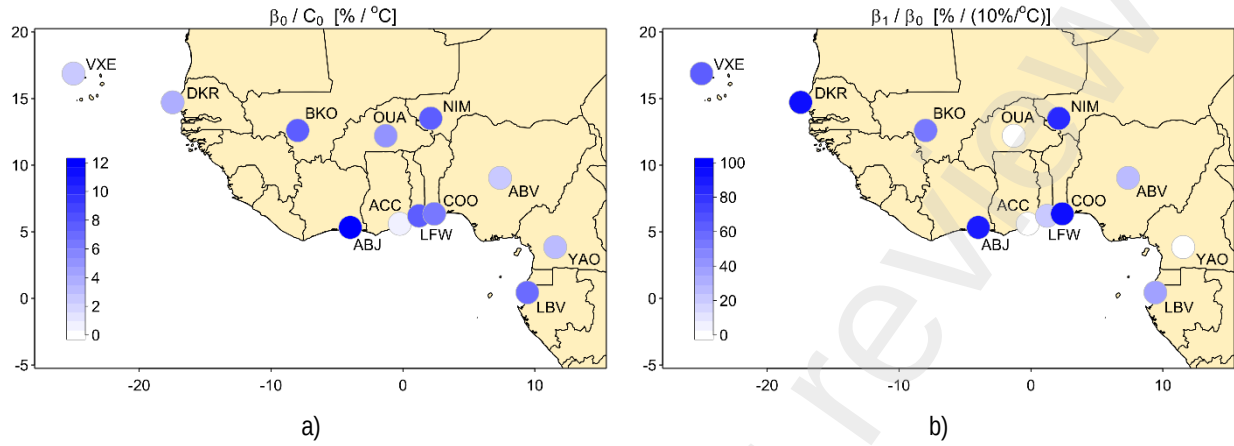


Figure 4: a) Relative temperature sensitivity (β_0/C_0 in [% per degree of temperature rise]): percentage increase of the daily electricity consumption per degree of temperature rise ; b) humidity-to-temperature sensitivity ratio (β_1/β_0 in [%], percentage increase induced by 10% of relative humidity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

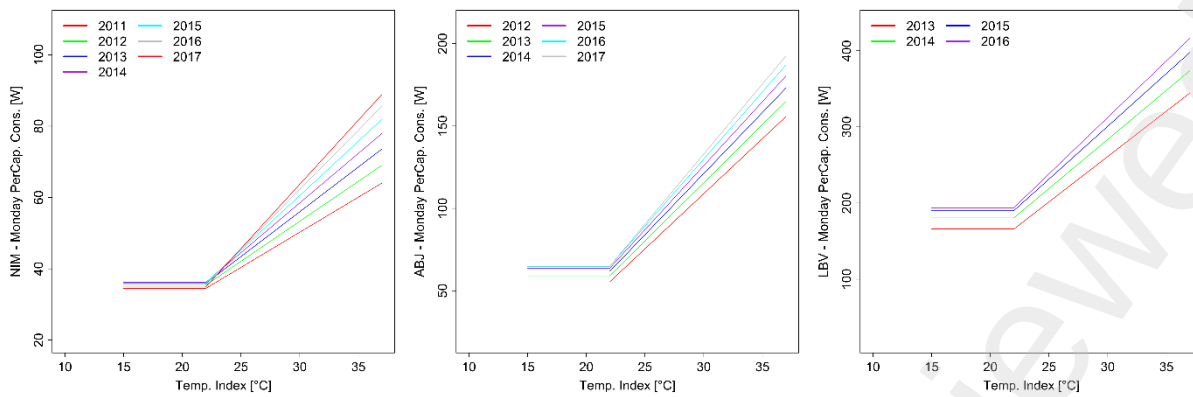


Figure 5 : Thermal component of the non-stationary change point regression model: year-to-year cooling electricity response to temperature change for a Monday (Niamey, Abidjan, Libreville). Relationship derived from the evolution of both the base consumption $C_0(t)$ and the thermal sensitivity $\beta_0(t)$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